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Global Value Chains, the China Trade Shock, and Labor Markets

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Jaerim Choi† — *Yonsei University*
Masahiro Endoh‡ — *Keio University*
Akira Sasahara§ — *Keio University*

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Abstract

This study investigates the effects of imports from China and exports to the rest of the world on labor markets using the data from two major trading partners of China: Japan and the US. An analysis shows that imports of final goods from China and exports to the rest of the world have the same effects on manufacturing employment in the two countries: the former effect is negative, and the latter is positive. In contrast, imported inputs are shown to have different effects on manufacturing employment across the two countries: positive in Japan but negative in the US. We show that these contrasting effects relate to the extent to which these countries integrate into global value chains. In particular, we focus on areas specializing in more downstream sectors in the two countries and uncover that cheaper access to Chinese intermediate inputs allow Japanese input buyers to boost manufacturing employment through input-output linkages. However, the US experienced negative employment effects in those areas, suggesting that the US input buyers do not take advantage of the complementary effects of global value chains, especially with China.

Key Words: The China trade shock, imported inputs, exports, global value chains, manufacturing employment
JEL codes: F14, F16, F66

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†School of Economics, Yonsei University. E-mail: jaerimchoi@yonsei.ac.kr
‡Faculty of Business and Commerce, Keio University. E-mail: endoh@keio.jp
§(Corresponding author) Faculty of Economics, Keio University. E-mail: sasahara@keio.jp

1 Introduction

An increase in imports with China has been shown to influence several aspects of local labor markets adversely, including declining manufacturing employment and higher unemployment rates (e.g., Autor et al., 2013; Pierce and Schott, 2016; and Acemoglu et al., 2016). Additionally, recent studies attempt to understand the mechanisms through which the China trade shock has had such sizable adverse effects on the US economy (e.g., Xu et al., 2023; Eriksson et al., 2021). In contrast, existing studies document that the negative effects of imports from China were limited in the Japanese context (e.g., Taniguchi, 2019; Kainuma and Saito, 2022). Nevertheless, manufacturing employment decreased at almost the same magnitude in the two countries during the 1990s and 2000s. However, employment adjustments reacting to imports from China are shown to be substantially greater in the US than in Japan.

This paper proposes one answer for contrasting responses to imports from China in the two major trading partners of China. We analyze how the cross-country differences in integration patterns to global value chains (hereafter GVCs) shapes labor market effects of international trade. Our analysis suggests that the difference comes from the role of imported inputs affecting manufacturing employment, which is driven by the extent to which these two countries participate in GVCs.

With the rise of GVCs over the past decades, firms in developed countries have taken advantage of global production sharing, especially relying on production tasks conducted in Chinese factories.[1] Despite its potential positive (or job-creating or export-facilitating) effects of GVC aspects of the China trade shock, much less has been explored on this channel. We identify these aspects by separating total imports from China into (i) final goods and (ii) intermediate goods: the former could capture the competing effect; the latter could capture the complementary effect.

Japan, as a comparison to the US, offers an ideal setting to investigate this research question, based on the following two characteristics. First, Japan has not only faced rising import competition from China, but it has also received increasing complementary shocks through intermediate input imports from China. The share of intermediate inputs within total imports from China grew from 30% to 40% during the 2000-2007 period according to the World Input-Output Tables of Timmer et al. (2015) and Woltjer et al. (2021). It shows how Japanese producers have relied on Chinese inputs in their production, thereby increasing the output. Second, a greater share of Japanese firms conduct both international import and export transactions than US firms.[2] This feature indicates that imports of intermediate goods and exports are tightly linked within each Japanese firm and therefore complementary shocks are expected to be observed more clearly in Japan than in the U.S.

We begin by investigating the effects of imports from China and exports to the rest of the world (hereafter ROW) on Japanese and US manufacturing employment. Our baseline analysis is based on commuting zone (hereafter CZ) level data and employs shift-share instruments to identify causal effects. We find that imports reduced employment

[1] Several examples illustrate how firms in developed countries can benefit by sending production tasks to China. For example, an article has documented that China specializes in labor-intensive products, while Japan concentrates on high-tech products (Brooke, 2002). The same article says that Nintendo produces 70% of its GameBoy Advance units in China while keeping other tasks in Japan.

[2] Based on Bernard et al. (2007), in 1997, 11% of all U.S. manufacturing firms engaged in both exporting and importing, the ratio is smaller than the ratios of firms only importing (14%) and only exporting (27%). On the contrary, according to the Basic Survey of Japanese Business Structure and Activities by METI, 15% of all medium-sized and large Japanese manufacturing firms conduct both exporting and importing, the ratio being larger than the ratios of import-only firms (6%) and export-only firms (10%). In 2016, these figures increased to 25%, 8%, and 12%, respectively, revealing that Japanese firms conducting both imports and exports still dominated the other two categories.

while exports had an employment-sustaining effect, confirming the existing studies in the US context (Autor et al., 2013, Feenstra et al., 2019) and providing new insight into the literature in the Japanese context where the effects of exports have been less explored.[3]

The second step of our analysis is to disaggregate import shocks into two components, (i) imported final goods and (ii) imported intermediate inputs. The results show that, although an increase in imported final goods from China had adverse effects on manufacturing employment in both countries, an increase in imported inputs from China had contrasting effects across the two countries. While imported inputs had positive employment effects in Japan, the same type of imports had negative employment effects in the US. The overall quantified effects of imported final goods and intermediate goods in Japan are calculated to be 70 thousand job gains for the 1990-2000s. On the other hand, the same calculation led to 1.82 million job losses in the US.

As the third step, based on our empirical observation suggesting that Japan is more deeply integrated into GVCs than the US, we examine how countries' integration patterns to GVCs affect the employment effects of imports. To do so, we use the 'upstreamness' and 'downstreamness' measures of Miller and Temurshoev (2017), which quantify the complexity and thickness of value chains sellers and buyers of intermediate goods face, respectively. The country-sector level measures of up/downstreamness are converted to the CZ level variables using sector-CZ employment as weights. Then, we estimate the effects of the exposure to trade on manufacturing employment by the level of up/downstreamness to examine how the integration level to GVCs affects the effects of import competition.

We find that, in the US, the adverse effects of imported inputs come from CZs with lower levels of 'upstreamness' or higher levels of 'downstreamness.' It suggests that, when the CZ is specializing in less upstream or more downstream sectors, imported inputs from China reduce manufacturing employment in the CZ greatly. Our conjecture is that, when US manufacturers are in an upstream position, a greater share of imported inputs are used to produce either next-round inputs or final goods, which in turn requires a greater amount of labor. On the other hand, when US manufacturers are in a downstream position with a fewer stages production going forward, imported inputs do not generate employment-creation effects and pro-competitive effects dominate. Results from Japan suggest that up/downstreamness matter less presumably because sectors in Japan are more strongly linked with GVCs, generating employment creation/sustaining effects of imported inputs in almost all manufacturing sectors. Our results are found to be robust to the approach proposed by Borusyak et al. (2022), re-constructing sector level variables to mitigate spacial correlation of exogenous shocks.

This study is related to three different strands of the literature. First, we contribute the literature on the China trade shock. In the US context, Autor et al. (2013), Acemoglu et al. (2016), and many other studies have found a sizable manufacturing job reduction caused by imports from China. Other studies attempt to understand why the adverse effects on US manufacturing employment were so large. For example, Xu et al. (2023) find that the US housing market collapse in the 2000s worked to magnify the effects of the China trade shock. Eriksson et al. (2021) find that the China trade shock hit the US labor markets when the US manufacturing industry was at later stages of the product

[3] Kainuma and Saito (2022) examine the effects of exports to China on manufacturing employment in Japan. In contrast, the current study examines the effect of exports to the ROW. Also, Kainuma and Saito (2022)'s "export growth" variable turns out to be statistically insignificant after controlling for their upstream and downstream variables.

cycle, which was responsible for generating large adverse effects. Our paper adds an additional explanation by arguing that limited employment-creation (or employment-sustaining) effects of imported inputs come from the difference in the countries' integration patterns to GVCs.[4] This paper echoes with Shen and Silva (2018) where they examine the effects of imports from China on US manufacturing employment by considering value-added contents of trade and the positions in GVCs. They find that the adverse effects on US manufacturing employment is greater when imports from China include a greater share of foreign-value added contents.[5]

In the Japanese context, imported inputs from China or the propagation effects of imports from China through the importing country's upstream sectors to downstream sectors have been shown to increase manufacturing employment by Taniguchi (2019), Kainuma and Saito (2022), and Endoh (2023) using region level data, Kiyota et al. (2021) using industry level data, and by Hayakawa et al. (2021) using firm level data.[6] They argue that imported inputs from China help Japanese firms in downstream industries to compete and survive in the domestic market, generating employment. This paper goes one step further from these prior studies by comparing the trade effects in the two countries and examining the sources of different effects.

Second, this paper contributes to the literature on the effects of offshoring on employment because we examine the effects of imported inputs from China, which could be seen as offshoring of tasks to China. In the context of the US economy, previous studies offer varied outcomes. For example, by utilizing variations in offshoring costs caused by bilateral tax treaties, Kovak et al. (2021) find that offshoring in general increased US employment, however, offshoring of sales activities reduced it during the 1987-2007 period. Wright (2014) finds that, using US data during the 2001-2007 period, offshoring reduced low-skilled employment and offshoring to China increased employment of all workers.[7] Other influential studies on the US economy include Harrison and McMillan (2011), Ottaviano et al. (2013), Monarch et al. (2017), and their results depend on certain factors and their strengthness.[8] In the Japanese context, existing studies find that expansion of offshoring had a positive effect on domestic employment (e.g., Yamashita and Fukao, 2010; Ito and Tanaka, 2014; Ando and Kimura, 2015; Kiyota et al., 2022). Overall, previous studies analyzing the effects on the US economy propose mixed results. In contrast, those analyzing the effects on the Japanese economy show positive effects, which are consistent with our findings from the two countries.

[4]Wang et al. (2018) incorporate the upstream and downstream effects of the China trade shock and show that the overall effects on employment are positive. Nevertheless, our paper is not inconsistent with their findings. First, our imported input variables are constructed differently. Their variables measure supply chains across China and the US and inter-sectoral linkages within each CZ. In contrast, our measures are simply imported intermediate inputs from China. Second, Wang et al. (2018) show that downstream effects positively affect non-manufacturing employment, and their effects on manufacturing employment are mostly null. The latter part is consistent with our findings and the former part–the effects on non-manufacturing employment– is not examined in the current study.

[5]Shen and Silva (2018)'s results–the adverse effects of imports from China are greater in CZs specializing in sectors with a greater downstreamness–is consistent our results. However, they use value-added contents in US final goods imports from China as a measure of "downstreamness" (a higher value-added content, a higher downstreamness). On the other hand, we use the up/downstreamness measure of Miller and Temurshoev (2017), which quantify the number and thickness of value chains comprehensively. In addition, although Shen and Silva (2018) examine the effects of overall value-added contents, we examine the effects of final goods imports and intermediate inputs imports separately to examine different roles of these two types of imports in shaping labor market effects of imports from China.

[6]The other existing studies examining the effects of import competition or offshoring in the Japanese context include Endoh (2018), Endoh (2021a), Endoh (2021b), Matsuura (2022), and Bellone et al. (2022).

[7]Wright (2014) finds that offshoring from the US to abroad reduced the employment of production workers (via the job replacement effects) and increased the employment of non-production workers (via the productivity effects).

[8]Harrison and McMillan (2011) finds that offshoring to low-income countries reduces domestic employment while offshoring of tasks that are not performed at domestic affiliates expands domestic employment. Ottaviano et al. (2013) illustrate that, using the data from the 2000-2007 period, the positive productivity effects of offshoring largely offset the negative displacement effects of offshoring. Monarch et al. (2017) show that increased offshoring reduced US employment and the adverse effects were stronger for less productive offshoring firms using the data from the 1999-2006 period.

In the context of the China trade shock, Mion and Zhu (2013) examine the effects of import competition from China and offshoring to China on Belgium manufacturing firms' employment during the 1996-2007 period. They show that, while import competition had an adverse effect on employment, offshoring had a positive effect. Aghion et al. (2023) find negative pro-competitive effects of imported final goods and positive complementary effects of imported inputs on sales, employment, and innovation using French firm level data. The results from these two studies, Mion and Zhu (2013) and Aghion et al. (2023), are similar to our findings. On the other hand, Flaaen and Pierce (2021) find that rising US tariffs on Chinese inputs (negative shocks reducing offshoring) during the 2018-19 US-China Trade War reduced manufacturing employment in the US. We conjecture that the difference in the sample period (1990-2011 in this study versus 2018-2019 in their study) and horizon (long-run effects in this study versus short-run effects in their study) are the primary sources of the difference in the results.

Third, this paper is related to the literature on estimating the employment effects of exports. Feenstra et al. (2019) find that, while imports from China reduced US manufacturing employment, US exports to the ROW increased (sustained) it. Kainuma and Saito (2022) examine employment effects of Japan's exports to China, and find limited effects. The current study examines the effect of exports to the ROW. The logic is as follows. While less expensive imports from China may have different pro-competitive effects on labor markets, a positive demand shock from any destination country should operate in the same manner to increase exports hence create employment in exporting countries theoretically. We find that exports to the ROW had positive and significant effects on employment in both Japanese and US contexts. Choi and Xu (2019) show that Korean exports to China had a positive effect on Korean manufacturing employment during the 1993–2013 period.[9]

The rest of the paper proceeds as follows. The next section provides an empirical background motivating our analysis. Section 3 outlines our empirical approach. Section 4 summarizes data sources and provides an overview of variables. Section 5 presents baseline regression results. Section 6 investigates the mechanisms leading to our main results. Section 7 concludes. Additional details are documented in Appendix.

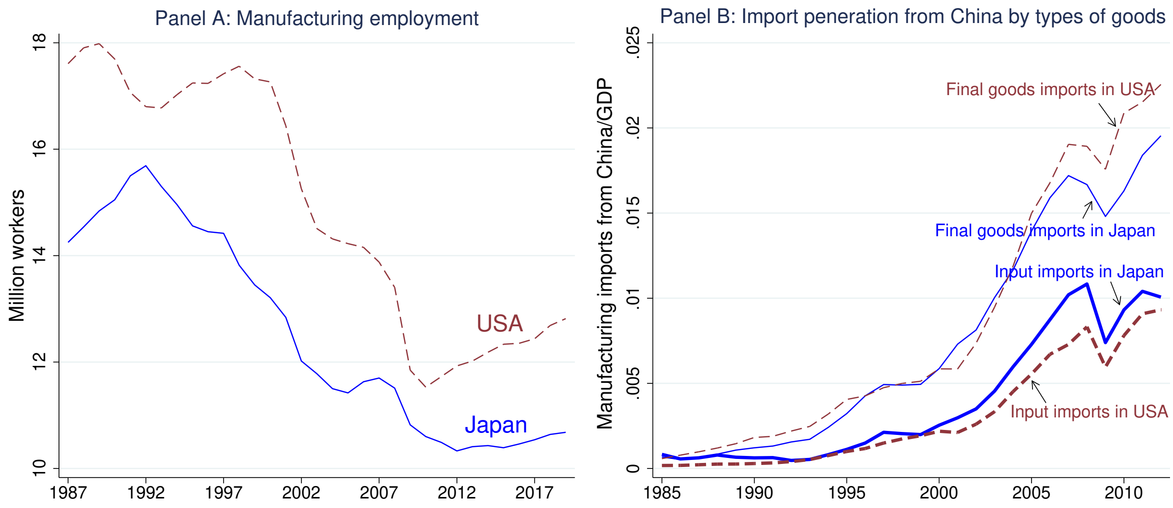
2 Background

This section provides an overview of empirical regularities motivating our analysis. Panel A of Figure 1 shows that, in the US, manufacturing employment decreased from 18 million to 12 million during the 1987-2012 period. In Japan, manufacturing employment was about 15.5 million at the peak and decreased to 11 million during the same period. Figure 1 Panel B shows manufacturing imports from China as a share of GDP in Japan and the US, by two types of imports, final goods and intermediate inputs. It indicates that imports from China are substantially increasing in both countries and both types of goods. One important difference between the two countries is that, while final

[9] The other existing studies investigating the labor market effects of exports to China (or the other countries or the ROW) include Sasahara (2019), Feenstra and Sasahara (2018), Kiyota et al. (2021), Nishioka and Olson (2022), and Choi et al. (2023). Sasahara (2019) and Feenstra and Sasahara (2018) use an input-output analysis to estimate the effects of exports on employment. Kiyota et al. (2021) estimate sector level regressions with shift-share instruments using data from many countries during the 2000–2014 period. Nishioka and Olson (2022) examine the effects of trade with Japan on political preferences in the US through labor markets using the data from the 1976–1992 period. Choi et al. (2023) investigate the effects of an increase in Chinese exports on Korean firms' product churning and product creation through the third market competition by affecting Korean firms' exports. All these studies find positive effects of exports–exports increase employment and product creation–although the effects may be statistically insignificant in some studies.

goods imports are rising more rapidly in the US than in Japan, intermediate input imports are rising more rapidly in Japan than in the US. These observations indicate that China and Japan have a tighter link within GVCs than China and the US.

FIGURE 1: Manufacturing employment and import penetration from China



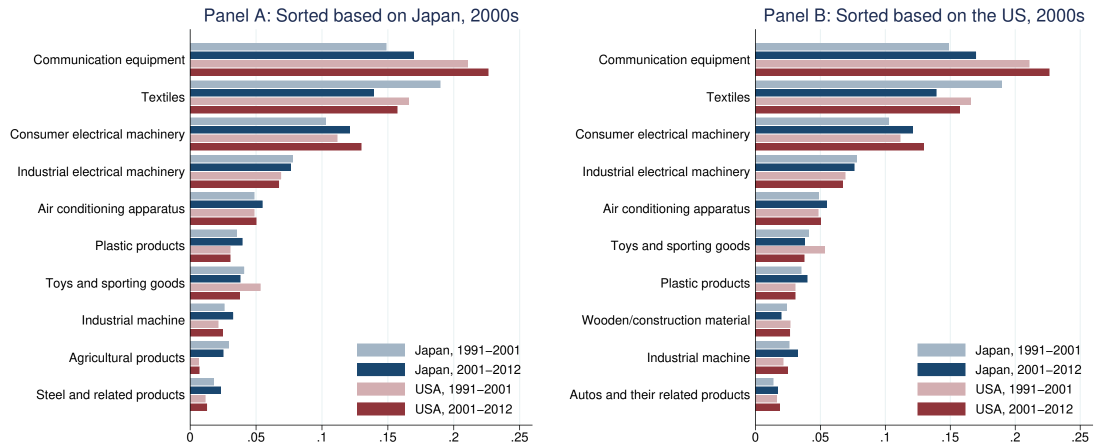
Note: The US manufacturing employment data in Panel A come from the Bureau of Labor Statistics and the Bureau of Economic Analysis. The Japanese employment data come from the Labor Force Survey of the Statistics Bureau, Ministry of Internal Affairs and Communications. Panel B shows the value of manufacturing imports from China divided by the import country's GDP. Authors' calculations based on the data from the WIOT 2022 version for the 1985-2000 period and the WIOT 2016 version for the 2001-2012 period.

The differences in the sectoral composition of imports from China are described in Figure 2. Each bar is a change in China's sector s's exports to the country $k =$ JPN, USA, as a share of overall change in China's exports to the same country $\Delta IM_{s,t}^{CHN\to k} / \sum_s \Delta IM_{s,t}^{CHN\to k}$. It shows that the largest increase in imports from China came from the textile industry in the 1990s in Japan, and the communication equipment industry took over the place in the 2000s. The communication equipment industry has continuously been the greatest import-growing sector in the US in the two decades. The consumer electrical machinery industry and the industrial electrical machinery industry are ranked in the 3rd and 4th places, respectively, in the two countries. Overall, the sectoral compositions of imports from China are not very different between the two countries.

We also discuss the sectoral composition of growth of exports to the ROW, $\Delta EX_{s,t}^{k\to ROW} / \sum_s \Delta EX_{s,t}^{k\to ROW}$, in Japan and the US. As Autor et al. (2013) emphasized, imports from China differ from imports from other countries at least in two respects. First, imports from China increased substantially due to its productivity growth and accession to the WTO in 2001. This increase can be seen as an exogenous shock. Second, China's products are less expensive, have a stronger pro-competitive effect, and are more likely to replace existing products. Therefore, on the import side, we focus on imports from China. However, when it comes to the export side, one would assume that exports to China and exports elsewhere would have the same labor market effects. Based on this consideration, we examine the effects of exports to the ROW.

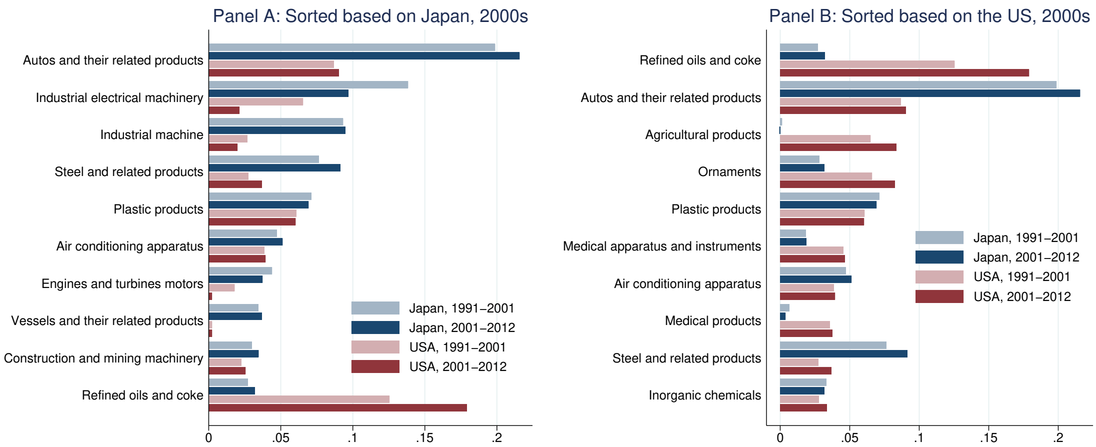
Figure 3 demonstrates that the two countries' sectoral composition of export growth differs. While the largest

FIGURE 2: The sectoral composition of imports from China



Note: The figure shows the share of the changes in exports to the rest of the world (ROW). The top 10 sectors out of 62 sectors in Japan's exports in the 2000s are shown. The data comes from the UN Comtrade.

FIGURE 3: Sectoral composition of exports to the ROW



Note: The figure shows the share of the changes in exports to the rest of the world (ROW). The top 10 sectors out of 62 sectors in Japan's exports in the 2000s are shown. The data comes from the UN Comtrade.

increase comes from the auto industry in Japan, it comes from the oil and coke industry in the US. The other growing industries in exports include the industrial electrical machinery industry and the industrial machinery industry in Japan. As there are higher shares of trade in parts and components in the auto and machinery industries, it is consistent with our understanding that Japan is more deeply connected with GVCs than the US.

We link this empirical observation with our regression analysis to investigate the mechanisms leading to different employment effects of imports across countries. To do so, we employ two measures of the degree of participation in GVCs, 'upstreamness' and 'downstreamness' of Miller and Temurshoev (2017). The 'upstreamness' quantifies the number and the thickness of value chains that input *suppliers* face, measuring the country-sector's forward integration to GVCs. Using an input-output table, it is defined as follows:

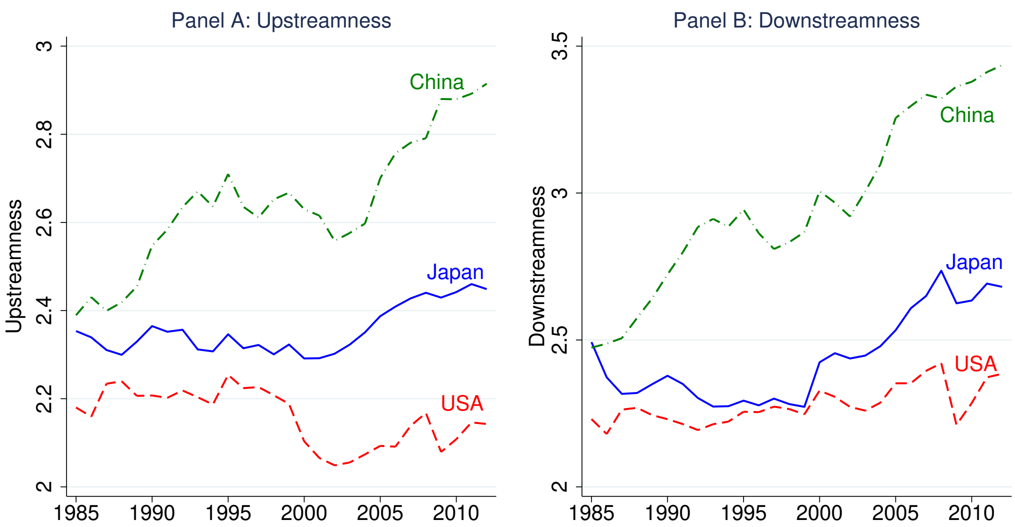
$$u_s^k = \frac{f_{(k,s)}}{x_{(k,s)}} + 2\frac{\sum_{k'}\sum_{s'} a_{(k,s),(k',s')} f_{(k',s')}}{x_{(k,s)}} + 3\frac{\sum_{k'}\sum_{s'}\sum_{k''}\sum_{s''} a_{(k,s),(k',s')} a_{(k,s),(k'',s'')} f_{(k'',s'')}}{x_{(k,s)}} + \ldots$$

The variable $f_{(k,s),k'}$ indicates the value of final goods produced by sector s of country k and purchased by country k'. As a result, $f_{(k,s)} = \sum_{k'} f_{(k,s),c'}$ indicates the total value of final goods produced in sector s of country k. We omit year subscript t for simplicity. The variable $a_{(k,s),(k',s')} = m_{(k,s),(k',s')}/x_{(k',s')}$ denotes the input-output coefficients, where $m_{(k,s),(k',s')}$ indicates the value of intermediate goods produced by sector s of country k and used by sector s' of country k', and $x_{(k',s')}$ denotes the gross output. Using the world input-output table, the upstreamness measures are computed as follows: $\mathbf{u} = (\mathbf{I} - \hat{\mathbf{x}}\mathbf{T})^{-1}\mathbf{i}$, where $\hat{\mathbf{x}}$ is a $(K \times S) \times (K \times S)$ matrix including gross output $x_{(k,s)}$ as diagonal entries and zeros in off-diagonal entries. K denotes the number of countries and S denotes the number of sectors. $\mathbf{T}$ denotes the input matrix. The "downstreamness" quantifies the number and the thickness of value chains that input *buyers* face, measuring backward integration to GVCs. It is defined as follows:

$$d_s^k = \frac{v_{(k,s)}}{x_{(k,s)}} + 2\frac{\sum_{k'}\sum_{s'} v_{(k,s)} v_{(k,s),(k',s')}}{x_{(k,s)}} + 3\frac{\sum_{k'}\sum_{s'}\sum_{k''}\sum_{s''} v_{(k,s)} b_{(k,s),(k',s')} b_{(k,s),(k'',s'')}}{x_{(k,s)}} + ...$$

where $v_{(k,s)}$ denotes value-added, and $b_{(k,s),(k',s')} = m_{(k,s),(k',s')}/x_{(k,s)}$ denotes 'output' coefficients. Using the world input-output table, it is computed as follows: $\mathbf{d}' = \mathbf{i}'\hat{\mathbf{x}}(\mathbf{I} - \hat{\mathbf{x}}\mathbf{T})^{-1}\hat{\mathbf{x}}^{-1}$.

FIGURE 4: Upstreamness and downstreamness



Note: Authors' calculations based on the data from the WIOT 2022 version for the 1985-2000 period and the WIOT 2016 version for the 2001-2012 period.

Figure 4 displays the value-added weighted average up/downstreamness in the manufacturing sectors in China, Japan, and the US, computed using the data from the WIOD.[10] It shows that China's up/downstreamness takes the highest values and the US takes the lowest values among the three countries, and Japan is in the middle throughout the sample period. It suggests that China's forward and backward integration to GVCs is at the highest level while the US's integration level is the lowest among the three. In particular, Panel A shows that US upstreamness declined around 2000 and stayed lower during the 2000s. In contrast, Panel B shows that US downstreamness increased since 2000 until the 2008-09 Global Financial Crisis. These trends suggest that the US was moving down the GVCs and

[10]We use the WIOD 2022 Release for the 1985-1999 period and the WIOD 2016 Release for the 2000-2012 period.

increased its specialization in products closer to final consumers. We argue that alterations in integration patterns within GVCs elucidate some of the employment effects of the exposure to trade.

To enhance our understanding of the value chains between China and Japan, and those between China and the US, we estimate the value-added content contributed by China and embedded in Japan and the US's domestic production, as well as to their exports. To do so, we take the approach outlined as the "value-added content in gross exports" in Johnson (2018). For simplicity, consider a world with two countries, country 1 and country 2, each of which consists of two sectors, manufacturing (denoted by M) and non-manufacturing (denoted by N) sectors. By including country 1's manufacturing sector's sales in country k, $f_{(1,M),k}$, as the only non-zero element in the final demand vector, value-added contents embedded in such final goods flows are estimated as follows:

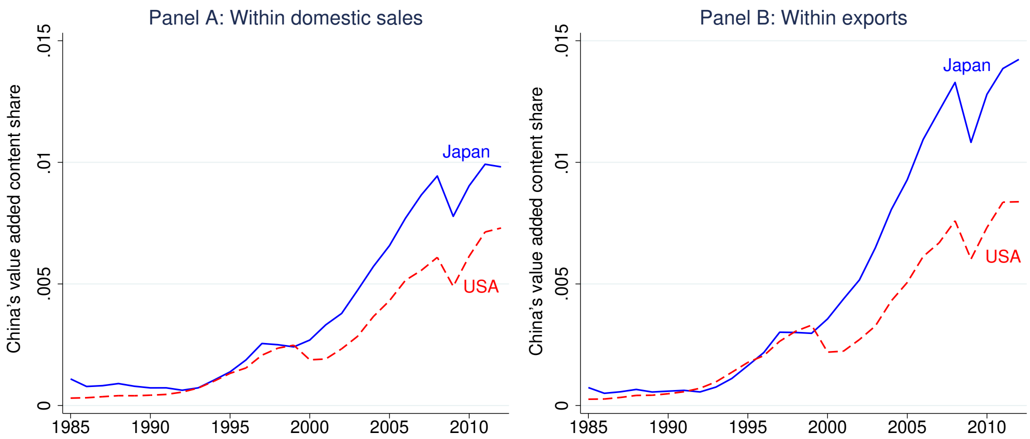
$$\begin{bmatrix} vax_{(1,M),k} \\ vax_{(1,N),k} \\ vax_{(2,M),k} \\ vax_{(2,N),k} \end{bmatrix} = \hat{\mathbf{v}}(\mathbf{I} - \mathbf{A})^{-1} \begin{bmatrix} f_{(1,M),k} \\ 0 \\ 0 \\ 0 \end{bmatrix},$$

where $\mathbf{A}$ denotes a 4×4 matrix of input-output coefficients, $\mathbf{I}$ denotes an identity matrix, $\hat{\mathbf{v}}$ denotes a vector including the value-added to gross output ratios as diagonal elements and zeros as off-diagonal elements. The share of value-added by country 2's manufacturing sector included in $f_{(1,M),k}$ is calculated as $vax_{(2,M),k}/f_{(1,M),k}$.

Figure 5 Panel A displays the share of value-added content by China's manufacturing sectors included in Japan and the US's manufacturing sectors' domestic sales, respectively. It shows that Japan and the US had similar shares and shared their trends until around 2000. On the contrary, in the 2000s, China's value-added contribution increased more rapidly in Japan than in the US. Figure 5 Panel B presents the share of value-added content by China's manufacturing sectors included in Japan and the US's manufacturing exports to the ROW, respectively. It shows similar patterns as Panel A: synchronized trends between Japan and the US by the end of the 1990s, and diversion in the 2000s. In addition, the share of China's value-added was more rapidly growing in Japan's exports than Japan's domestic sales in the 2000s. Interestingly, although the up/downstreamness measures in Figure 4 suggest the US is moving down along GVCs, the value-added content measures in Figure 5 indicate that the level of the US's backward integration to value chains with China is less rapidly increasing relative to Japan.

Overall, the data suggest three facts regarding the US's integration to GVCs: (i) the US's forward integration to GVCs (upstreamness) was declining since around 2000, (ii) the US's backward integration to GVCs (downstreamness) was almost constant during the 1990s and 2000s, and (iii) China's value-added embedded in US domestic sales and exports was less rapidly increasing than Japan since 2000s. These facts imply that, after China's accession to the WTO and the acceleration of China's integration to the world economy, the deepness of the US's integration to value chains with China was declining. Combined with the exceptional increase in US imports of final goods from China shown in Figure 1, we argue that import penetration from China in the US was predominantly a penetration of final goods, generation a stronger pro-competitive effect rather than a complementary or productivity-enhancing effect.

FIGURE 5: China's value-added content included in Japanese and US production



Note: The figure shows China's manufacturing sectors' value-added included in Japan and the US's manufacturing sales in the domestic market (Panel A) and their manufacturing exports (Panel B). Authors' calculations based on the data from the WIOT 2022 version for the 1985-2000 period and the WIOT 2016 version for the 2001-2012 period.

3 Methodology

3.1 Baseline regression model

Our empirical approach follows the ones used in Autor et al. (2013) and Feenstra et al. (2019), investigating the effects of trade shocks on manufacturing employment and other labor market outcomes. Specifically, our benchmark regression model for country $k =$ JPN, USA, is as follows:

$$\Delta l_{it}^{k} = \beta_1 \Delta IPW_{it}^{CHN \to k} + \beta_2 \Delta EOW_{it}^{k \to ROW} + \mathbf{X}_{it}\boldsymbol{\beta}_3 + \alpha_t + \alpha_r + u_{it}, \tag{1}$$

where i indicates CZ and t indicates period.[11] The dependent variable $\Delta l_{it}^{k} = \left(\frac{L_{it+1}^{k}}{WAP_{it+1}^{k}} - \frac{L_{it}^{k}}{WAP_{it}^{k}} \right)$ is the decennial change in manufacturing employment share of the working-age population.[12] α_t indicates period fixed effects and α_r denotes the regional fixed effects (i.e., the region dummies for Japan and the statistical division dummies for the US).

One of our key explanatory variables, $\Delta IPW_{it}^{CHN \to k}$, captures import penetration from China in CZ i during the period t, and it is defined as

$$\Delta IPW_{it}^{CHN \to k} = \sum_{s \in S_M} \left(\frac{L_{ist}^{k}}{\sum_{s' \in S_A} L_{is't}^{k}} \times \frac{\Delta im_{st}^{CHN \to k}}{\sum_{i'} L_{i'st}^{k}} \right). \tag{2}$$

The variable L_{ist}^{k} denotes the number of employees in sector s of CZ i at the beginning of period t in country k. The variable $\Delta im_{st}^{CHN \to k}$ denotes the change in imports of sector s's goods from China.[13] S_A is the set of all sectors and

[11]Throughput the paper, subscript t indicates "period" unless otherwise indicated. Depending on the context, t also indicates the start year of a period.

[12]The data on working age population comes from the Census of Japan, which provides us with the data in every five years, 1990, 1995, 2000, 2005, 2010. The manufacturing employment data come from the Establishment and Enterprise Census and the Economic Census for Business Activity of Japan, which provide us with the data in 1991, 1996, 2001, 2006, and 2012. As a result, there is a one-year gap (and a two-year gap for the last year) when calculating L_{it}/WAP_{it}.

[13]The data on imports from China are obtained from UN Comtrade and expressed in nominal USD. Therefore, we convert the data to Japanese yen using the exchange rate from Penn World Table and adjust them to real values using Japanese sectoral CPI. As indicated, this import penetration variable is the weighted average of decennial changes in sectoral imports from China where the weights are sector level employment. The sectoral

S_M is the set of manufacturing sectors. This variable is the employment-weighted average of the per worker exposure to the import competition. As the denominator of the weight includes all sectors including non-manufacturing sectors, the exposure to import competition takes a lower value if the CZ has a lower share of manufacturing employment in the first place.

In addition to import penetration, we include country k's exports to the ROW, by replacing imports from China $\Delta im_{st}^{CHN\to k}$ in equation (2) with exports to the ROW $\Delta ex_{st}^{k\to ROW}$ leads to the following.

$$\Delta EOW_{it}^{k\to ROW} = \sum_{s\in S_M}\left(\frac{L_{ist}^{k}}{\sum_{s'\in S_A} L_{is't}^{k}} \times \frac{\Delta ex_{st}^{k\to ROW}}{\sum_{i'} L_{i'st}^{k}}\right). \tag{3}$$

The variable $\mathbf{X}_{it}$ denotes a vector of control variables including. When running regressions with the Japanese data, $\mathbf{X}_{it}$ includes (1) the initial manufacturing employment share, (2) the unemployment rate, (3) the labor market participation rate, (4) the foreign population share, (5) the urban population share, (6) the female employment share, (7) log of "manufacturing employment divided by the number of manufacturing affiliates," (8) the share of non-full-time manufacturing employment as a share of total manufacturing employment, (9) log of population density, (10) the share of population of aged 15 or less to total population, and (11) the region dummies.

When running regressions with the US data, $\mathbf{X}_{it}$ includes (1) the initial manufacturing employment share, (2) the share of educated population, (3) the share of foreign-born population, (4) the share of female employment, (5) the share of employment with routine occupations, (6) the average offshorability index, and (7) the statistical division dummies. To allow different slope parameters for control variables across periods, the period dummy d_t interacts with the controls $\mathbf{X}_{it}$ (besides the region dummies and statistical division dummies). The error term is denoted by u_{it}.

3.2 Identification

The variables, $\Delta IPW_{it}^{CHN\to k}$ and $\Delta EOW_{it}^{k\to ROW}$, are endogenous because labor market conditions can potentially affect imports and exports through various channels (e.g., purchasing powers of consumers and firms' economic activities in country k). Therefore, we employ the instrumental variable approach with shift-share instruments following Autor et al. (2013) for the import side and Feenstra et al. (2019) for the export side.

In particular, $\Delta IPW_{it}^{CHN\to k}$ is instrumented by the following variable:

$$\Delta IPW_{it}^{CHN\to OTH\backslash k} = \sum_{s\in S_M}\left(\frac{L_{ist-1}^{k}}{\sum_{s'\in S_A} L_{is't-1}^{k}} \times \frac{\Delta im_{st}^{CHN\to OTH\backslash k}}{\sum_{i'} L_{i'st-1}^{k}}\right), \tag{4}$$

where $\Delta im_{st}^{CHN\to OTH\backslash k}$ indicates decennial changes in China's exports of sector s's goods to eight other developed countries from the view point of country k.[14] China's exports to these countries are used to capture China's supply shocks leading to export growth, including, for example, its accession to the WTO and productivity growth. The

weighted average is computed using employment data in all sectors, not only manufacturing sectors but also non-manufacturing sectors following Autor et al. (2013).

[14]The eight countries are selected following Autor et al. (2013). For the Japanese perspective, it includes Australia, Denmark, Finland, Germany, New Zealand, Spain, Switzerland, and the US. For the US perspective, it includes Japan instead of the United States.

employment data used to compute the weighted average come from the previous period.[15] The reason for using lagged employment data is to alleviate the potential endogeneity issue where workers may choose their locations to work with their expectations on the upcoming arrival of the China trade shocks.

We take the symmetric approach for the export side. The instrument used for the endogenous variable $\Delta EOW_{it}^{k\to ROW}$ is

$$\Delta EOW_{it}^{OTH\backslash k\to ROW} = \sum_{s\in S_M}\left(\frac{L_{ist-1}^{k}}{\sum_{s'\in S_A} L_{is't-1}^{k}} \times \frac{\Delta ex_{st}^{OTH\backslash k\to ROW}}{\sum_{i'} L_{i'st-1}^{k}}\right), \tag{5}$$

where $\Delta ex_{st}^{OTH\backslash k\to ROW}$ indicates decennial changes in exports from sector s in the eight other developed countries to the ROW. This variable is meant to capture the world's demand shocks. As in equation (4), we use the lagged employment data to compute the weighted average of the world's demand shocks.

3.3 Disaggregating the import variables

As found in previous studies (e.g., Taniguchi, 2019; Endoh, 2023; and Aghion et al., 2023), we assume different labor market effects across types of goods because final goods are expected to have a greater pro-competitive effect in the goods market than inputs. Echoing these prior studies, we classify imported goods into imported final goods and intermediate goods. The variable $f_{(CHN,s),J}$ indicates the dollar value of final goods produced in China's sector s and consumed by Japan, and $m_{(CHN,s),(J,s')}$ indicates the dollar value of intermediate goods produced in China's sector s and used by Japan's sector s'. Hereafter, time subscripts t are dropped for simplicity except the employment variables.

The degree of import penetration of final goods from China is measured by

$$\Delta IPW_{\text{Final},i}^{CHN\to k} = \sum_{s\in S_M}\left(\frac{L_{ist}^{k}}{\sum_{s'\in S_A} L_{is't}^{k}} \times \frac{\Delta f_{(CHN,s),k}}{\sum_{i'} L_{i'st}^{k}}\right), \tag{6}$$

where the decennial change in final goods imports from China per employment $\Delta f_{(CHN,s),k}/\sum_{i'} L_{i'st}^{k}$ is utilized to find the weighted average of the exposures to final goods imports from China. Similarly, the degree of import penetration of intermediate goods from China is measured by

$$\Delta IPW_{\text{Inputs},i}^{CHN\to k} = \sum_{s\in S_M}\left(\frac{L_{ist}^{k}}{\sum_{s'\in S_A} L_{is't}^{k}} \times \frac{\sum_{s'} \Delta m_{(CHN,s),(k,s')}}{\sum_{i'} L_{i'st}^{k}}\right), \tag{7}$$

where the decennial change in imported inputs from China is used to find the exposure to imported inputs from China.

We also introduce a slightly different measure of imported inputs to quantify the amount of inputs used by sectors in the importing country. By replacing the sector subscripts for summation in the variable $m_{(CHN,s),(k,s')}$, we construct the following variable:

$$\Delta IPW_{\text{Inputs used},i}^{CHN\to k} = \sum_{s\in S_M}\left(\frac{L_{ist}^{k}}{\sum_{s'\in S_A} L_{is't}^{k}} \times \frac{\sum_{s'} \Delta m_{(CHN,s'),(k,s)}}{\sum_{i'} L_{i'st}^{k}}\right), \tag{8}$$

[15] Due to the availability of the Japanese employment data, we use the 1986 employment data for the 1991-2001 change, the 1996 employment data for the 2001-2012 change to construct instruments for the Japanese analysis.

where the decennial change in imported inputs from China that are used by Japan's sector s per employment $\Delta m_{(CHN,s'),(k,s)}$ is used to find the exposure to imported inputs from China. We expect that imported inputs used in each sector in Japan (rather than imported inputs produced in each sector in China) are more appropriate to measure the effect of the utilization of imported inputs from China.

These variables are constructed using the input-output tables from the WIOD 2016 Release for the 2000s and using the WIOD 2022 Release for the 1990s. Limitations of using the datasets include (i) the sectoral aggregation is less detailed, covering 17 manufacturing sectors for the 2016 version and 12 manufacturing sectors for the 2022 version,[16] and (ii) the list of the eight developed countries used to construct the instruments differ from the eight developed countries used to construct equations (4) and (5) because New Zealand is not included as a separate country in either version of the WIOD and Switzerland is not included in the WIOD 2022 Release. See Appendix C for details.

We construct the corresponding instruments for each of the endogenous variables (6)-(8).[17] Hereafter, we omit the superscript "$\rightarrow k$" to simplify the notations. For example, we express $\Delta IPW_{\text{Final},i}^{CHN\rightarrow k}$ as $\Delta IPW_{\text{Final},i}^{CHN}$ and we express $\Delta IPW_{it}^{CHN\rightarrow OTH\backslash k}$ as $\Delta IPW_{it}^{CHN\rightarrow OTH}$.

3.4 Upstreamness and downstreamness

We investigate the role of the upstreamness and downstreamness in affecting the effects of imports from China on manufacturing employment. The measure of upstreamness u_{st}^k and downstreamness d_{st}^k obtained from the input-output table are at the country k-sector s level in the start year of period t. Japan and the US's sector level upstreamness and downstreamnes measures are converted to CZ level by taking the weighted average as follows:

$$u_{it}^k = \sum_{s\in S_M}\left(\frac{L_{ist}^k}{\sum_{s'\in S_M} L_{is't}^k}\times u_{st}^k\right) \text{ and } d_{it}^k = \sum_{s\in S_M}\left(\frac{L_{ist}^k}{\sum_{s'\in S_M} L_{is't}^k}\times d_{st}^k\right), \quad (9)$$

where the denominator of the weight, $\sum_{s'\in S_M} L_{is't}^k$, includes the manufacturing employment only. Without excluding the non-manufacturing employment from the denominator, the upstreamness and downstreamness variables would have high correlations with the exposure variables to trade by construction because these variables would take lower values in the CZs with lower manufacturing employment shares. These two CZ level variables are utilized to examine the effects of the exposure to trade differ depending on the level of the upstreamness and downstreamness.[18]

3.5 The BHJ approach

Studies have clarified conditions under which shift-share instruments are valid. Adão et al. (2019) show that if observations are exposed to a shock at similar degrees, it leads to correlated residuals and incorrect standard errors. To overcome the issue, Goldsmith-Pinkham et al. (2020) propose an approach with exogenous exposure shares and

[16] We construct a crosswalk between the WIOD's more aggregated manufacturing sectors and 392 manufacturing sectors used in Autor et al. (2013) and Feenstra et al. (2019). Then, we aggregate the sector-CZ level employment data from Feenstra et al. (2019) to the WIOD aggregation level, and utilize them to construct variables (6)-(8) and their instruments. We take the same approach to construct the CZ level up/downstreamness of equation (9) and the CZ level capital-labor ratios used in Appendix F.

[17] See Appendix C for the equations of the instruments used to identify the explanatory variables (6)-(8). See Appendix D for first-stage regression results predicting these endogenous explanatory variables.

[18] See Figure A1 in Appendix E for the spatial distribution of the CZ level upstreamness and downstreamness in Japan and the US, respectively.

a (possibly) endogenous shock. In addition, Borusyak et al. (2022) propose an approach with (possibly) endogenous exposure shares and an exogenous shock.

We re-run regressions by taking the approach by Borusyak et al. (2022) (hereafter BHJ) and confirm the robustness of our results. Specifically, as the first step, we regress the dependent variable on the set of control variables and obtain residuals, $\tilde{y}_i$, which is at the CZ level with CZ subscript i. A residualized endogenous explanatory variable $\tilde{x}_i$ and instrument $\tilde{z}_i$ are also obtained by taking the same step. As the second step, convert the CZ level residualized variables, $\tilde{y}_i$, $\tilde{x}_i$, and $\tilde{z}_i$ are converted to the sector level by taking sectoral employment-weighted averages, $\hat{y}_s$, $\hat{x}_s$, and $\hat{z}_s$. As the last step, regress $\hat{y}_s$ on $\hat{x}_s$ with the instrument $\hat{z}_s$, where regressions are weighted by sectoral employment. We report results from the BHJ approach in every regression table for the second-stage.

One limitation of our dataset when conducting this test is that the underlying sectoral aggregation levels differ between variables (4)-(5) and variables (6)-(8). Variables (4)-(5) are constructed using the employment and trade data from 63 Japanese manufacturing sectors and 292 US manufacturing sectors. On the other hand, variables (6)-(8) are based on 12 or 17 sectors manufacturing sectors both in Japanese data and US data because we use more aggregated data from the WIOD. When taking the BHJ approach for regressions with variables (6)-(8), CZ level import competition variables based on 12 or 17 sectors are converted to 63 Japanese sectors or 292 US sectors, which could potentially lead to bias. Nevertheless, as we obtain broadly consistent results from the CZ level regressions and sector level regressions.

4 Data

4.1 Data sources

Our Japanese dataset is constructed using data from multiple sources. First, the employment data come from two sources including (1) the Establishment and Enterprise Census of Japan (Jigyōsho Kigyō Tōkei Chōsa, hereafter EECJ), where the survey years include 1986, 1991, 1996, and 2001, and (2) the Economic Census for Business Activity of Japan (Keizai Sensasu Katsudō Chōsa, hereafter ECBAJ), where the survey year is 2012. The control variables are constructed based on the data from the databases (1)-(2) and the Regional Statistics Database (System of Social and Demographic Statistics) of Japan. The population-related variables come from the Census of Japan, which provides us with the data in every five years, 1990, 1995, 2000, and 2005, which are used for the 1991-1996, 1996-2001, 2001-2006, 2006-2012, respectively. The Japanese manufacturing value-added data are obtained from the Census of Manufacturer (Kōgyo Tōkei Chōsa). The value-added data are deflated using prefecture level GDP deflators obtained from the Prefectural Accounts of the Cabinet Office (Naikakufu).

We construct trade shock variables for Japan using trade flows retrieved from UN Comtrade. To do so, we create a sectoral concordance connecting the EECJ (the ECBAJ for 2012) and UN Comtrade. Maintaining a consistent list of sectors throughout the sample period for EECJ and ECBAJ yields 63 sectors.[19] The data on trade flows obtained from UC Comtrade are converted to real JPY values, in the 2020 prices, using the exchange rate from the Penn World

[19]See Table A1 in Appendix A for the list of 63 sectors. We use the same secoral aggregation and concordance table as Sasahara et al. (2023).

Table and CPIs from the Statistics Bureau of Japan (Sōmushō Tōkei Kyoku). The cross-sectional unit of our dataset is 'commuting zones' constructed by Adachi et al. (2021), including 308 CZs, which is strongly balanced across the two stacked periods.[20] Given the availability of the data in the Japanese dataset, the first period spans from 1991 to 2001, and the second period spans from 2001 to 2012. The variables for the second period is re-scaled to the decennial length by multiplying 10/11.

The US CZ level dataset is based on the data from Autor et al. (2013) and Feenstra et al. (2019), with 722 CZs in the contiguous US. The manufacturing employment data and trade shock variables and their instruments come from Feenstra et al. (2019).[21] The control variables, the percentage of educated workers, the percentage of foreign-born workers, the percentage of female workers, and the percentage of routine occupations, come from Autor et al. (2013).

Additionally, we use the World Input-Output Tables (hereafter WIOT) of Timmer et al. (2015) and Woltjer et al. (2021) when constructing variables such as imported final goods and imported inputs. Therefore, the definition of imported inputs in this study is a 'broad' definition including not only parts and components but also finished goods used as inputs. Trade flows obtained from the WIOT are converted to real values using the price indices obtained from the Socio Economic Accounts of the same database. Japanese trade variables are converted to JPY using the exchange rates, while the original USD data are used to construct instruments of Japanese trade variables and US trade variables.

4.2 Summary statistics

Table 1 Panel A shows summary statistics of variables in the Japanese data and Panel B shows those in the US data. Each of these tables displays summary statistics of the dependent and key control variables, endogenous explanatory variables, and instruments in the stacked cross-section data for the two periods, the 1990s and 2000s.[22] Table 1 shows that, for example, the average change in the share of manufacturing employment is -1.48 percentage points (hereafter pp). The average of the import penetration from China, ΔIPW^{CHN}, is 101 thousand JPY. The average of the export opportunities to the ROW, ΔEOW^{ROW}, is 198 thousand JPY.

Table 1 Panel B presents the summary statistics of US variables. It shows that, for example, the average change in the manufacturing employment as a share of the working age population is 1.34 pp, with minimum of -17 pp and the maximum of 15 pp. The key explanatory variables ΔIPW^{CHN} and ΔEOW^{ROW} and their instruments come from Feenstra et al. (2019) and these variables are normalized variables. The average of ΔIPW^{CHN} is 0.80 and the average of ΔEOW^{ROW} is 1.34. The other trade exposure variables are authors' calculations and the unit of these variables is 1,000 USD in the current prices.

[20] We employ Adachi et al. (2021)'s commuting zones based on the 1995 commuting patterns, originally including 315 CZs. However, after excluding CZs with no manufacturing employment and those with exceptional population changes (i.e., the one in Fukushima where there was evacuation due to the explosion in the Fukushima Daiichi Nuclear Powerplants), the number of CZs in our sample is reduced to 308. While previous studies employ other cross-sectional units such as prefectures (e.g., Taniguchi, 2019) and sectors (Kiyota et al., 2021), CZs are considered as the right cross-sectional units when investigating labor market outcomes (see Adachi et al., 2021, for further details). Existing studies using CZ level datasets include Kainuma and Saito (2022) and Endoh (2023).

[21] Feenstra et al. (2019) obtained manufacturing employment data from the County Business Patterns (CBP). Their trade data come from UN Comtrade with the 6-digit HS product classification, and they merge the trade data with 392 manufacturing industries following the steps by Acemoglu et al. (2016).

[22] See Tables A2 and A6 in Appendix B for summary statistics of the instruments and control variables, and correlation matrices of the variables.

TABLE 1: Summary statistics of main variables

Panel A: Japan, $k = JPN$

	Mean	Std. dev.	Min	Max
Dependent and control variables				
100 $\times\Delta$(mnfg emp / working age pop)	-1.48	2.36	-14.88	14.75
Initial 100$\times$(mnfg emp / working age pop)	12.59	6.40	0.32	35.57
Upstreamness (Up)	2.22	0.22	1.58	2.97
Downstreamness ($Down$)	2.40	0.10	2.20	2.72
Endogenous explanatory variables				
$\Delta IPW^{CHN\to k}$	1.01	0.76	-0.09	5.19
$\Delta EOW^{k\to ROW}$	1.98	2.29	-0.25	13.73
$\Delta IPW^{CHN\to k}_{\text{Final goods}}$	1.12	0.88	0.00	5.67
$\Delta IPW^{CHN\to k}_{\text{Inputs}}$	0.37	0.38	0.00	1.82
$\Delta IPW^{CHN\to k}_{\text{Inputs used}}$	0.24	0.27	-0.05	1.82
$\Delta IPW^{CHN\to k}_{\text{Final goods}} \times Up$	0.53	0.60	0.00	3.87
$\Delta IPW^{CHN\to k}_{\text{Inputs used}} \times Up$	0.13	0.19	-0.02	1.55
$\Delta IPW^{CHN\to k}_{\text{Final goods}} \times Down$	0.57	0.65	0.00	4.02
$\Delta IPW^{CHN\to k}_{\text{Inputs used}} \times Down$	0.14	0.21	-0.03	1.97

Panel B: The US, $k = USA$

	Mean	Std. dev.	Min	Max
Dependent and control variables				
100 $\times\Delta$(mnfg emp / working age pop)	-1.34	3.05	-17.98	14.95
Initial 100 $\times$(mnfg emp / working age pop)	9.57	6.33	0.00	37.86
Upstreamness (Up)	2.44	0.23	1.66	3.34
Downstreamness ($Down$)	2.41	0.17	2.00	2.80
Endogenous explanatory variables				
$\Delta IPW^{CHN\to k}$	0.80	0.92	-0.02	9.51
$\Delta EOW^{k\to ROW}$	1.34	1.51	-4.35	23.11
$\Delta IPW^{CHN\to k}_{\text{Final goods}}$	1.04	1.20	0.00	11.02
$\Delta IPW^{CHN\to k}_{\text{Inputs}}$	0.38	0.38	0.00	3.28
$\Delta IPW^{CHN\to k}_{\text{Inputs used}}$	0.24	0.22	0.00	2.07
$\Delta IPW^{CHN\to k}_{\text{Final goods}} \times Up$	0.66	1.02	0.00	10.83
$\Delta IPW^{CHN\to k}_{\text{Inputs used}} \times Up$	0.15	0.19	0.00	1.66
$\Delta IPW^{CHN\to k}_{\text{Final goods}} \times Down$	0.68	1.06	0.00	11.37
$\Delta IPW^{CHN\to k}_{\text{Inputs used}} \times Down$	0.16	0.20	0.00	2.19

Note: In Panel A, the sample size is 616 for all variables, consisting of 308 CZs for the two periods. The unit of the endogenous explanatory variables is 100,000 JPY (in the 2000 prices). The unit of the instruments is 1,000 USD (nominal prices).
In Panel B, the sample size is 1,444 for all variables, consisting of 722 CZs for the two periods. Panel B's manufacturing employment variables, ΔIPW^{CHN} and ΔEOW^{ROW}, and these two endogenous variables' instruments come from Feenstra et al. (2019). These endogenous variables and instruments are normalized variables. The other trade exposure variables and their instruments are authors' calculations, and the unit of these variables is 1,000 USD (nominal prices).

4.3 Trade exposures in Japan

To gain a better grasp of the spatial distribution of the trade exposure variables, we present top three, median, and bottom three CZs (among 40 largest CZs) in terms of the key trade exposure variables computed as the sum of the two decades.

Table 2 Panel A displays the ranking based on overall import penetration from China, ΔIPW^{CHN}. It indicates that CZs including Ohta-shi, Gunma, Otsu-shi, Shiga, and Yao-shi, Osaka–where these locations specialize in import-oriented manufacturing–had the greatest exposure to import penetration. On the other hand, CZs including Fukuoka-shi, Fukuoka, Sapporo-shi, Hokkaido, and Naha-shi, Okinawa–where these locations specialize in non-manufacturing industries–had the smallest exposure. The median CZs were those include Kobe-shi, Hyogo, and Takasaki-shi, Gunma.

TABLE 2: Commuting zones with top, median, and bottom exposures, Japan

Panel A: Import penetration from China

No.	Commuting zone	Δvar	Δl
1	Ohta-shi and Ashikaga-shi, Gunma and Tochigi	6.79	-9.07
2	Otsu-shi and Higashiomi-shi, Shiga	5.20	-5.46
3	Yao-shi and Matsubara-shi, Osaka	4.33	-3.59
20	Kobe-shi and Akashi-shi, Hyogo	2.43	-3.56
21	Takasaki-shi and Maebashi-shi, Gunma	2.42	-4.28
38	Fukuoka-shi and Kasuga-shi, Fukuoka	0.66	-1.93
39	Sapporo-shi and Ebetsu-shi, Hokkaido	0.42	-1.68
40	Naha-shi and Okinawa-shi, Okinawa	0.20	-0.65

Panel B: Export opportunities to the ROW

No.	Commuting zone	Δvar	Δl
1	Toyota-shi and Okazaki-shi, Aichi	17.04	-5.05
2	Mito-shi and Hitachi-shi, Ibaraki	14.31	-4.84
3	Yokkaichi-shi and Tsu-shi, Mie	12.01	-4.16
20	Shizuoka-shi and Yaizu-shi, Shizuoka	6.35	-4.69
21	Gifu-shi and Kakamigahara-shi, Gifu	6.17	-5.43
38	Kagoshima-shi and Satsumasendai-shi, Kagoshima	1.42	-1.24
39	Sapporo-shi and Ebetsu-shi, Hokkaido	1.09	-1.68
40	Naha-shi and Okinawa-shi, Okinawa	0.95	-0.65

Panel C: Imported inputs used − final goods from China

No.	Commuting zone	Δvar	Δl
1	Toyota-shi and Okazaki-shi, Aichi	-0.07	-5.05
2	Hiroshima-shi and Kure-shi, Hiroshima	-0.11	-3.13
3	Naha-shi and Okinawa-shi, Okinawa	-0.21	-0.65
20	Kagoshima-shi and Satsumasendai-shi, Kagoshima	-0.93	-1.24
21	Takamatsu-shi and Marugame-shi, Kagawa	-0.94	-3.09
38	Gifu-shi and Kakamigahara-shi, Gifu	-1.76	-5.43
39	Ohta-shi and Ashikaga-shi, Gunma and Tochigi	-2.02	-9.07
40	Otsu-shi and Higashi-Ohmi-shi, Shiga	-2.08	-5.46

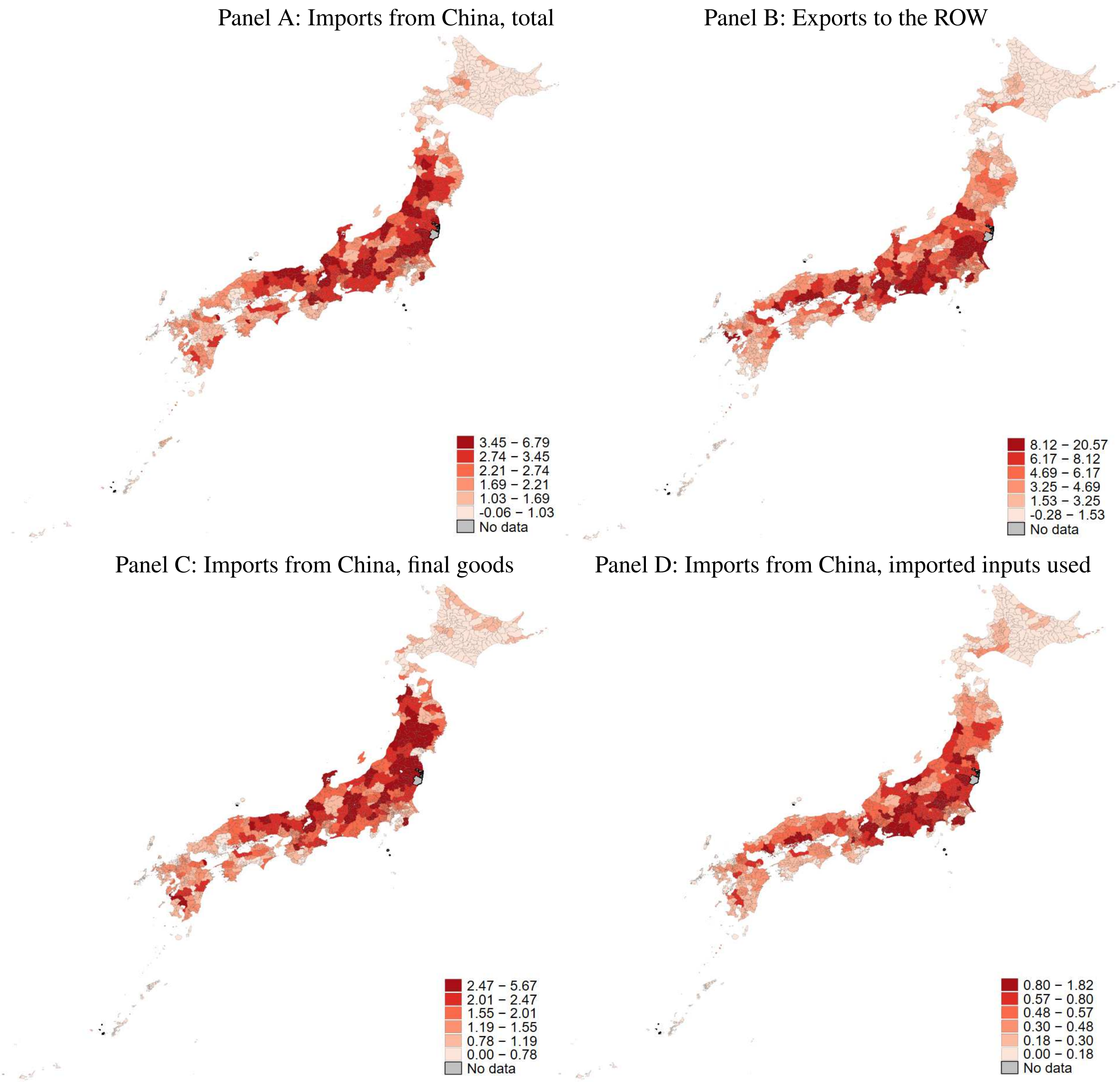
Note: In Panels A, B, and C, Δvar indicates ΔIPW^{CHN}, ΔEOW^{ROW}, and $\Delta IPW^{CHN}_{\text{Inputs used}} - \Delta IPW^{CHN}_{\text{Final goods}}$, respectively. The table shows the exposure to each type of trade shocks in the top 40 commuting zones in terms of the total population size in 1991. The municipalities listed are representative municipalities of the CZs and not the full list of municipalities in the CZs. The unit of the trade shocks is 100,000 JPY (in the 2000 prices). The unit of Δl is the percentage point change as a share of working age population. See the main text for data sources.

The table also shows that CZs with greater import exposures experienced greater reductions in the share of manufacturing employment (i.e., 9.1 pp, 5.5 pp, and 3.6 pp reductions in the top three CZs, respectively).

Table 2 Panel B summarizes the exposure to export opportunities, ΔEOW^{JPN}, showing that CZs including export-oriented manufacturing industries such as Toyota-shi, Aichi, Mito-shi, Ibaraki, and Yokkaichi-shi, Mie were exposed to greater export opportunities. On the other hand, CZs in Hokkaido and Okinawa were less exposed to those shocks because these locations are specializing in non-manufacturing sectors such as agriculture and tourism, exposed to export opportunities at a smaller extent.

Table 2 Panel C displays the exposure to "imported inputs used − imported final goods from China." We use the "imported inputs used" (equation (8)) rather than the conventional "imported inputs" (equation (7)) because the former captures the imported inputs *used* in the manufacturing sectors in Japan, more suited in our analysis shedding

FIGURE 6: Exposures to imports from China and exports to the ROW, Japan



Note: The figure shows the exposures to the imports from China and exports to the rest of the world (ROW). All panels are based on the averages of the two periods, the 1990s and 2000s. Authors' calculations using the data obtained from the data sources written in the text.

light on GVCs. A greater value indicates that the CZ is exposed to imported inputs more greatly than imported final goods. It shows that CZs including Toyota-shi, Aichi, Hiroshima-shi, Hiroshima, and Naha-shi, Okinawa were facing greater amounts of imported inputs rather than imported final goods from China. On the other hand, CZs including Gifu-shi, Gifu, Ohata-shi, Gunma, and Otsu-shi, Shiga were facing greater amounts of imported final goods rather than imported inputs from China.

Figure 6 displays nation-wide geographical distributions of the trade variables in Japan. Panels A, B, C, D display imports from China, exports to the ROW, imported final goods from China, and inputs *used* by Japanese sectors and imported from China, respectively. The darker colored CZs are those with greater exposures. These panels show that the exposures to trade shocks are not uniformly distributed across space.

TABLE 3: Commuting zones with top, median, and bottom exposures, the US

Panel A: Import penetration from China

No.	Commuting zone	Δvar	Δl
1	San Jose CA	5.25	-10.27
2	Providence RI	3.28	-7.53
3	Los Angeles CA	1.97	-5.89
20	Columbus OH	1.17	-3.58
21	Miami FL	1.13	-3.65
38	Orlando FL	0.59	-3.13
39	Washington DC	0.55	-0.63
40	New Orleans LA	0.32	-1.89

Panel B: Export opportunities to the ROW

No.	Commuting zone	Δvar	Δl
1	Providence RI	10.76	-7.53
2	San Jose CA	8.75	-10.27
3	Milwaukee WI	4.46	-4.18
20	Houston TX	2.28	-1.96
21	Columbus OH	2.21	-3.58
38	West Palm Beach FL	1.09	-2.69
39	Washington DC	0.62	-0.63
40	Seattle WA	0.34	-4.96

Panel C: Imported inputs used − final goods from China

No.	Commuting zone	Δvar	Δl
1	New Orleans LA	-0.51	-1.89
2	West Palm Beach FL	-0.55	-2.69
3	Washington DC	-0.56	-0.63
20	Sacramento CA	-1.29	-1.75
21	Columbus OH	-1.30	-3.58
38	Providence RI	-2.64	-7.53
39	Buffalo NY	-3.14	-5.88
40	San Jose CA	-5.36	-10.27

Note: In Panels A, B, and C, Δvar indicates ΔIPW^{CHN}, ΔEOW^{ROW}, and $\Delta IPW^{CHN}_{\text{Inputs used}} - \Delta IPW^{CHN}_{\text{Final goods}}$, respectively. The table shows the exposure to each type of trade shocks in the top 40 commuting zones in terms of the total population size in 1991. The trade variables come from Feenstra et al. (2019) and they note that "the change in US import (or export) exposure is computed by dividing 100 $\times$ the annualized increase in the value of US imports (exports) over the indicated periods by 1991 US market value (1991 US industry output) in that industry." The unit of Δl is the percentage point change as a share of the working age population.

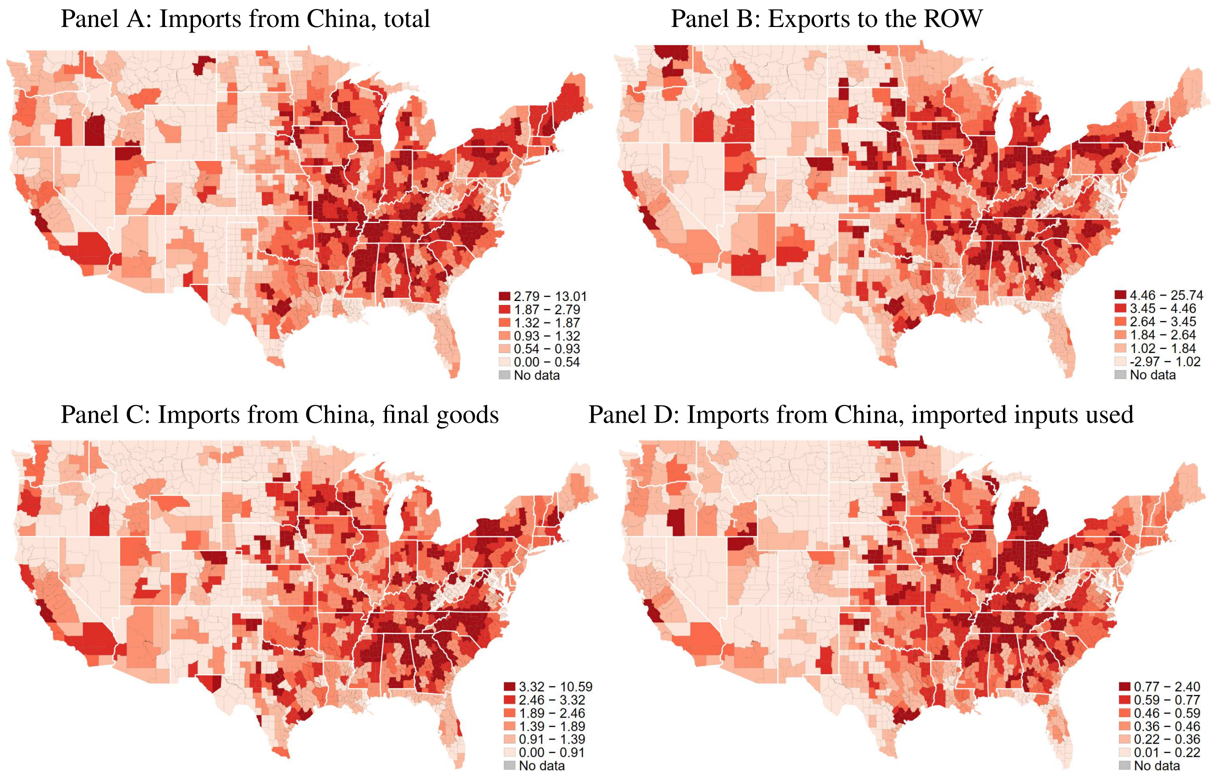
4.4 Trade exposures in the US

The top three, medium and bottom three CZs (among the largest 40 CZs) in terms of the three trade exposures in the US are shown in Table 3. Panel A shows that CZs, including San Jose, CA, and Providence, RI, and Los Angeles, CA had the greatest exposures to import penetration from China. On the other hand, those including Orlando, FL, Washington, DC, and New Orleans, LA, had the smallest exposures in terms of import penetration.

Table 3 Panel B shows that the top two CZ in import penetration, San Jose, CA, and Providence, RI, are also listed at the top two CZs in terms of export opportunities. The bottom CZs in terms of the exposure to export opportunities are West Palm Beach, FL, Washington DC, and Seattle, WA. Washington D.C. is also listed as one of the CZs with the smallest exposure to import penetration. It has a smaller exposure to trade shocks in general because its share of manufacturing employment is small. Panel C displays the top, medium, and bottom CZs in terms of "imported inputs used − imported final goods from China." It lists New Orleans LA, West Palm Beach FL, and Washington, DC as the top three CZs and Providence RI, Buffalo, NY, and San Jose, CA as the bottom CZs.

The geographical distribution of these trade variables in the US are presented in Figure 7, imports from China, exports to the ROW, imported final goods from China, and inputs *used* by US sectors and imported from China in Panels A, B, C, and D, respectively. Again, as in the case of Japan, the figure shows that the exposure to the trade shocks vary substantially across locations within the US.

FIGURE 7: Exposures to imports from China and exports to the ROW, the US



Note: The figure shows the exposures to the imports from China and exports to the rest of the world (ROW). All panels are based on the averages of the two periods, the 1990s and 2000s. Authors' calculations using the data obtained from the data sources written in the text.

5 Baseline results

5.1 Baseline first-stage results

We discuss our regression results, starting with first-stage results. Table 4 summarizes the results from regressing the endogenous explanatory variables on the instruments and the control variables, using the initial population as weights. Columns (1)-(4) report the results from the Japanese data and columns (5)-(8) reports the results from the US data, and both are structured symmetrically. Column (1) and (5) regress ΔIPW^{CHN} on $\Delta IPW^{CHN\rightarrow OTH}$ and the control variables. Both coefficients are positive and statistically significant at the 1%, and corresponding F-statistics for excluded instruments are 477 and 213, respectively, indicating that the instrument $\Delta IPW^{CHN\rightarrow OTH}$ works well to explain the endogenous variable ΔIPW^{CHN}.

Columns (2) and (6) regress the same endogenous variable ΔIPW^{CHN} on $\Delta IPW^{CHN\rightarrow OTH}$ and $\Delta EOW^{OTH\rightarrow ROW}$ because we include the two endogenous variables in the same regression equation in our main specifications. In column

(2), although $\Delta EOW^{OTH \to ROW}$ has a significant negative coefficient, the coefficient is tiny, -0.004.[23] In column (6), $\Delta EOW^{OTH \to ROW}$ has an insignificant coefficient. In either case (in columns (2) and (6)), $\Delta IPW^{CHN \to OTH}$ continue to have significant positive coefficients and these two regressions produce high enough first-stage F-statistics, 256 and 109, respectively.

TABLE 4: First-stage regression results

	k =JPN				k =USA			
Dep. var.	$\Delta IPW^{CHN \to k}$		$\Delta EOW^{k \to ROW}$		$\Delta IPW^{CHN \to k}$		$\Delta EOW^{k \to ROW}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Delta IPW^{CHN \to OTH \setminus k}$	0.19***	0.19***		-0.07	1.02***	1.03***		-0.01
	(0.01)	(0.01)		(0.06)	(0.07)	(0.07)		(0.14)
$\Delta EOW^{OTH \setminus k \to ROW}$		-0.004***	0.08***	0.08***		-0.01	0.39***	0.39***
		(0.00)	(0.01)	(0.01)		(0.01)	(0.05)	(0.06)
Obs.	616	616	616	616	1,444	1,444	1,444	1,444
R-sq.	0.94	0.94	0.87	0.87	0.82	0.82	0.61	0.61
F-stat.	476.82	255.75	32.72	17.62	213.48	109.28	54.94	31.08
p-value of F-stat.	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Note: The table shows the results from first-stage regressions. All regressions include constant term and control variables and region fixed effects, prefecture dummies for Japan, and statistical division dummies for the US. The total initial population weights all regressions. Standard errors, clustered at the prefecture level for Japan, and the state level for the US, are in parentheses. The shown F-statistics are those for excluded instruments only. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Columns (3) and (7) regress ΔEOW^{ROW} on $\Delta EOW^{OTH \to ROW}$ and the controls. The two columns show highly significant positive coefficients with F-statistics of 33 and 55, respectively. Lastly, columns (4) and (8) regress ΔEOW^{ROW} on $\Delta EOW^{OTH \to ROW}$ and $\Delta IPW^{CHN \to OTH}$. Although $\Delta IPW^{CHN \to OTH}$ does not have significant coefficients in the two columns, F-statistics remain high, 18 and 31, respectively.

Figure 8 visually describes the goodness-of-fit of the first-stage regressions, taking the endogenous variable on the vertical axis and the predicted endogenous variable using the corresponding instruments on the horizontal axis. The top two panels are based on Japanese data and the bottom two are based on the US data. Panels A and C display the correlations between the import penetration variable and its predicted variable. Panels B and D display the correlations between the export opportunity variable and its predicted variable. All panels show that there are striking positive correlations between the two variables.

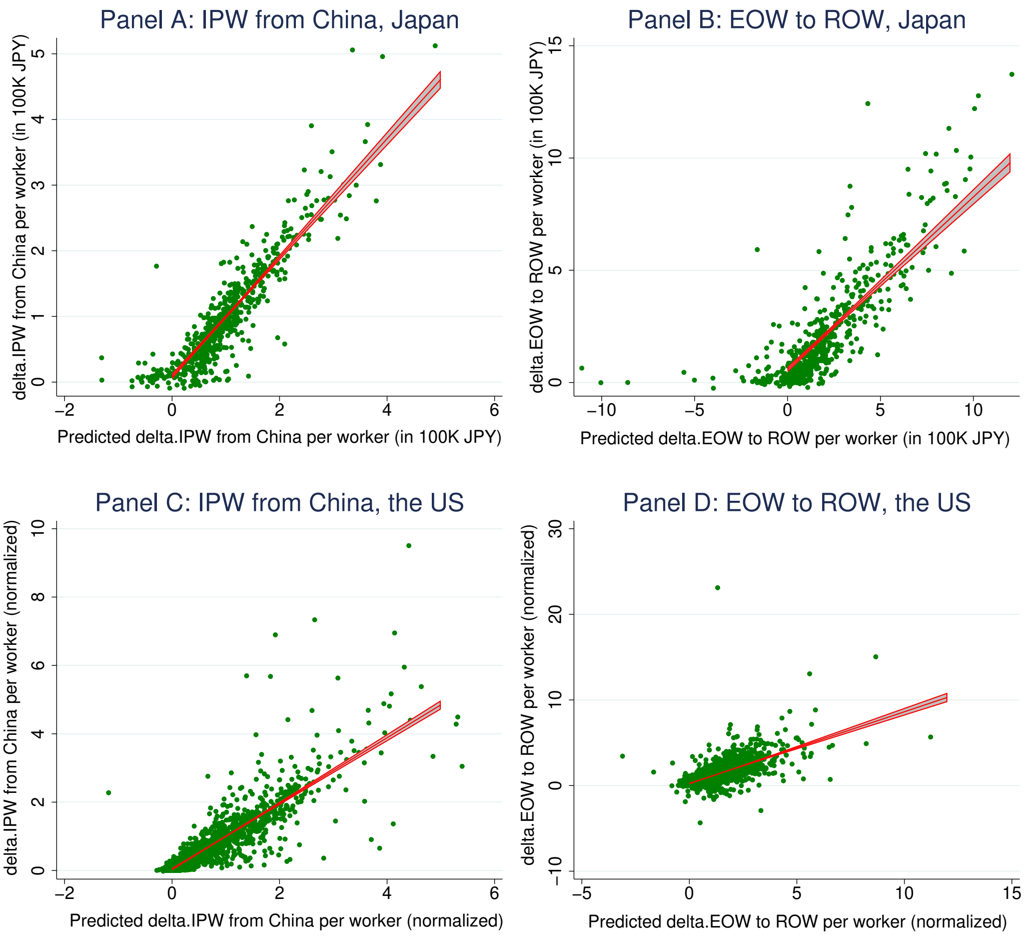
5.2 Baseline second-stage results

Using the instruments shown to be valid in the previous section, this section discusses second-stage results. Table 5 shows results from Japan in Panel A and results from the US in Panel B, constructed symmetrically. In column (1), using OLS, we regress changes in the manufacturing employment as a share of working age population, $\Delta l_{it} = 100 \times (L_{it+1}/WAP_{it+1} - L_{it}/WAP_{it})$, on import penetration from China, ΔIPW^{CHN}. The variable ΔIPW^{CHN} has statistically significant and negative coefficients in both panels, meaning that imports from China reduced manufacturing employment in the two countries.

As the OLS results include endogeneity bias potentially, column (2) uses $\Delta IPW^{CHN \to OTH}$ as an instrument.

[23]This suggests that the Japanese sectors that were expecting increasing global demand (greater $\Delta EOW^{OTH \to ROW}$) were facing smaller import penetration from China, reflecting the fact that Japanese CZs specializing in import-competing sectors differ from Japanese CZs specializing in export-oriented sectors.

FIGURE 8: First-stage fits



Note: The figure shows the scatter plots showing the correlations between the endogenous explanatory variables and their predictions based on the corresponding instruments.

The absolute values of the IV coefficients are greater than the OLS coefficients in both panels, suggesting that there is attenuation bias caused by measurement errors and other types of endogeneity leading to upward bias. The bottom of each panel shows the quantified causal effects of the trade shock on manufacturing employment.[24] It shows that, in Japan, the import penetration from China reduced 350 thousand and 730 million jobs in the 1990s and 2000s, leading to a 1.08 million job reduction in the two periods. The corresponding number of job losses is slightly lower in the US, 230 thousand in the 1990s and 730 thousand in the 2000s, a total of 960 thousand.

Column (3) replaces the explanatory variable with ΔEOW^{ROW}. It uses the OLS approach, showing that exports to the ROW has a positive effect on manufacturing employment in both countries. Column (4) shows that using the IV approach does not change the result qualitatively. The bottom of column (4) lists the employment effects of exports, displaying that Japan had 59 thousand job gains and the US had 18 thousand job gains during the two periods.

The two variables ΔIPW^{CHN} and ΔEOW^{ROW} are jointly included in the same regressions in the last two

[24] To quantify the causal effect of the trade shock on manufacturing employment during the period starting at year t with h-year horizon, we use the following equation: $\Delta L_t^{\text{causal}} = \frac{1}{2}(WAP_t + WAP_{t+h}) \times \overline{\Delta IPW}_t^{CHN} \times \hat{\beta}_{IV}/100 \times R^2$ where WAP_t denotes the number of working age population, $\overline{\Delta IPW}_t^{CHN}$ denotes the working age population weighted average of the trade shock, β_{IV} denotes the IV coefficient of the trade variable, and R^2 is a Partial R-squared. Autor et al. (2013) and Dauth et al. (2014) find the "causal" component of the effect using the combination of the OLS coefficient, IV coefficient, and the coefficient from a residual regression. That component is replaced with a Partial R-squared as done in Acemoglu et al. (2016), Asquith et al. (2019), and Kainuma and Saito (2022).

TABLE 5: Effects of imports and exports on manufacturing employment

Panel A: Japan

	(1) OLS	(2) IV	(3) OLS	(4) IV	(5) OLS	(6) IV	(7) BHJ
$\Delta IPW^{CHN \to JPN}$	-0.58**	-0.73***			-0.53***	-0.62***	-0.65*
	(0.24)	(0.26)			(0.19)	(0.21)	(0.34)
$\Delta EOW^{JPN \to ROW}$			0.31***	0.37***	0.30***	0.34***	0.38***
			(0.07)	(0.05)	(0.06)	(0.06)	(0.13)
Obs.	616	616	616	616	616	616	126
K.-P. rk Wald F-stat.		476.82		32.72		16.73	7.28
Quantified employment effects (million workers)							
1991-2001		-0.35		0.15		-0.13	
2001-2012		-0.73		0.44		-0.15	
1991-2012		-1.08		0.59		-0.29	

Panel B: The US

	(1) OLS	(2) IV	(3) OLS	(4) IV	(5) OLS	(6) IV	(7) BHJ
$\Delta IPW^{CHN \to USA}$	-0.32***	-0.51***			-0.36***	-0.58***	-0.60***
	(0.07)	(0.12)			(0.07)	(0.13)	(0.21)
$\Delta EOW^{USA \to ROW}$			0.11*	0.15*	0.13**	0.24**	0.35**
			(0.06)	(0.09)	(0.06)	(0.11)	(0.15)
Obs.	1,444	1,444	1,444	1,444	1,444	1,444	784
K.-P. rk Wald F-stat.		213.48		54.94		25.75	8.15
Quantified employment effects (million workers)							
1991-1999		-0.23		0.10		-0.11	
1999-2011		-0.73		0.08		-0.70	
1991-2011		-0.96		0.18		-0.80	

Note: The dependent variable is $100 \times (L^k_{i,t+1}/WAP^k_{i,t+1} - L^k_{i,t}/WAP^k_{i,t})$ for $k = JPN, USA$. All regressions include constant term and control variables and region fixed effects, prefecture dummies for Japan, and statistical division dummies for the US. The total initial population weights all regressions. Standard errors, which are clustered at the prefecture level and the state level in the CZ level regressions in Japan and the US, respectively, and clustered at the sector level in the BHJ approach, are in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

columns, with OLS in column (5) and IV in column (6). As shown in Panel A, in Japan, the quantified employment effects of the two trade shocks are 29 thousand job reductions in the two periods. The negative effects of imports from China slightly outweigh the positive effects of exports to the ROW. As shown in Panel B, in the US, the trade shocks led to a reduction of 80 thousand jobs, comparable to the estimate of 65 thousand job reduction by Feenstra et al. (2019).[25]

Column (7) displays the results from the BHJ approach, indicating that the coefficients remain qualitatively similar and statistical significance is also in line with the CZ level results in column (6). Overall, the results in Table 5 suggest that these trade shocks had greater adverse effects on US manufacturing employment than in Japan.

5.3 Considering types of imports from China

We seek to answer the question presented in the previous section: Why does the adverse effect of trade much greater in the US than in Japan. A potential candidate explaining the difference between the two countries is the difference in the "composition" of trade. As discussed in Section 2, Japan imports a greater share of inputs than final

[25]The slight difference comes from the fact that we use a different set of instruments. Feenstra et al. (2019) use several instruments including the "predicted" instruments constructed by regressing trade flows on tariffs, an uncertainty variable, and other variables. We use only a simpler instrument conducted by foreign demand and supply. This is because our analysis includes not only the US but also Japan, and China did not face a change in the Permanent Normal Trade Relation Status when it comes to trade with Japan.

goods from China compared with the US. These two types of imports, final goods and imported inputs, may have different effects on manufacturing employment, as shown in existing studies in the Japanese context (Taniguchi, 2019; Endoh, 2023).

Table 6 shows results from introducing separate import penetration variables: final goods and inputs. Although our baseline regressions in the previous sub-section include the export opportunity variable, we omit the variable in this section to keep the number of endogenous variables minimal, ensuring the effectiveness of the instruments.

Columns (1)-(4) display results with the Japanese data, and columns (5)-(8) display results with the US data. Columns (1) and (5) regress Δl on $\Delta IPW^{CHN}_{\text{Final},i}$ and $\Delta IPW^{CHN}_{\text{Inputs},i}$ (equation (7)). It shows that, in Japan, while imported final goods from China has a job-reducing effect, imported inputs work to sustain manufacturing employment. The quantified effects on employment is shown to be 250 thousand job losses in the 1990s and 240 thousand job losses in the 2000s, leading to a total of 480 thousand job losses, suggesting that the negative effects of final goods imports outweigh the positive effects of imported inputs.

Contrary to the positive effect of imported inputs in Japan, column (5) show that imported inputs have a negative effect on manufacturing employment in the US. The effect of final goods imports is shown to be insignificant, although the sign of the coefficient is negative. The quantified job losses in the 1990s and 2000s add up to 1.15 million in the US. These CZ level regression results are generally supported by the results from the BHJ approach shown in columns (2) and (6), respectively.

TABLE 6: Effects of imports from China by types of imports, IV

	k =JPN				k =USA			
	CZ level	BHJ	CZ level	BHJ	CZ level	BHJ	CZ level	BHJ
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Delta IPW^{CHN\to k}_{\text{Final goods}}$	-0.90***	-0.89**	-0.84***	-0.47	-0.14	0.04	-0.24**	-0.12
	(0.21)	(0.38)	(0.15)	(0.36)	(0.12)	(0.08)	(0.11)	(0.10)
$\Delta IPW^{CHN\to k}_{\text{Inputs}}$	1.51***	-1.90			-0.85*	-1.24**		
	(0.52)	(2.05)			(0.45)	(0.55)		
$\Delta IPW^{CHN\to k}_{\text{Inputs used}}$			3.39***	4.60***			-2.18***	-3.07***
			(0.65)	(1.55)			(0.72)	(0.88)
Obs.	616	126	616	126	1,444	784	1,444	784
K.-P. Wald F-stat.	1678.02	144.68	255.62	389.23	62.34	53.03	103.05	32.78
Quantified effects (million workers)								
1990s	-0.25		-0.09		-0.26		-0.45	
2000s	-0.24		0.15		-0.88		-1.37	
1990s and 2000s	-0.48		0.07		-1.15		-1.82	

Note: The dependent variable is $\Delta l^k_{it} = 100 \times (L^k_{it+1}/WAP^k_{it+1} - L^k_{it}/WAP^k_{it})$. All regressions include the control variables explained in the text, including region dummies. The initial total population weights all regressions. Standard errors, which are clustered at the prefecture level and the state level in the CZ level regressions in Japan and the US, respectively, and clustered at the sector level in the BHJ approach, are in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Columns (3) and (7) regresses Δl on $\Delta IPW^{CHN}_{\text{Final},i}$ and $\Delta IPW^{CHN}_{\text{Inputs used},i}$ (equation (8)). Column (3) shows that, in Japan, while imported final goods have a significant negative effect on manufacturing employment, imported inputs *used* by Japanese sectors have a positive effect. Both coefficients are statistically significant at the 1% level. These results are supported by the BHJ approach result presented in column (4). The suggested effect is that these two shocks overall let to 70 thousand job gains in Japan during the two periods as shown in the bottom of column (3).

In contrast, column (7) shows that, in the US, both final goods imports and imported inputs *used* by US sectors have negative effects on manufacturing employment. The coefficients of the two variables are negative and significant at the 5% and 1% level, respectively. The BHJ approach shown in column (8) also supports the CZ level result. The bottom part of column (7) shows that, in the US, these two trade shocks let to a 1.82 million job losses.

Overall, the results suggest that, in Japan, imported inputs have a positive effect on manufacturing employment as shown in existing studies (e.g., Taniguchi, 2019). However, the results do not support such positive effects of imported inputs in the US context. We further examine the differential effects in the next section.

6 Mechanisms leading to different effects

6.1 Input-output linkages

We have uncovered the different effects of imported inputs on manufacturing employment across the two countries. Our results suggest that Japan and the US differ not only in the composition of imports from China but also the employment effects. This section introduces an additional element, i.e. downstreamness, as a measure to quantify the degree to which a country integrates GVCs, into the regression model to understand the mechanisms behind the different employment effects. The downstreamness measures the number of input-output linkages and the size of transactions through those linkages that *input buyers* are facing. Therefore, a greater value of downstreamness means that the sector is at a downstream position of GVCs. In particular, we run regressions by focusing on a sample such that the value of downstreamness (equation (9)) is above the median, where we use the median value of all observations in the stacked cross-section data from each country. If cheaper access to Chinese intermediate inputs has complementary effects, then input buyers can benefit from global value chains and thus increase manufacturing employment more. This input-output linkage can be tested once we focus on areas specializing in more downstream sectors.

Column (4) in Panel A shows that final goods imports have adverse effects on manufacturing employment and imported inputs have positive effects. The result suggests that in Japan downstream firms can purchase cheaper Chinese intermediate inputs, thereby expanding production and consequently employment. In other words, Japan is more integrated into GVCs, especially with China, and takes advantage of complementary effects. In contrast, results from the US shown in Panel B indicate that the effects of intermediate inputs differ from the ones in Japan. Column (4) in Panel B indicates that the effects of imported inputs are negative in CZs specializing in sectors with higher downstramness. The result suggests that the degree to which a country integrates into GVCs is related with the employment effects of input imports. If a country is deeply integrated into GVCs, a greater amount and wider range of imported inputs are combined with domestic inputs, which in turn generating job-creating effects of imports. On the contrary, a country that could not benefit from imported inputs through GVCs lose competitiveness in global markets relative to other countries, such as Japan, those that reap the benefits of cheaper inputs, and thereby yielding job-reducing effects of imports.

Our results from the US data may seem to contradict the findings by Flaaen and Pierce (2021), where they find that rising US input tariffs on Chinese products during the 2018-19 US-China Trade War reduced US manufacturing employment. We argue that there are several reasons why results could be different between the two studies. First, most importantly, Flaaen and Pierce (2021) focused on tariffs specific to the US and China, unlike the China trade shock which had huge impacts on other countries. The intermediate input channel allowed Japanese firms to purchase cheaper inputs via global value chains, thereby increasing competitiveness in global markets. On the contrary, the same channel worked in the opposite direction, which reduced competitiveness of US firms in global markets. Second, Flaaen and Pierce (2021) analyze the data in the late 2010s, a period marked by a substantial slowdown in the decline of manufacturing employment. Third, they use monthly data. Hence, their results quantify the short-run effects of an acute and sudden rise of input tariffs, whereas almost all 'China shock' studies, including ours, examine decennial data, quantifying the long-run effects. Fourth, Flaaen and Pierce (2021) use the sector level data whereas our analysis is based on the CZ level observations, capturing labor market and goods market effects within each CZ.

Table 7 summarizes results. Columns (1) and (2) show results based on the sample with lower and higher upstreamness, respectively. Columns (3) and (4) are based on downstreamness. Finally, columns (5) and (6) are based on upstreamness minus downstreamness. Panel A displays the results from Japan. It shows that there is no systematic and sizable difference based on the upstreamness or downstreamness. In either case, final goods imports have adverse effects on manufacturing employment and imported inputs have positive effects. The employment effects of import competition do not differ depending on the upstreamness or downstreamness presumably because all sectors in Japan are more integrated into GVCs than the US as demonstrated in Figure 4.[26]

TABLE 7: Up/downstreamness and imports from China, IV

Panel A: Japan

Selection based on	Up		Down		Up−Down	
Sample	Low	High	Low	High	Low	High
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta IPW^{CHN\to k}_{\text{Final goods}}$	-1.05***	-0.72***	-1.03**	-0.64***	-0.88***	-0.61***
	(0.18)	(0.19)	(0.44)	(0.15)	(0.15)	(0.23)
$\Delta IPW^{CHN\to k}_{\text{Inputs used}}$	4.01***	2.93***	3.35*	3.51***	3.52***	4.17***
	(0.91)	(0.92)	(1.90)	(0.76)	(0.67)	(1.07)
Obs.	308	308	308	308	308	308
K.-P. Wald F-stat.	99.4	228.1	31.5	146.9	111.8	103.6

Panel B: The US

Selection based on	Up		Down		Up−Down	
Sample	Low	High	Low	High	Low	High
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta IPW^{CHN\to k}_{\text{Final goods}}$	-0.09	-0.44***	0.22	-0.63***	-0.48***	0.09
	(0.13)	(0.13)	(0.17)	(0.11)	(0.10)	(0.16)
$\Delta IPW^{CHN\to k}_{\text{Inputs used}}$	-4.31***	-0.37	1.39	-1.22**	-1.72***	-1.11
	(1.01)	(0.61)	(2.30)	(0.62)	(0.66)	(0.93)
Obs.	722	722	722	722	722	722
K.-P. Wald F-stat.	32.8	88.6	74.4	73.9	52.6	84.4

Note: The dependent variable is $100 \times (L^k_{i,t+1}/WAP^k_{i,t+1} - L^k_{i,t}/WAP^k_{i,t})$ for $k = JPN, USA$. The interaction terms are instrumented by the interaction terms between the instruments for the import competition variables and the upstreamness (downstreamness) variable. All regressions include constant term and control variables and region fixed effects, prefecture dummies for Japan, and statistical division dummies for the US. The total initial population weights all regressions. Standard errors, clustered at the prefecture level for Japan, and the state level for the US, are in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

In contrast, results from the US shown in Panel B indicate that the effects of import penetration differ depending

[26]The summary statistics shown in Table 1 indicate that the CZ level upstreamness and downstreamness take greater values in the US than in Japan, which is due to fact that these are weighted averages based on sector-CZ level employment. On average, Japanese CZs might be more specializing in sectors with lower levels of upstreamness or downstreamness than the US.

on the level of the upstreamness and downstreamness. Columns (1) and (2) show that the effects of imported inputs are negative in CZs specializing in sectors with lower levels of upstreamness. In comparison, the effects are not statistically significant in CZs with higher levels of upstreamness. Our interpretation is as follows: as the upstreamness measures the number of input-output linkages and the size of transactions through those linkages that *input sellers* are facing, a greater value of upstreamness means that the sector is at an upstream position of GVCs. When a producer is at an upstream position, imported inputs are used to produce next-round inputs to supply, which requires more labor, mitigating the pro-competitive effects of imported inputs.

Columns (3) and (4) are based on downstreamness. The results indicate that the effects of imported inputs are negative in CZs specializing in sectors with higher downstramness while it is statistically insignificant in the other CZs. The downstreamness measures the number of input-output linkages and the size of transactions through those linkages that *input buyers* are facing. Therefore, a greater value of downstreamness means that the sector is at a downstream position of GVCs. When a producer is at a downstream position, as imported inputs would go through a fewer stages of production going forward, positive employment effects of imported inputs were so weak that they were overshadowed by the pro-competitive effects of inputs, leading to adverse employment effects.

The last two columns, columns (5) and (6), are based on the upstreamness minus downstreamness, meant to be a positive measure of the 'upstream' position in GVCs. It shows that adverse employment effects of imported inputs come from CZs with lower values of $Up - Down$ and the effects are insignificant in CZs with higher values of the variable. In these columns, a similar pattern is observed for the effects of final goods also although these are not our main focus in this section. Overall, the results in these columns are consistent with those in columns (1)-(4).

To summarize, the results show that there is no difference in the employment effects depending on the level of upstreamness or downstreamness in Japan presumably because Japan's integration to GVCs is at a higher level. On the other hand, in the US, the job-reducing effects of imported inputs come from CZs specializing in sectors with lower upstreamness or higher downstreamness. These results suggest that the degree to which a country integrates into GVCs is related with the employment effects of imports. If a country is deeply integrated into GVCs, a greater amount and wider range of imported inputs are combined with domestic inputs, which in turn requires more labor, mitigating the job-reducing effects of imports.[27]

6.2 Other possible mechanisms

There might be other explanations behind the different effects across the two countries. This section summarizes other mechanisms that could potentially lead to our empirical results.

1. The balance between direct job replacement effects and productivity effects: Ottaviano et al. (2013) and Wright (2014) find that offshoring has two employment effects working in different directions: the direct replacement effect reducing employment at home, and the productivity effect improving the productivity of firms outsourced their tasks, increasing employment. If such adjustments occur within the manufacturing sector, it could be the case that

[27] This result is echoing with Kurokawa (2011) who finds that an increase in the number of variety offshored has labor market effects through skill-variety complementarity.

the job creation effect dominates the job replacement effect of offshoring in Japan, whereas vice versa might occur in the US. Due to data limitations, our paper cannot identify the contribution of each of these channels. Nevertheless, we show in Appendix F that, while imported inputs have positive effects on labor productivity in the US, we find inconclusive results regarding the effects of the same type of imports on labor productivity from the Japanese data. Although the previous studies suggest that improved productivity increases labor demand, our results suggest that labor productivity increased more in CZs that experienced greater reductions in manufacturing employment. A positive link between labor productivity growth and increased manufacturing employment is not observed from the Japanese data either, which makes us think that job-creating productivity-enhancing effects of offshoring are not strongly working in the context of the effects of the China shock at the CZ level in the US and Japan.

2. Different labor market institutions: The Japanese labor markets are known to be more rigid than those of the other advanced countries such as the US. Ono (2010) argue that "[j]ob mobility remains considerably lower in Japan than in other advanced economies (particularly the US)" because of Japan's "informal lifetime employment contracts." Japan's rigid labor markets appear in other aspects also. For example, Genda et al. (2010) document that a negative macroeconomic shock has as a persistent long-term effect on the cohort graduating in the recession years while the effect is temporary in the US. They also find that starting wages are almost constant from the 1980s until the late 2000s. Sasahara et al. (2023) find that imports from China had limited effects on wages using Japan's prefecture level data. Part of the contrasting empirical results between Japan and the US in this study could come from different labor market institutions between the two countries. Due to data limitations, our paper does not investigate the role of labor market institutions.

3. Different degree of China shock-induced servification of manufacturing: Fort et al. (2018) find that US manufacturing value-added had been rising while US manufacturing employment was declining rapidly during the 'China shock' period. Fort (2023) also find that US manufacturing firms rapidly expanded their knowledge workers and conducted domestic innovation actively. These findings suggest that US manufacturing employment was reallocated into service sectors, including the R&D sector. In Appendix F, we examine the effects of imports and exports on manufacturing labor productivity and find suggestive evidence of such productivity-enhancing effects of import competition from the US data but not from the Japanese data. Caliendo et al. (2019) and Feenstra and Sasahara (2018) also document similar inter-sectoral labor reallocation towards services. However, such inter-sectoral adjustments may be limited in Japan.

4. Different production functions: Another potential explanation is that the production function could be different across countries. For instance, final goods' production function in the US could be a CES or Cobb-Douglas form combining labor and intermediate inputs. In this case, labor and inputs are substitutes, meaning that an increase in the input usage reduces labor used for production. In contrast, in the Japanese case, using imported inputs may entirely change the cost structure, leading to an increase in labor input. However, it is beyond the scope of the current study.

5. The China shock affecting the production functions differently: Lastly, the exposure to trade may have altered each country's production function differently. A greater exposure to import competition in Japan may have increased its labor share because, for example, tasks associated with handling inputs from China are labor-intensive.

In contrast, import competition in the US may have increased the capital share because, for example, it transformed its production process in a cost-saving manner. In Appendix F, we pursue this possibility by examining the effects on the capital-labor ratios. Results suggest that, in the US, the capital-labor ratios increased due to an increase in final goods imports and intermediate goods imports. On the other hand, in Japan, results were somewhat inconsistent between CZ level regressions and the BHJ regressions.

6.3 Limitations and a remaining puzzle

We have analyzed the effects of trade on labor markets by focusing on GVC aspects. In so doing, this study runs reduced-form regressions. This section acknowledges a need for caution when interpreting the results. Caliendo and Parro (2022) notes, in the context of reduced-form shift-share analysis, "the estimation strategy does not identify the overall impact of trade liberalization on the outcome, but it instead measures whether some districts (authors' note: CZs in our context) are affected more than others."[28] Autor et al. (2021) also acknowledge the same point: "This strategy identifies the relative impact of the trade shock–e.g., whether manufacturing employment fell by more in more-trade-exposed locations–but not the absolute impact of the shock, e.g., whether the trade shock reduced manufacturing employment nationally."[29] In our context, for example, although our results suggest that imports from China contributed to sustain 70 thousand manufacturing jobs, this counterfactual analysis assumes that CZs with zero exposure to the trade shock experienced no change in manufacturing employment (Helpman, 2018), which may not be the case. To overcome this issue of a reduced-form analysis, Caliendo et al. (2019) and Caliendo and Parro (2023) use quantitative trade models and demonstrate that the China trade shock is not the main cause of the decrease in the US manufacturing employment.

Our analysis implies that the adverse effect of the trade shock on Japanese manufacturing employment is less than that of the US (and the effect is even positive). Nevertheless, as shown in Figure 1, Japanese manufacturing employment decreased by about 4 million since the early 1990s, which is almost the same magnitude as the US. The open question now is: Why did Japanese manufacturing employment decrease by almost the same magnitude as the US?

7 Concluding remarks

This paper has examined the effect of imports from China and exports to the rest of the world on manufacturing employment in Japan and the US. We have documented the differences between the two countries in terms of their trade with China: (i) Japan imported a greater share of intermediate inputs from the US throughout the sample period, and (ii) while imported inputs from China had positive effects on manufacturing employment in Japan, such positive effects of imported inputs were not observed in the US data.

We have examined a mechanism leading to different employment effects of imported inputs between the two countries by focusing on their integration patterns into GVCs, quantified by up/downstreamness. The results show that,

[28] See pages 227-228 in Caliendo and Parro (2022). They mention that Topalova (2010) makes the same point.

[29] See page 3 in Autor et al. (2021). They note this point by referencing Heckman et al. (1998) and Helpman (2018).

in the US, the adverse effects of imported inputs from China are particularly strong in CZs specializing in less upstream and more downstream sectors. On the other hand, the Japanese data do not suggest such different employment effects of imported inputs based on up/downstreamness, presumably because Japan's integration to GVCs is at a higher level than the US. This study has highlighted cross-country differences in the effects of exposure to the China trade shock and proposed an explanation based on GVCs. We hope that it fosters a deeper comprehension of the variations in interactions between trade shocks and labor markets across countries.

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Appendix for “A Tale of Two Countries: Global Value Chains, the China Trade Shock, and Labor Markets”

Jaerim Choi, Masahiro Endoh, and Akira Sasahara

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A List of manufacturing sectors in the Japanese data

Table A1 shows the list of sectors used to construct trade exposure variables in the analysis with the Japanese data.

TABLE A1: Sectors used when constructing trade exposures in the analysis with the Japanese data

No.	Description	No.	Description
1	Live stock food products	33	Nonferrous metals
2	Seafood products	34	Tin, aluminium, and other metals
3	Vegetable, fruits, agricultural products	35	Hardware
4	Beverages (non alcoholic)	36	Air conditioning apparatus
5	Alcoholic drinks	37	Architectural metal products
6	Teas and coffees	38	Bolts, nuts, and rivets
7	Fertilizers	39	Engines and turbines motors
8	Tobaccos	40	Industrial machine
9	Textiles	41	Agricultural machinery
10	Wooden products and construction materials	42	Construction and mining machinery
11	Paper and pulp	43	Textile machinery
12	Chemical fertilizers	44	Office machinery
13	Inorganic chemicals	45	Electrical measuring instrument
14	Organic chemicals	46	Medical apparatus and instruments
15	Fats and oils processed products	47	Optical instruments
16	Medical products	48	Communication equipment
17	Other chemical products	49	Industrial electrical machinery
18	Refined oils and coke	50	Consumer electrical machinery
19	Paving material	51	Electric lighting fixtures
20	Plastic products	52	Autos and their related products
21	Tires and robber products	53	Rail cars and their related products
22	Leather and fur	54	Vessels and their related products
23	Bags	55	Aircrafts and their related products
24	Glass	56	Other transportation equipment
25	Cement	57	Ornaments
26	Clay for construction	58	Watches and clocks
27	Ceramics	59	Musical instruments and records
28	Refractories	60	Toys and sporting goods
29	Carbon and graphite	61	Office supplies and equipment
30	Abrasive	62	Weapons
31	Masonry materials	63	Miscellaneous
32	Steel		

B Summary statistics and correlations between variables

This section provides summary statistics of control variables and correlation matrices between variables. Table A2 shows the summary statistics of the control variables used in the regressions with the Japanese data. Table A3 shows correlation coefficients between the trade exposure variables used in the analysis with the Japanese data. The correlation coefficient between ΔIPW^{CHN} and ΔEOW^{ROW} is 0.67. The correlation between $\Delta IPW^{CHN}_{\text{Final goods}}$ and $\Delta IPW^{CHN}_{\text{Inputs used}}$ is 0.73. These pairs of variables included in the same regression equation. Although the correlation coefficients are not so low, these are not substantially high to be concerned about the multicollinearity. Table A4 shows correlation coefficients between the instrumental variables in the Japanese data. Table A5 shows correlation coefficients between the control variables in the Japanese data.

TABLE A2: Summary statistics of the instruments control variables, Japan, $k = JPN$

	Mean	Std. dev.	Min	Max
Controls				
Unemployment rate	3.24	1.46	0.00	10.78
Labor market participation rate	51.89	4.04	39.97	81.74
Foreign population share	0.61	0.55	0.00	3.71
Urban population share	15.24	24.45	0.00	97.44
Female employment share	42.92	3.32	21.02	54.13
ln(Affiliate size)	1.98	0.24	0.70	2.46
Non-full-time employee share	11.54	7.88	0.00	69.86
ln(Population density)	1.53	1.09	-1.89	4.54
Young population share	0.25	0.02	0.16	0.34
Decade dummy, the 2000s = 1	0.50	0.50	0	1
Region dummy, Hokkaido and Tohoku	0.16	0.37	0	1
Region dummy, Kanto	0.07	0.26	0	1
Region dummy, Chubu	0.08	0.27	0	1
Region dummy, Kansai	0.13	0.34	0	1
Region dummy, Chugoku	0.20	0.40	0	1
Region dummy, Shikoku	0.05	0.22	0	1
Region dummy, Kyushu and Okinawa	0.30	0.46	0	1
Instruments				
$\Delta IPW^{CHN \to OTH \setminus k}$	4.02	4.07	0.00	22.92
$\Delta EOW^{OTH \setminus k \to ROW}$	15.04	15.70	-11.73	103.13
$\Delta IPW^{CHN \to OTH \setminus k}_{\text{Final goods}}$	2.64	2.39	0.01	15.53
$\Delta IPW^{CHN \to OTH \setminus k}_{\text{Inputs}}$	0.91	0.93	0.00	4.54
$\Delta IPW^{CHN \to OTH \setminus k}_{\text{Inputs used}}$	0.51	0.48	0.00	3.31
$\Delta IPW^{CHN \to OTH \setminus k}_{\text{Final goods}} \times Up$	1.38	1.61	0.00	10.38
$\Delta IPW^{CHN \to OTH \setminus k}_{\text{Inputs used}} \times Up$	0.27	0.34	0.00	2.81
$\Delta IPW^{CHN \to OTH \setminus k}_{\text{Final goods}} \times Down$	1.47	1.74	0.00	11.62
$\Delta IPW^{CHN \to OTH \setminus k}_{\text{Inputs used}} \times Down$	0.29	0.37	0.00	3.57

Note: The sample size 616. The female employment share is the share of female manufacturing employment as a share of total manufacturing employment. ln(Affiliate size) is the natural log of the number of manufacturing employees divided by the number of manufacturing affiliates. The young population share is the share of the population younger than 15 years old as a share of the population between the ages 15 and 64.

TABLE A3: Correlations between the endogenous explanatory variables, Japan, $k = JPN$

		(1)	(2)	(3)	(4)	(5)	(6)
(1)	Δ mnfg share	1					
(2)	$\Delta IPW^{CHN \to k}$	-0.16	1				
(3)	$\Delta EOW^{k \to ROW}$	0.08	0.67	1			
(4)	$\Delta IPW^{CHN \to k}_{\text{Final goods}}$	-0.08	0.81	0.58	1		
(5)	$\Delta IPW^{CHN \to k}_{\text{Inputs}}$	0.10	0.72	0.87	0.76	1	
(6)	$\Delta IPW^{CHN \to k}_{\text{Inputs used}}$	0.06	0.71	0.88	0.73	0.97	1

Note: The sample size 616.

TABLE A4: Correlations between the instruments, Japan, $k = JPN$

		(1)	(2)	(3)	(4)	(5)	(6)
(1)	Δ mnfg share	1					
(2)	$\Delta IPW^{CHN \to OTH \setminus k}$	0.04	1				
(3)	$\Delta EOW^{OTH \setminus k \to ROW}$	0.08	0.77	1			
(4)	$\Delta IPW^{CHN \to OTH \setminus k}_{\text{Final goods}}$	-0.14	0.90	0.65	1		
(5)	$\Delta IPW^{CHN \to OTH \setminus k}_{\text{Inputs}}$	0.04	0.90	0.87	0.85	1	
(6)	$\Delta IPW^{CHN \to OTH \setminus k}_{\text{Inputs used}}$	0.02	0.82	0.90	0.76	0.95	1

Note: The sample size 616.

TABLE A5: Correlations between the control variables, Japan, $k = JPN$

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
(1)	Δ mnfg share	1												
(2)	Initial mnfg emp. share	-0.51	1											
(3)	Unemployment rate	0.18	-0.17	1										
(4)	Labor market part. rate	0.03	0.13	-0.51	1									
(5)	Foreign population share	-0.22	0.47	-0.08	0.13	1								
(6)	Urban population share	-0.05	-0.02	0.28	-0.11	0.26	1							
(7)	Female employment share	-0.08	0.04	0.34	-0.27	-0.26	-0.09	1						
(8)	ln(Affiliate size)	-0.11	0.35	0.24	0.01	0.36	0.43	-0.11	1					
(9)	Non-full-time emp. share	0.14	-0.28	-0.29	0.21	-0.05	-0.05	-0.33	-0.31	1				
(10)	ln(Population density)	-0.24	0.33	0.43	-0.28	0.44	0.44	0.26	0.44	-0.30	1			
(11)	Young population share	0.11	-0.08	0.19	-0.26	0.06	-0.05	-0.01	-0.07	-0.07	0.06	1		
(12)	Upstreamness	-0.07	0.26	0.25	-0.04	0.18	0.15	0.13	0.36	-0.44	0.34	-0.14	1	
(13)	Downstream	0.34	-0.06	0.38	0.09	-0.001	0.09	0.12	0.22	-0.27	0.12	-0.02	0.47	1

Note: The sample size is 616. The female employment share is the share of female manufacturing employment as a share of total manufacturing employment. ln(Affiliate size) is the natural log of the number of manufacturing employees divided by the number of manufacturing affiliates. The young population share is the share of the population younger than 15 years old as a share of the population between the ages 15 and 64.

Table A6 shows the summary statistics of the control variables used in the regressions with the US data. Table A7 shows correlation coefficients between the trade exposure variables used in the analysis with the US data. The correlation coefficient between ΔIPW^{CHN} and ΔEOW^{ROW} is 0.31. The correlation between $\Delta IPW^{CHN}_{\text{Final goods}}$ and $\Delta IPW^{CHN}_{\text{Inputs used}}$ is 0.46. These correlation coefficients are not so high to be concerned about the multicollinearity. Table A8 shows correlation coefficients between the instrumental variables in the US data. Table A9 shows correlation coefficients between the control variables in the US data.

TABLE A6: Summary statistics of the instruments and control variables, the US, $k = USA$

	Mean	Std. dev.	Min	Max
Instruments				
$\Delta IPW^{CHN \to OTH \backslash k}$	0.75	0.78	-0.97	5.25
$\Delta EOW^{OTH \backslash k \to ROW}$	2.47	3.00	-9.48	28.93
$\Delta IPW^{CHN \to OTH \backslash k}_{\text{Final goods}}$	1.15	1.59	0.00	15.19
$\Delta IPW^{CHN \to OTH \backslash k}_{\text{Inputs}}$	0.65	0.76	0.00	6.94
$\Delta IPW^{CHN \to OTH \backslash k}_{\text{Inputs used}}$	0.41	0.48	-0.02	3.45
$\Delta IPW^{CHN \to OTH \backslash k}_{\text{Final goods}} \times Up$	0.71	1.26	0.00	10.79
$\Delta IPW^{CHN \to OTH \backslash k}_{\text{Inputs used}} \times Up$	0.25	0.37	-0.02	3.11
$\Delta IPW^{CHN \to OTH \backslash k}_{\text{Final goods}} \times Down$	0.74	1.32	0.00	11.48
$\Delta IPW^{CHN \to OTH \backslash k}_{\text{Inputs used}} \times Down$	0.26	0.39	-0.03	3.65
Controls				
Share of educated population	45.26	9.09	19.94	70.56
Share of foreign-born population	4.96	5.86	0.38	48.91
Share of female employment	62.74	7.06	33.24	79.61
Share of employment with routine occupations	28.57	3.14	19.99	37.75
Average offshorability index	-0.51	0.43	-1.64	1.24
Decade dummy, the 2000s = 1	0.50	0.50	0	1
Census division dummy 1	0.02	0.15	0	1
Census division dummy 2	0.04	0.19	0	1
Census division dummy 3	0.12	0.32	0	1
Census division dummy 4	0.23	0.42	0	1
Census division dummy 5	0.15	0.35	0	1
Census division dummy 6	0.10	0.30	0	1
Census division dummy 7	0.15	0.36	0	1
Census division dummy 8	0.13	0.34	0	1

TABLE A7: Correlations between the endogenous explanatory variables, the US, $k = USA$

		(1)	(2)	(3)	(4)	(5)	(6)
(1)	Δ mnfg share	1					
(2)	$\Delta IPW^{CHN \to k}$	-0.47	1				
(3)	$\Delta EOW^{k \to ROW}$	-0.08	0.31	1			
(4)	$\Delta IPW^{CHN \to k}_{\text{Final goods}}$	-0.45	0.55	0.14	1		
(5)	$\Delta IPW^{CHN \to k}_{\text{Inputs}}$	-0.55	0.55	0.38	0.59	1	
(6)	$\Delta IPW^{CHN \to k}_{\text{Inputs used}}$	-0.52	0.55	0.43	0.46	0.91	1

Note: The sample size 1,444.

TABLE A8: Correlations between the instruments, the US, $k = USA$

		(1)	(2)	(3)	(4)	(5)	(6)
(1)	Δ mnfg share	1					
(2)	$\Delta IPW^{CHN \to k}$	-0.56	1				
(3)	$\Delta EOW^{k \to ROW}$	-0.47	0.60	1			
(4)	$\Delta IPW^{CHN \to k}_{\text{Final goods}}$	-0.53	0.64	0.52	1		
(5)	$\Delta IPW^{CHN \to k}_{\text{Inputs}}$	-0.58	0.63	0.71	0.78	1	
(6)	$\Delta IPW^{CHN \to k}_{\text{Inputs used}}$	-0.58	0.64	0.79	0.70	0.94	1

Note: The sample size 1,444.

TABLE A9: Correlations between the control variables, the US, $k = USA$

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1)	Δ mnfg share	1								
(2)	Initial mnfg employment share	-0.41	1							
(3)	Share of educated population	0.01	-0.28	1						
(4)	Share of foreign-born population	-0.04	-0.23	0.20	1					
(5)	Share of female employment	-0.02	0.19	0.62	-0.17	1				
(6)	Share of employment with routine occupations	-0.31	0.52	0.16	0.05	0.29	1			
(7)	Average offshorability index	-0.11	0.34	0.24	0.21	0.34	0.71	1		
(8)	Upstreamness	-0.07	-0.21	0.10	-0.05	-0.10	-0.06	-0.26	1	
(9)	Downstream	-0.42	0.10	0.28	0.15	0.23	0.18	-0.14	0.17	1

Note: The sample size 1,444.

C Instrumental variables for the other import competition variables

The instrument used to identify the exposure to imported final goods (equation (6)) is

$$\Delta IPW_{\text{Final},i}^{CHN\to OTH\backslash k} = \sum_{s\in S_M} \left(\frac{L_{ist}^{k}}{\sum_{s'\in S_A} L_{is't}} \times \frac{\sum_{k'\in OTH\backslash k} \Delta f_{(CHN,s),k'}}{\sum_{i'} L_{i'st}^{k'}} \right), \tag{A1}$$

where the superscript in the left-hand side $CHN \to OTH\backslash k$ indicates that it is exports from China to "other" countries from country k's perspective. In the right-hand side, $\sum_{k'\in OTH\backslash k} \Delta f_{(CHN,s),k'}$ denotes the sum of exports from China's sector s to country k' over destination countries k' included in the set of the "other" countries. The instrument used to identify the exposure to imported imported inputs (equation (7)) is

$$\Delta IPW_{\text{Inputs},i}^{CHN\to OTH\backslash k} = \sum_{s\in S_M} \left(\frac{L_{ist}^{k}}{\sum_{s'\in S_A} L_{is't}} \times \frac{\sum_{k'\in OTH\backslash k} \sum_{s'} \Delta m_{(CHN,s),(k',s')}}{\sum_{i'} L_{i'st}^{k}} \right). \tag{A2}$$

The instrument used to identify the exposure to imported imported inputs *used* by sectors in the destination country (equation (8)) is

$$\Delta IPW_{\text{Inputs used},i}^{CHN\to OTH\backslash k} = \sum_{s\in S_M} \left(\frac{L_{ist}^{k}}{\sum_{s'\in S_A} L_{is't}} \times \frac{\sum_{k'\in OTH\backslash k} \sum_{s'} \Delta m_{(CHN,s'),(k',s)}}{\sum_{i'} L_{i'st}^{k}} \right). \tag{A3}$$

When constructing $\Delta IPW_i^{CHN\to OTH\backslash JPN}$, the eight developed countries used are: Australia, Denmark, Finland, Germany, New Zealand, Spain, Switzerland, and the US. However, some of these countries are not included in the WIOD.

We use the Long-run WIOD Version 1.1, March 2022 Release, covering the 1965-2000, to construct variables (6)-(8) and (A1)-(A3) for the 1990s (1991-2000 for Japan; 1991-1999 for the US). For the WIOD 2022 version, the eight developed countries used to construct the instruments for Japan are Australia, Canada, Denmark, Finland, Germany, Spain, the UK, and the US. The eight developed countries used to construct the instruments for the US are Australia, Canada, Denmark, Finland, Germany, Japan, Spain, the UK.

We use the WIOD 2016 Release, covering the 2000–2014 period, to construct variables (6)-(8) and (A1)-(A3) for the 2000s (2001-2012 for Japan; 2000-2011 for the US). For the WIOD 2016 version, the eight developed countries used to construct the instruments for Japan are Australia, Canada, Denmark, Finland, Germany, Spain, Switzerland, and the US. The eight developed countries used to construct the instruments for the US are Australia, Canada, Denmark, Finland, Germany, Japan, Spain, and Switzerland. Table A10 summarizes the lists of the "eight developed" countries.

TABLE A10: The list of eight developed countries used to construct instruments

	ISO	Country	UN Comtrade	WIOD 2022 version (1990s)	WIOD 2016 version (2000s)
1	AUS	Australia	✓	✓	✓
2	CAN	Canada		✓	✓
3	CHE	Switzerland	✓		✓
4	DEU	Germany	✓	✓	✓
5	DNK	Denmark	✓	✓	✓
6	ESP	Spain	✓	✓	✓
7	FIN	Finland	✓	✓	✓
8	GBR	The UK		✓	
9	NZL	New Zealand	✓		
10	USA	The USA	✓	✓	✓

The lists of manufacturing sectors used to construct variables (6)-(8) and (A1)-(A3) are shown in Tables A11 and A12.

TABLE A11: The list of manufacturing sectors in WIOD 2022 Release, used for the 1990s' trade data

	WIOD code	Sector description
1	D15t16	Food, beverages, and tobacco
2	D17t19	Textiles, leather and footwear
3	D21t22	Pulp, paper, printing and publishing
4	D23	Coke, refined petroleum and nuclear fuel
5	D24	Chemicals and chemical products
6	D25	Rubber and plastics
7	D26	Other non-metallic mineral
8	D27t28	Basic metals and fabricated metal
9	D29	Machinery, nec
10	D30t33	Electrical and optical equipment
11	D34t35	Transport equipment
12	Dnec	Manufacturing, nec; recycling

TABLE A12: The list of manufacturing sectors in WIOD 2016 Release, used for the 2000s' trade data

	WIOD code	Sector description
1	C10-C12	Manufacture of food products, beverages, and tobacco products
2	C13-C15	Manufacture of textiles, wearing apparel and leather products
3	C16	Manufacture of wood and of products of wood and cork
4	C17, 18	Manufacture of paper products, printing of recorded media
5	C19	Manufacture of coke and refined petroleum products
6	C20	Manufacture of chemicals and chemical products
7	C21	Manufacture of basic pharmaceutical products
8	C22	Manufacture of rubber and plastic products
9	C23	Manufacture of other non-metallic mineral products
10	C24	Manufacture of basic metals
11	C25	Manufacture of fabricated metal products
12	C26	Manufacture of computer, electronic and optical products
13	C27	Manufacture of electrical equipment
14	C28	Manufacture of machinery and equipment n.e.c.
15	C29	Manufacture of motor vehicles, trailers and semi-trailers
16	C30	Manufacture of other transport equipment
17	C31, 32	Manufacture of furniture; other manufacturing

Note: In the original input-output tables, C17 and C18 are available as separate sectors. However, we combine these two sectors to match with the employment data.

D First-stage for the other import competition variables

Table A13 shows first-stage regression results with different import competition variables. The import competition variables, (1) final goods imports from China $\Delta IPW^{CHN \to JPN}_{\text{Final goods}}$, (2) imported inputs from China $\Delta IPW^{CHN \to JPN}_{\text{Inputs}}$, and (3) imported inputs from China *used* by Japanese sectors $\Delta IPW^{CHN \to JPN}_{\text{Inputs used}}$, are regressed on the corresponding instruments. The results show that the instruments have strong statistical power in explaining the corresponding endogenous variables. Table A14 shows first-stage results from the US. The results suggest that the instruments work well in explaining the corresponding endogenous variables in the US data as well.

TABLE A13: First-stage regression results, different types of imports, Japan

Dep. Var. =	Final goods (1)	Inputs (2)	Final goods (3)	Inputs (4)	Inputs used (5)	Final goods (6)	Inputs used (7)
$\Delta IPW^{CHN \to OTH \setminus k}_{\text{Final goods}}$	0.35***		0.37***	-0.02***		0.34***	0.02***
	(0.01)		(0.01)	(0.00)		(0.01)	(0.00)
$\Delta IPW^{CHN \to OTH \setminus k}_{\text{Inputs}}$		0.36***	-0.21***	0.39***			
		(0.01)	(0.05)	(0.01)			
$\Delta IPW^{CHN \to OTH \setminus k}_{\text{Inputs used}}$					0.43***	-0.34***	0.44***
					(0.02)	(0.06)	(0.02)
R-sq.	0.97	0.99	0.97	0.99	0.98	0.97	0.98
F-stat.	1062.2	2112.3	800.0	1661.7	487.3	509.4	374.1
p-value of F-stat.	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Note: The table shows the results from first-stage regressions with the import variables with different types of goods, $k = JPN$. The sample size of the regressions is 616. All regressions include constant term and control variables and region fixed effects, and the prefecture dummies. The total initial population weights all regressions. Standard errors, clustered at the prefecture level, are in parentheses. The shown F-statistics are those for excluded instruments only. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

TABLE A14: First-stage regression results, different types of imports, the US

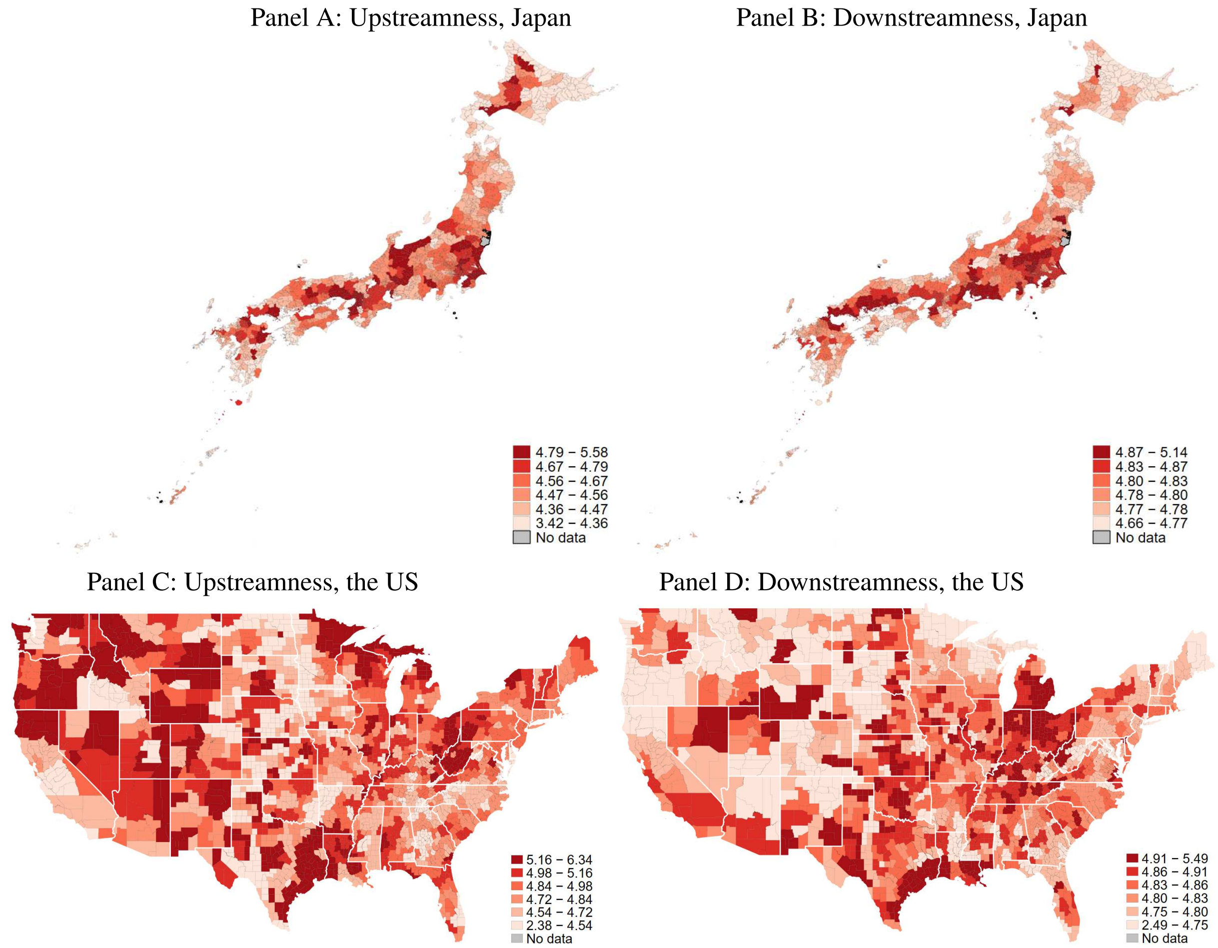
Dep. Var. =	Final goods (1)	Inputs (2)	Final goods (3)	Inputs (4)	Inputs used (5)	Final goods (6)	Inputs used (7)
$\Delta IPW^{CHN \to OTH \setminus k}_{\text{Final goods}}$	0.78***		0.76***	-0.06***		0.78***	-0.04***
	(0.04)		(0.04)	(0.02)		(0.03)	(0.01)
$\Delta IPW^{CHN \to OTH \setminus k}_{\text{Inputs}}$		0.39***	0.14**	0.45***			
		(0.04)	(0.07)	(0.04)			
$\Delta IPW^{CHN \to OTH \setminus k}_{\text{Inputs used}}$					0.36***	0.09	0.39***
					(0.04)	(0.09)	(0.03)
R-sq.	0.89	0.85	0.89	0.87	0.87	0.89	0.89
F-stat.	505.7	89.5	295.5	66.1	105.0	261.8	109.0
p-value of F-stat.	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Note: The table shows the results from first-stage regressions with the import variables with different types of goods, $k = USA$. The sample size of the regressions is 1,444. All regressions include constant term and control variables and region fixed effects, and the statistical division dummies. The total initial population weights all regressions. Standard errors, clustered at the state level, are in parentheses. The shown F-statistics are those for excluded instruments only. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

E Upstreamness and downstreamness

Figure A1 Panels A and B show the spatial distributions of upstreamness and downstreamness based on equation (9) in Japan. Panels C and D show those from the US.

FIGURE A1: CZ level upstreamness and downstreamness



Note: The figure shows the upstreamness and downstremaness converted to the CZ level. All panels are based on the averages of the two periods, the 1990s and 2000s. Authors' calculations using the data obtained from the data sources written in the text.

F Additional analyses

This section examines the effects of imports and exports on additional variables. First, we examine the effects on the annualized manufacturing labor productivity growth rate by using

$$lpg_{i,t}^{k} = \frac{100}{h} \times \left[\ln(VA_{i,t+h}^{k}/L_{i,t+h}^{k}) - \ln(VA_{i,t}^{k}/L_{i,t}^{k})\right]$$

as the dependent variable, where k indicates country, i indicates CZ, and t indicates the start year of the period. The variable $VA_{i,t}^{k}$ denotes the real manufacturing value-added and in CZ i in year t in country k and $L_{i,t}^{k}$ denotes the manufacturing employment for $k = JPN, USA$, and h indicates the number of years in that period. Although t indicates 'period' in the main text, it indicates 'year' in this section. The data on Japanese manufacturing value-added come from the Census of Manufacture of Japan (Kōgyō Tōkei Hyō), 1991, 2001, and 2012. The nominal manufacturing value-added are deflated by the prefecture level GDP deflator, which are dividing by manufacturing employment to convert to the real value-added per worker. The data on US manufacturing value-added come from the Regional Economic Accounts, CAGDP9 Manufacturing (31-33), thousands of chained 2012 dollars. As the data series starts at 2001, we report regression results from the 2000s only for the US.

Second, we examine the effect of the exposure to trade shocks on the manufacturing capital-labor ratio. As the CZ level capital-labor ratio is not available, we obtain the sector level capital-labor ratio and convert it to the CZ level by taking the employment-based weighted average:

$$kl_{i,t}^{k} = \sum_{s \in S_M} \left\{ \frac{L_{ist}^{k}}{\sum_{s' \in S_M} L_{is't}} \times \frac{100}{h} \left[\ln\left(\frac{K_{s,t+h}^{k}}{L_{s,t+h}^{k}}\right) - \ln\left(\frac{K_{s,t}^{k}}{L_{s,t}^{k}}\right) \right] \right\},$$

where where $K_{s,t}^{k}$ denotes the capital stock in sector s in year t and $L_{s,t}^{k}$ denotes the employment. It measures the employment-weighted average of the annualized capital-labor ratio growth rate. The denominator of the weight includes manufacturing sectors only because it is the summation over sectors in the set S_M. The data come from the WIOD 2016 Release. The data on capital stock are the "nominal capital stock (in millions of national currency, Series K)" deflated by dividing by the "price levels of intermediate inputs, 2010=100 (Series II_PI)." The labor is the "number of persons engaged (thousands, Series EMP)."

Third, we examine the effect of imports on exports by utilizing equation (5) as the dependent variable. Table A15 shows summary statistics of the variables used for an additional analysis. See Table 1 for summary statistics of the export variable (5). Figure A2 displays the spatial distribution of the labor productivity growth rates and capital-labor ratio growth rates in the two countries. See Figures 6 and 7 for the spatial distribution of the export variable. All regressions in this section are estimated using the same instrumental variable approach as the main text.

F.1 Effects on manufacturing labor productivity

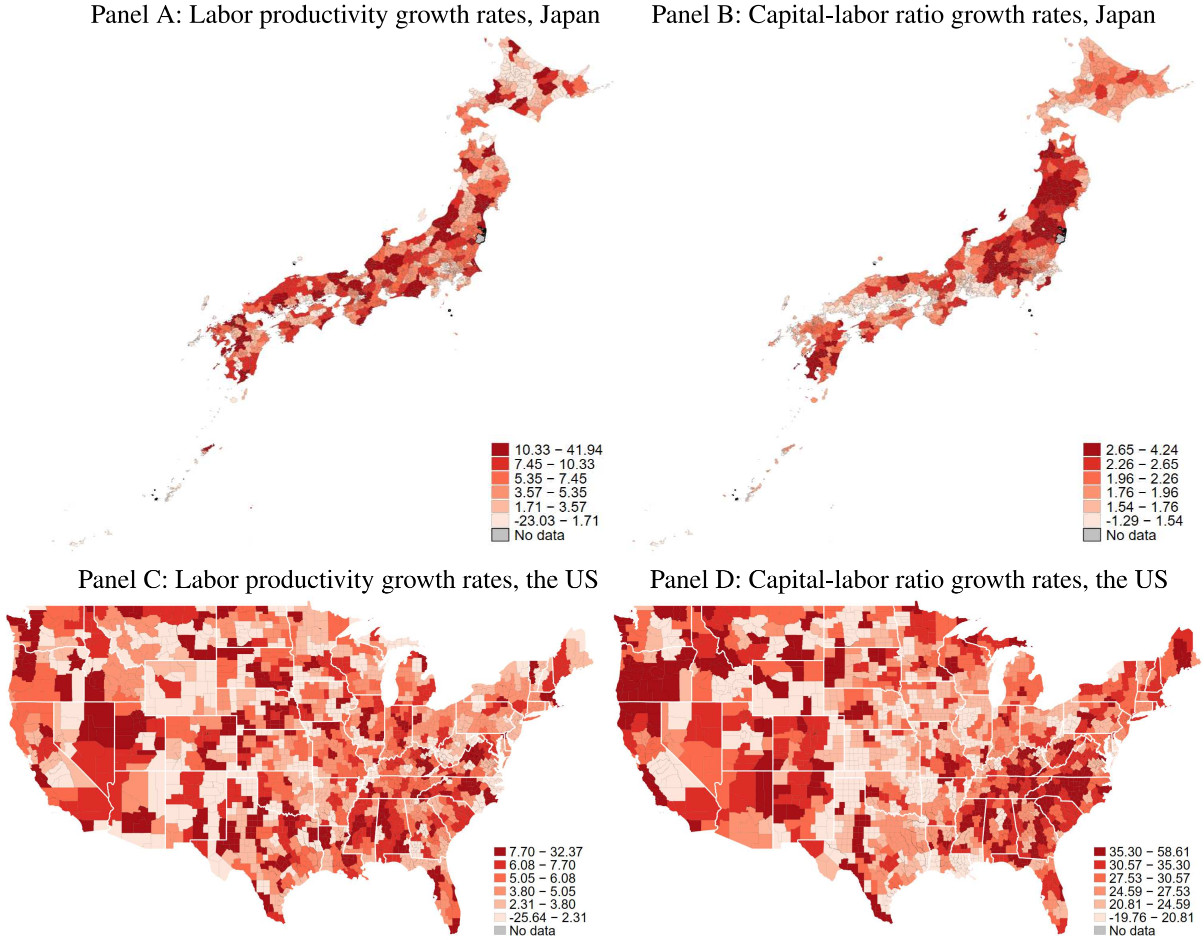
Table A16 Panel A reports regression results for Japan, and Panel B reports the result for the US. In Japan, columns (1) and (2) show that while overall import penetration has no effect on manufacturing labor productivity,

TABLE A15: Summary statistics of the variables used for an additional analysis

	Sample period	Obs	Mean	Std. dev.	Min	Max
Panel A: Japan						
Annualized labor productivity growth	1990s and 2000s	553	3.15	5.42	-26.57	46.65
ln(Initial labor productivity)/10	1990s and 2000s	558	61.78	8.20	13.92	79.67
Annualized capital-labor ratio growth rate	2000s	308	2.01	0.66	-1.29	4.24
ln(Initial capital-labor ratio)/10	2000s	308	95.84	1.71	91.74	105.01
Panel B: The US						
Annualized labor productivity growth	2000s	688	5.13	4.39	-25.64	32.37
ln(Initial labor productivity)/10	2000s	689	41.54	6.89	-7.99	61.49
Annualized capital-labor ratio growth rate	2000s	722	2.80	0.98	-1.98	5.86
ln(Initial capital-labor ratio)/10	2000s	722	44.38	2.46	37.05	59.26

Note: Authors' calculations using the data obtained from the data sources written in the text.

FIGURE A2: CZ level labor productivity and capital-labor ratios



Note: Panel A is based on the average of the two periods, the 1990s and 2000s. Panels B-D are based on one period, the 2000s. Authors' calculations using the data obtained from the data sources written in the text.

export opportunities have a positive effect on it. On the other hand, in the US, while overall import penetration has a positive effect on labor productivity, export opportunities have no effect on it. These two contrasting results across the two countries are somewhat surprising given the results reported in Table 5 which demonstrates that overall import penetration reduced manufacturing employment and export opportunities increased it in both countries.

The contrasting effects on manufacturing labor productivity suggest that, in Japan, export opportunities not only sustain manufacturing employment but also increase the labor productivity of the sustained employment. On the other hand, in the US, reduced manufacturing employment due to import competition contributes to increasing labor productivity.

TABLE A16: Effects of imports and exports on manufacturing labor productivity, IV

Panel A: Japan, $k = JPN$

	CZ level	BHJ	CZ level	BHJ	CZ level	BHJ
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta IPW^{CHN \to OTH \setminus k}$	0.15	-0.13				
	(0.33)	(0.37)				
$\Delta EOW^{OTH \setminus k \to ROW}$	0.42***	0.30*				
	(0.16)	(0.18)				
$\Delta IPW^{CHN \to k}_{\text{Final goods}}$			-0.72**	-0.70**	-0.49	-0.96***
			(0.34)	(0.30)	(0.34)	(0.23)
$\Delta IPW^{CHN \to k}_{\text{Inputs}}$			2.76***	0.23		
			(0.87)	(1.06)		
$\Delta IPW^{CHN \to k}_{\text{Inputs used}}$					2.48*	-2.00***
					(1.31)	(0.54)
Obs.	553	126	553	126	553	126
K.-P. Wald F-stat.	14.6	7.3	324.6	167.6	329.3	393.7

Panel B: The US, $k = USA$

	CZ level	BHJ	CZ level	BHJ	CZ level	BHJ
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta IPW^{CHN \to OTH \setminus k}$	1.25***	1.48***				
	(0.41)	(0.39)				
$\Delta EOW^{OTH \setminus k \to ROW}$	-0.07	0.25				
	(0.31)	(0.46)				
$\Delta IPW^{CHN \to k}_{\text{Final goods}}$			0.25	-0.22	0.57**	0.32
			(0.24)	-0.265	(0.22)	(0.23)
$\Delta IPW^{CHN \to k}_{\text{Inputs}}$			3.21***	6.65***		
			(1.11)	(1.78)		
$\Delta IPW^{CHN \to k}_{\text{Inputs used}}$					3.33**	7.51***
					(1.37)	(2.77)
Obs.	688	392	688	392	688	392
K.-P. Wald F-stat.	95.0	10.2	62.9	29.0	103.6	26.4

Note: The dependent variable is $100 \times \left[\ln(VA^k_{i,t+1}/L^k_{i,t+1}) - \ln(VA^k_{i,t}/L^k_{i,t})\right]$ for $k = JPN, USA$. All regressions include constant term, the initial productivity level, the control variables and region fixed effects, prefecture dummies for Japan, and statistical division dummies for the US. The total initial population weights all regressions. Standard errors, clustered at the prefecture level for Japan, and the state level for the US, are in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Columns (3)-(4) display the effects of final goods imports and intermediate goods imports from China. In Japan, according to the BHJ result in column (4), while final goods imports have a negative effect on manufacturing labor productivity, intermediate goods imports have no effect on it. In the US, both columns show that while final goods imports do not affect manufacturing labor productivity, intermediate goods imports have a positive effect on it. Combined with the results shown in Table 6, in the US, imported inputs had an adverse effect on manufacturing employment, which in turn improved labor productivity.

Columns (5)-(6) display the effects of final goods imports and intermediate goods imported from China and *used* by sectors in the importing country. The BHJ result shown in column (6) indicates that, in Japan, both final goods and intermediate goods imports reduced the manufacturing labor productivity. In contrast, in the US, both columns show that imported inputs increased manufacturing labor productivity.

These results are consistent with Fort (2023)'s findings where the US manufacturing sectors are increasing the allocation of their resources to productivity-enhancing activities however, as we do not observe such productivity-enhancing effects of import penetration from the Japanese data, such resource allocations may be limited in the Japanese context.

F.2 Effects on manufacturing capital-labor ratio

Table A17 presents results from regression the annualized capital-labor ratio growth rate on the 'exposure to trade' variables. Columns (1) and (2) show that import competition increases the capital-labor ratio while export opportunities have no effects in Japan and the US. We acknowledge that the first-stage F-statistics are not high enough in Japan and in the BHJ result in the US as we need to interpret the results cautiously.

Columns (3)-(4) examine the effects of final goods imports and imported inputs. As for Japan, while column (3) shows that the exposure to imported inputs has a negative coefficient in the CZ level regression, the BHJ result in column (4) indicates that the effect turns out to be positive. The same pattern is observed in columns (5)-(6), where the second import competition variable is the variable measuring imported inputs *used* by importing sectors. The effects of final goods imports on the capital-labor ratios are estimated to be positive except in column (4). Overall, while the inconsistent results between the CZ level regressions and the BHJ regressions in columns (3)-(6) require cautious interpretation, they suggest that increased imports from China increases the capital-labor ratios.

In the case of the US, columns (1)-(2) indicate that while an increase in imports from China raises capital-labor ratios, a rise in exports to the ROW reduces them, echoing the trends observed in Japan. Columns (3)-(4) overall suggest that an increase in final goods and intermediate goods imports increases the capital-labor ratios in the US.

The effects of imported inputs from China differ between the two countries: positive in Japan and negative in the US. However, based on the results from the BHJ approach, the effects on the capital-labor ratios are similar across the two countries. It suggests that, in Japan, imported inputs from China increase capital stock more than labor.

F.3 Effects on manufacturing exports to the rest of the world

Results from regressing the 'exports to the world' variable on the import competition variables are presented in Table A18. The dependent variable is equation (3), which is the employment-weighted averages of changes in per worker sectoral exports to the world. It does not quantify actual exports from each CZ. Nevertheless, we use this variable as a proxy of exports by assuming that the same amount of labor in a sector in all CZs generates the same amount of exports in the same sector.

Regarding the effects in Japan, the result from a CZ level regression in column (1) suggests that overall imports from China increase exports. However, as shown in the next column, this result is not robust to the BHJ approach. Columns (3)-(6) also show that the CZ level results and BHJ results differ. Although the effect of final goods imports on exports is negative in CZ level regressions presented in columns (3) and (5), the results are null in the corresponding BHJ results, respectively. Regarding the effects of imported inputs, although CZ level regressions suggest a positive effect on exports, the results are null in the corresponding BHJ approach.

TABLE A17: Effects of imports and exports on manufacturing capital-labor ratio, IV

Panel A: Japan, $k = JPN$

	CZ level (1)	BHJ (2)	CZ level (3)	BHJ (4)	CZ level (5)	BHJ (6)
$\Delta IPW^{CHN \to OTH \setminus k}$	0.25**	0.45***				
	(0.10)	(0.16)				
$\Delta EOW^{OTH \setminus k \to ROW}$	-0.07	-0.05				
	(0.05)	(0.10)				
$\Delta IPW^{CHN \to k}_{\text{Final goods}}$			0.55***	0.32	0.53***	0.59***
			(0.13)	(0.21)	(0.09)	(0.14)
$\Delta IPW^{CHN \to k}_{\text{Inputs}}$			-0.65**	1.37**		
			(0.31)	(0.68)		
$\Delta IPW^{CHN \to k}_{\text{Inputs used}}$					-0.88***	0.72**
					(0.31)	(0.35)
Obs.	280	63	280	63	280	63
K.-P. Wald F-stat.	4.9	3.2	111.9	27.3	141.0	183.6

Panel B: The US, $k = USA$

	CZ level (1)	BHJ (2)	CZ level (3)	BHJ (4)	CZ level (5)	BHJ (6)
$\Delta IPW^{CHN \to OTH \setminus k}$	0.25***	0.32***				
	(0.05)	(0.07)				
$\Delta EOW^{OTH \setminus k \to ROW}$	-0.07	-0.23				
	(0.06)	(0.24)				
$\Delta IPW^{CHN \to k}_{\text{Final goods}}$			0.10***	-0.01	0.18***	0.15***
			(0.04)	(0.05)	(0.04)	(0.02)
$\Delta IPW^{CHN \to k}_{\text{Inputs}}$			0.75***	1.54***		
			(0.12)	(0.29)		
$\Delta IPW^{CHN \to k}_{\text{Inputs used}}$					0.76***	1.60***
					(0.22)	(0.20)
Obs.	722	392	722	392	722	392
K.-P. Wald F-stat.	101.4	9.3	54.9	30.4	79.2	25.7

Note: The dependent variable is $\sum_{s \in S_M} \left\{ \frac{L^k_{ist}}{\sum_{s' \in S_M} L_{is't}} \times \frac{100}{h} \left[\ln \left(\frac{K^k_{s,t+h}}{L^k_{s,t+h}} \right) - \ln \left(\frac{K^k_{s,t}}{L^k_{s,t}} \right) \right] \right\}$ for $k = JPN, USA$. All regressions include constant term, the initial capital-labor ratio, the control variables and region fixed effects, prefecture dummies for Japan, and statistical division dummies for the US. The total initial population weights all regressions. Standard errors, clustered at the prefecture level for Japan, and the state level for the US, are in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

Regarding the effects in the US, column (1) shows that overall imports from China increase exports; however, this result is not robust to the BHJ approach, as shown in column (2), indicating a null result. On the other hand, CZ level results are broadly consistent with BHJ results in columns (3)-(6), examining the effects of final goods imports and intermediate goods imports separately. These columns suggest show that imported final goods reduce exports while imported inputs increase exports.

To summarize, combined with the other results presented in this study, an increase in imported inputs from China reduces manufacturing employment, however, it increases manufacturing labor productivity, capital-labor ratio, and exports to the ROW. In contrast, in Japan, an increase in imported inputs sustains manufacturing employment. However, it does not lead to clear positive effects on manufacturing labor productivity, capital-labor ratio, and exports to the ROW.

TABLE A18: Effects of imports from China on manufacturing exports to the world, IV

Panel A: Japan, $k = JPN$

	CZ level (1)	BHJ (2)	CZ level (3)	BHJ (4)	CZ level (5)	BHJ (6)
$\Delta IPW^{CHN \to OTH \setminus k}$	0.51**	0.53				
	(0.21)	(0.86)				
$\Delta IPW^{CHN \to k}_{\text{Final goods}}$			-0.94***	-0.19	-0.66***	0.001
			(0.23)	(0.54)	(0.16)	(0.59)
$\Delta IPW^{CHN \to k}_{\text{Inputs}}$			4.04***	2.96		
			(0.88)	(2.73)		
$\Delta IPW^{CHN \to k}_{\text{Inputs used}}$					4.78***	-0.46
					(1.28)	(6.85)
Obs.	558	126	558	126	558	126
K.-P. Wald F-stat.	826.1	173.3	393.6	265.2	140.6	25.2

Panel B: The US, $k = USA$

	CZ level (1)	BHJ (2)	CZ level (3)	BHJ (4)	CZ level (5)	BHJ (6)
$\Delta IPW^{CHN \to OTH \setminus k}$	0.42***	0.13				
	(0.10)	(0.13)				
$\Delta IPW^{CHN \to k}_{\text{Final goods}}$			-0.30***	-0.34***	-0.14	-0.19***
			(0.10)	(0.09)	(0.09)	(0.07)
$\Delta IPW^{CHN \to k}_{\text{Inputs}}$			2.29***	1.94***		
			(0.32)	(0.56)		
$\Delta IPW^{CHN \to k}_{\text{Inputs used}}$					3.24***	1.99*
					(0.79)	(1.17)
Obs.	1,444	784	1,444	784	1,444	784
K.-P. Wald F-stat.	357.4	211.4	124.9	56.5	164.3	67.7

Note: The dependent variable is $\Delta EOW^{k \to ROW}_{it} = \sum_{s \in S_M} \left(\frac{L^k_{ist}}{\sum_{s' \in S_A} L^k_{is't}} \times \frac{\Delta ex^{k \to ROW}_{st}}{\sum_{i'} L^k_{i'st}} \right)$ for $k = JPN, USA$. All regressions include constant term, the control variables and region fixed effects, prefecture dummies for Japan, and statistical division dummies for the US. The regressions for Japan includes the employment-weighted average of the initial export level as a control. The total initial population weights all regressions. Standard errors, clustered at the prefecture level for Japan, and the state level for the US, are in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

G Robustness checks

This section provides results from the BHJ approach associated with regressions in Table 7, examining (potentially) different effects of the exposure to trade on manufacturing employment by up/downstreamness. To take the BHJ approach, we generate the CZ level residualized dependent variable, residualized endogenous explanatory variables, and residualized instruments. These CZ level residualized variables and the CZ level upstramness variables are converted to the sector level using sector-CZ level employment as weights. As the last step, we regress the residualized dependent variable on the residualized explanatory variables using the residualized instruments as instruments, separately for the (i) observations with lower upstreamness variable and (ii) observations with higher upstreamness variable. We take the same step for the downstream variable. The cutoff for division is the median value among all observations in the stacked cross-sections.

Table A19 shows results from the BHJ approach. The results are broadly consistent with results from CZ level regressions in Table 7. Results from Japan are presented in Panel A. It shows that the effects of imported inputs are positive and statistically significant in less upstream or downstream sector-year observations as shown in columns (1) and (2). However, the effects of imported inputs turn out to be insignificant sector-year observations with more upstream or downstream sectors as shown in columns (3) and (4). These results are inconsistent with the results in

Table 7. Nevertheless, the results presented in columns (5) and (6) indicate that the effects of imported inputs are similar: positive and statistically significant in sector-year observations with low and high levels of "uptreamness − downstreamness."

Results from the US are presented in Panel B. Columns (1) and (2) show that the adverse effects of imported inputs are greater in sector-year observations with low upstreamness variable, which is consistent with the results from Table 7. Columns (3) and (4) show that less downstream sector-year observations are less adversely affected by imported inputs than those with more downstream sector-year observations, which is consistent with Table 7. The last two columns show that adverse effects of imported inputs come from sector-year observations with lower levels of "uptreamness − downstreamness," which is also consistent with Table 7.

TABLE A19: Up/downstreamness and imports from China, BHJ

Panel A: Japan

Selection based on	Up		Down		Up−Down	
Sample	Low	High	Low	High	Low	High
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta IPW^{CHN\to k}_{\text{Final goods}}$	-0.86***	1.34	-1.09***	-0.67**	-0.95***	1.51
	(0.10)	(1.47)	(0.34)	(0.27)	(0.10)	(0.94)
$\Delta IPW^{CHN\to k}_{\text{Inputs used}}$	3.41***	4.14	9.55**	0.09	3.08***	3.68*
	(0.50)	(2.58)	(3.90)	(0.41)	(0.53)	(1.88)
Obs.	62	64	63	63	63	63
K.-P. Wald F-stat.	199.4	43.7	12.6	38.5	179.4	55.6

Panel B: The US

Selection based on	Up		Down		Up−Down	
Sample	Low	High	Low	High	Low	High
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta IPW^{CHN\to k}_{\text{Final goods}}$	0.05	-0.38***	1.91***	-0.55***	-0.43***	1.54***
	(0.25)	(0.12)	(0.37)	(0.11)	(0.14)	(0.32)
$\Delta IPW^{CHN\to k}_{\text{Inputs used}}$	-4.11***	-3.03**	5.15*	-3.89	-4.49***	-1.23
	(1.48)	(1.31)	(2.66)	(2.70)	(1.65)	(1.31)
Obs.	392	392	392	392	392	392
K.-P. Wald F-stat.	83.2	45.0	59.3	7.9	15.7	19.5

Note: The table shows results from the BHJ approach associated with the CZ level regressions in Table 7. Standard errors, clustered at the sector level, are in parentheses. In Panel A, the observations are not split into the same size of sub-samples because there is an observation that takes the exact same value as the median. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.