Gains from Foreign Employment in Japan: Regional and Sectoral Implications [*]

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Abstract

This paper examines the impact of immigrant workers on the regional economies of the host country. We focus on Japan, which has expanded the foreign employment in the total workforce over the last three decades in response to the shrinking domestic workforce. We develop a quantitative spatial model to evaluate the gains of foreign employment, i.e., the consequences of an inflow of foreign workers on aggregate welfare, local wages, employment, and production. Our model features three crucial aspects—occupation, region, and sector—that interact with each other to shape the local labor market and production responses to immigration shocks. We quantify the model using the newly available micro-level data on foreign workers and conduct counterfactual exercises to evaluate the past and future immigration policy reforms. We find that in regions where foreign workers tend to gravitate, there was a substantial negative impact on the wages of low-education domestic workers. At a nationwide level, there is a minimal gain of social welfare. We argue that these results suggest that the Japanese labor market is segmented spatially, particularly for low-education workers. We also highlight the importance of the sectoral dimension in understanding the impact of foreign workers. Specifically, the skewed occupational distribution of foreign workers has pronounced implications on sectors that are intensive in occupations with a larger proportion of foreign workers and sectoral input-output linkage plays a key role in determining the regional impacts.

1 Introduction

During the last three decades, the world has witnessed a pronounced increase in the mobility of people across countries.[1] In advanced economies in particular, with falling fertility and an aging demography, net migration has played a more substantial role in ensuring population stability and increasing the labor force (United Nations, 2017; Peri, 2020). The United Nations introduced the notion of ”replacement migration” in its report in 2001, referring to an international migration needed to offset a decline in the population (United Nations Population Division, 2001).

Foreign immigrants are not simply a replacement for native workers, however. Foreign and native workers will differ in their skills, productivity, and preferences. These heterogeneities result in foreign workers gravitating to certain places, called *immigrant magnets* (Frey, 1996), and working in certain occupations and industries.Therefore, accepting immigrants may have various implications for the host economies.

This paper examines the gains of foreign employment in Japan, a nation with a particularly ageing population among the advanced economies. While Japan remains more closed to immigration, the economy increased its dependence on foreign employment over the last three decades as the labor shortage has become the central economic concern. Until the 1990s, the 1988 Sixth Basic Act on Employment Measures strictly limited work visas in Japan to skilled workers. In 1990, foreign workers accounted for only 0.2% of the total workers. Since then, the government has introduced new visa categories that significantly expand foreign employment and diversify the types of foreign workers. As of 2020, the number of foreign workers exceeds 1.7 million, comprising 2.6% of total workers. Regarding skill composition, approximately 40% of foreign workers do not have a 4-year college degree.

Foreign employment has been controversial in the policy discussions. The manufacturing sector, facing a particularly severe labor shortage, has voiced that accepting foreign workers is essential to maintaining domestic production. In 2018, the Manufacturing Bureau at the Ministry of Economy, Industry, and Trade highlighted the potentially important role of foreign workers in coping with the tight labor supply.[2] Furthermore, several anecdotes during the COVID-19 pandemic revealed the reliance of local manufacturing on foreign employment. For example, an article from the *Japan Times* on March 20, 2020, states that *”A textile manufacturer in Fukui said ... the arrivals of five*

[1]The United Nations Department of Economic and Social Affairs estimates that in 2020, almost 281 million people live in a country other than their country of birth, termed international migrants. This number is approximately 1.8 times the estimated number of international migrants in 1990 (United Nations International Organization for Migration, 2022).

[2]”Labor Shortage in Manufacturing and Employment of Foreign Workers,” in Japanese, archived at https://warp.da.ndl.go.jp/info:ndljp/pid/12166597/www.meti.go.jp/press/2018/07/20180712005/20180712005-2.pdf

new trainees [foreign workers admitted under the Technical Intern Trainee Program visa] from this spring have been postponed ... It may be just a few people, but for small and midsize businesses it means a significant drop in manpower." [3]

On the other hand, there is a social concern that an inflow of foreign workers may harm the wages and employment of domestic workers. A report to the Advisory Board on Foreign Employment in 2002 mentions that *"in accepting foreign workers, ... we should consider the risks of contracting job opportunities and dampening wages of Japanese workers."* The Japanese Trade Union Confederation also summarized the survey results in 2018[4] that approximately 20% of workers expressed a hostile position towards accepting foreign workers. The survey further asked those opposed to foreign employment for their reasons, and 46% of them responded that an inflow of foreign workers might negatively impact the employment conditions of natives.

We present a theoretical framework to examine the consequence of an inflow of foreign labor to the local economies. We use the model to evaluate the aggregate welfare implications and the impacts on local labor market outcomes and sectoral production. Our structural model has three crucial aspects that interact with each other to determine the local labor market and the production implications of foreign workers. We feature workers' sorting into occupations based on their comparative advantage, the regional heterogeneity in productivity and amenities, and the sectoral heterogeneity in production technologies.

One example may illustrate that the interaction of regional, sectoral, and occupational aspects is crucial to understanding foreign workers' spatial and occupational distributions and, therefore, to studying their economic implications. In 1990, the government introduced the new visa category, the Long-Term Resident, targeting the Japanese diasporas in Latin American countries, typically Brazil.[5] Brazilians accounted for 8% of foreign workers in Japan as of 2020, and they are highly concentrated in particular regions. The largest share of Brazilians resides in Aichi(28%), followed by the neighboring prefectures, Shizuoka (15%), Mie (6%), and Gifu (5%). Those four prefectures, called *Tokai region*, embrace over half of the Brazilians in Japan, while the fraction of domestic workers in this area is just above 10% of the population.

Brazilian workers' occupational comparative advantage, in conjunction with the Tokai region's sectoral composition, is a driving force behind this geographic concentration. 64% of Brazilians

[3]"Japanese businesses hit by lack of Chinese trainees amid virus outbreak": https://www.japantimes.co.jp/news/2020/03/20/business/japan-businesses-hit-lack-chinese-trainees-amid-virus-outbreak/

[4]The survey was completed in 2018 and collected 1,000 responses from workers aged between 20 and 69.

[5]Unlike other work visas, Brazilians admitted under this visa faced no skill requirements or work restrictions. As of 2020, 99% of Brazilian workers have visas without work restrictions, either as Long-Term Resident, Permanent Resident, Spouse of Japanese, or Spouse of Permanent Resident.

were engaged in production occupations (e.g., assembling) in 2020, compared with just 13% of native workers. We attribute the heterogeneity in occupation sorting between Brazilians and domestic workers to different pattrns of occupational comparative advantage. Second, the Tokai region is the manufacturing cluster of the Japanese economy centered around the auto industry.[6] Those two facts suggest that the region attracts more Brazilians because of a higher demand for production jobs from the local manufacturing sector and their occupational comparative advantage. Indeed, 68% of Brazilians are employed in the manufacturing sector, compared with 24% of natives in the region. Furthermore, some local features may offer better amenities for Brazilian workers; e.g., some public schools provide language support for foreign children.

Do Brazilian workers harm the wages of natives? The answer will depend crucially on the pattern of the occupational comparative advantages. If Brazilians sort into occupations where natives are less likely to work, they will not be direct competitors. Thus, the occupational sorting of workers may mitigate the direct negative impacts on natives' wages. Moreover, the extent to which domestic workers reallocate across occupations and locations determine if the impacts are primarily on the regions with higher exposure of foreign workers or they disseminate nationwide. Another important angle to understand the regional impacts of the foreign employment is an industry input-output linkage. As four prefectures in the Tokai region are deeply connected through the inter-prefectural trade, a particularity large inflow of foreign into Aichi, for example, will impact the output of nearby regions. In support of this view, Yokkaichi City, a major industrial city in Mie, emphasized in its report in 2007 the role of Brazilian workers for the entire Tokai region's manufacturing.[7]

Guided by the example above, we build a spatial general equilibrium model rich enough to incorporate heterogeneity across worker groups, occupations, sectors, and regions. Our model consists of three major components. First, we formulate the worker's sorting into locations following Redding (2016). This captures the uneven spatial distribution of foreign and domestic workers conditional on real wage differences. Second, we allow workers to self-select into occupations as in the classical Roy's (1951) assignment framework. Workers choose the occupation that offers the highest wage, following the Fréchet-Roy model of Burstein et al. (2019, 2020). Here, the relative wage difference captures the occupational comparative advantage. Third, the multi-region and multi-sector Eaton and Kortum (2002) model of trade with an input-output linkage, *à la* Caliendo and Parro (2015), highlights the heterogeneous sectoral productivity across regions. Our frame-

[6]For instance, the headquarters and flagship plants of Toyota, Suzuki, Yamaha, and Honda are located in this region.

[7]The official public relations magazine says that *"Japanese diasporas have supported the manufacturing in Tokai area"*, and continues: *"foreign labor force will be further needed in the future."*. The article is archived at https://www.city.yokkaichi.mie.jp/koho/200702/1st/sp_02.htm.

work builds primarily on Burstein et al. (2020), a major innovation is introducing a sectoral aspect, which is crucial in examining the channel through which a foreign workers has differential impacts across regions and industries.

We bring the model to the data from the Japanese economy covering 47 prefectures, 24 occupations, and seven sectors. We take advantage of the novel micro-level data available from Japanese government statistics,the Basic Survey of Wage Structure. As of 2019, the Wage Survey can identify the sampled foreign workers' visa category (status of residence). This information allows us to construct the aggregate moments, such as average wages and the allocation of foreign and native workers across regions and occupations.

We consider two counterfactual exercises, looking backward and forward. We first evaluate the gains from foreign employment by eliminating completely all foreign workers to see what would happened if the country had not opened up to immigration. We find that the welfare drops by 0.08%, and the aggregate GDP drops by 2.53% from a move to labor market autarky. We find that the welfare of low-education male workers rises most and argue that the patterns of occupational sorting are a key determinant. There is a greater production implication for manufacturing sectors than the service sector, which is in line with the classical Rybczynski prediction. We also report that regions differ substantially in real wage responses while highlighting the role of input-output linkage. Second, we perform what turns out to be the more forward-looking exercise of asking what would happen if the economy further increased the amount of foreign employment. We consider an increase in the country's labor supply to its peak level in 1995 through immigration (equivalent to a 10% increase in domestic workers). We show that limiting the incoming foreign workers to the highly educated maximizes social welfare and the GDP. Our results also indicate that gains from foreign employment outweigh the gains of alternative domestic policies that encourage domestic female or senior workers to enter the workforce. We find that, in regions where foreign workers tend to gravitate, there was a substantial negative impact on the wages of low-education domestic workers with quantitatively minimal impact nationwide. We argue that these results suggest that the Japanese labor market is segmented spatially, particularly for low-education workers, which contrasts the result in previous works such as Monras (2020). We also highlight the importance of the sectoral dimension in understanding the impact of foreign workers. Specifically, the skewed occupational distribution of foreign workers has pronounced implications on sectors that are intensive in occupations with a larger proportion of foreign workers.

This paper contributes to several strands of literature. First, a large body of literature has studied the impacts of immigrants on the labor market at the national, regional, sectoral, and occupational levels (Borjas, 2003; Ottaviano and Peri, 2012; Altonji and Card, 1991; Card, 2001; Dustmann and Glitz, 2015; Peri and Sparber, 2009). This paper highlights workers' sorting into occupations based on comparative advantage, which governs the impacts on wages and employment. This is also the first application of the newly available micro-level data data to the quantitative study of foreign workers in JapanAs surveyed in Kambayashi and Hashimoto (2019), studies on foreign workers in Japan started in the 1990s with a questionnaire- or case study-based approach. Quantitative studies such as Otake and Ohkusa (1993), Mitani (1997), and Nakamura et al. (2009) investigated the substitutability between foreign and domestic workers, but the results differed depending on region and sectors.

We also believe that Japan offers an ideal setting to study the economic implications of foreign workers for the following reasons. Unlike the US, which has a long history of immigration, the inflow of foreign workers in Japan occurred in the last three decades. Therefore, the assimilation of foreign workers in skills and preferences and the generational status of foreign workers should be less relevant, allowing us to examine the impacts of an inflow of foreign workers in a cleaner experimental setting. Furthermore, this paper provides lessons for other advanced economies with an ageing population. For instance, the US Census Bureau projects that the proportion of older adults will reach 23% in the next 40 years, which is the same level as Japan in 2010. Our analysis proposes accepting foreign workers as a policy measure to sustain economic activities in aged developed countries.

Second, recently, there is a growing literature in the field of international trade and spatial economics that studies the impacts of immigrant workers using a quantitative general equilibrium framework, e.g., Bryan and Morten (2019), Khanna and Morales (2019), Monras (2020). This paper is most closely related to Burstein et al. (2019, 2020), which developed a general equilibrium framework using the Fréchet-Roy model of occupation sorting. This paper extends their studies by embedding multiple sectors into the model to study the sectoral production implications across space. This simple yet essential extension captures the key channel through which an inflow of foreign workers has differential regional impacts.

The rest of this paper is structured as follows: Section 2 outlines the quantitative model, Section 3 calibrates the model using the Japanese data and conducts the counterfactual exercises, and Section 4 presents a conclusion.

2 A Quantitative Framework

We develop a quantifiable spatial general equilibrium model that features workers sorting into locations and occupations (tasks) *à la* Roy (1951). The model uses a finite number of domestic regions (prefectures) in Japan ($\mathcal{R}$) and the rest of the world (ROW) indexed by $r, m \in \mathcal{R} \cup ROW$. Locations can differ from one another in terms of sectoral productivity, amenities, and geographic location. Labor is the only primary factor of production. There is a continuum of workers indexed by z. Workers are partitioned into a finite number of groups. Each group is identified by the pair of (k, s), where $k \in \{D, F\}$ indicates Domestic or Foreign, and $s \in \mathcal{S}$ refers to other attributes of workers (education level, gender, and age group). The set of workers in group (k, s) in each country is given by $\mathcal{Z}(k, s)$ for Japan, which has the mass given by $L(k, s)$. We abstract from the workers' composition in the rest of the world. The set of workers in each country is exogenous in the model. A worker in Japan is mobile across domestic locations and determines first the work location followed by the occupation choice. There is a finite number of occupations indexed by $o \in \mathcal{O}$. At the predetermined work location, workers choose an occupation to work, inelastically supply one unit of labor to the occupation production unit, and consume a bundle of final goods.[8] Lastly, there is a finite number of industries indexed by $i, j \in \mathcal{I}$. In each industry, there is a continuum of intermediate goods, which will be aggregated to form a final good. In the following subsections, we will consider workers and producers in Japan unless otherwise specified.

Consumer Preferences

Preferences for workers $z \in \mathcal{Z}(k, s)$ residing in domestic region $r \in \mathcal{R}$ depend on goods consumption C_r and the idiosyncratic amenity shock to the utility from residing in that location $b_r(z)$:

$$U_r(z) = b_r(z) C_r(z).$$

The goods consumption index (C_r) is defined over the consumption of the bundle of final goods of all sectors (C_r^i) in a Cobb-Douglas fashion:

[8] In Appendix A, we briefly discuss the order of a worker's decision and outline the model in which a worker's occupation choice follows the location choice.

$$C_r(z) = \prod_{i \in \mathcal{I}} \left(C_r^i(z) \right)^{\alpha^i},$$

where α^i is the share of expenditures on the final good i and $\sum_i \alpha^i = 1$. The corresponding dual price index for the goods consumption is:

$$P_r = A \prod_i (P_r^i)^{\alpha^i} \tag{1}$$

where P_r^i is the price index of the final good i at location r. A is a constant. We assume that the workers in the rest of the world consume the bundle of final goods according to the same Cobb-Douglas aggregator.

The idiosyncratic amenity shocks $b_r(z)$ capture heterogeneous preferences for living in each location $r \in \mathcal{R}$. Following Redding (2016), we assume that the shocks are drawn independently across domestic locations and workers from a Fréchet distribution with a cumulative distribution function:

$$b_r(z) \sim G_r^b(b; k, s) = \exp(-B_r(k, s) b^{-\eta}), \quad \eta > 1,$$

where the location parameter $B_r(k, s)$ determines the average amenities of location r for group (k, s) workers. The average amenities are worker group-specific, which captures the concentration of workers of a given type in particular locations, conditional on differences in real wages. The shape parameter η governs the dispersion of amenities across workers within a group. The corresponding indirect utility function of worker z residing in location r is given by:

$$U_r(z) = \frac{E_r(z)}{P_r} b_r(z), \tag{2}$$

where $E_r(z)$ is the nominal expenditure of worker z. Each worker chooses the location that offers the highest utility after observing the idiosyncratic amenity shocks. Workers make the location choice before determining the occupation. Therefore, a worker forms expectations on the expenditure at each potential destination when choosing her location.

Occupation Production Units

We follow Burstein et al. (2019, 2020) and introduce the perfectly competitive occupation production units in each domestic location. Each unit hires labor, produces the occupational service, and supplies it to intermediate good producers. An occupation production unit o hiring l efficiency units of group (k, s) workers produces $S(k, s, o) \times l$ units of occupational service o. $S(k, s, o)$ denotes the productivity of an efficiency unit of type (k, s) labor in o. This parameter governs the occupational comparative advantages of different types of workers.

While $S(k, s, o)$ governs *across-group* heterogeneity in efficiency, we also introduce *within-group* heterogeneity. We assume that a worker in location r, $z \in \mathcal{Z}_r(k, s)$, supplies $\varepsilon(z, o)$ efficiency units of labor if worked in occupation o. Each worker is associated with a vector of $\varepsilon(z, o)$ for each o, allowing workers within a type (k, s) to vary in their relative productivities across occupations. $\varepsilon(z, o)$ is assumed to be drawn independently across occupations from a Fréchet distribution with a cumulative distribution function:

$$\varepsilon(z, o) \sim G^{\varepsilon}(\varepsilon) = \exp(-\varepsilon^{-\zeta}), \quad \zeta > 1.$$

A worker chooses the occupation that offers the highest wage, given by $w_r(k, s, o) \times \varepsilon(z, o)$, where $w_r(k, s, o)$ is wage per efficiency unit of labor. The probabilistic formulation of within-worker heterogeneity in efficiency across occupations generates the worker's self-selection into an occupation in line with Roy's (1951) assignment framework. The output of occupation service is then given by:

$$\ell_r(o) = \sum_{k \in \mathcal{K} s \in \mathcal{S}} S(k, s, o) \sum_{z \in \{\mathcal{Z}_r(k,s) | \text{choose } o\}} \varepsilon(z, o)$$

Note that we assume that workers are perfect substitutes within an occupation. We abstract from the occupation choice of workers in the rest of the world.

Intermediate Good Producers

The production side of the model is a Ricardian trade model of Eaton and Kortum (2002) with sectoral roundabout production *à la* Caliendo and Parro (2015). In each sector i, there exists a unit continuum of intermediate goods indexed by $\kappa^i \in [0,1]$. The production of each κ^i requires two types of inputs: composites of occupational services and intermediate inputs from all sectors. Producers of intermediate goods differ in efficiency. We denote by $a_r^i(\kappa^i)$ the efficiency of producing intermediate good κ^i in sector i at location $r \in \mathcal{R} \cup ROW$. Intermediate good κ^i is produced according to the constant returns to scale production function:

$$y_r^i(\kappa^i) = a_r^i(\kappa^i) \ell_r^i(\kappa^i)^{\beta^{\ell,i}} \prod_{j \in \mathcal{I}} \left(m_r^{j,i}(\kappa^i) \right)^{\beta^{j,i}},$$

where $y_r^i(\kappa^i)$ is the output of intermediate good, $\ell_r^i(\kappa^i)$ is the input of composite occupation service, and $m_r^{j,i}(\kappa^i)$ is the composite intermediate good input from sector j. $\beta^{\ell,i}$ and $\beta^{j,i}$, respectively, are the expenditure shares of the composite occupation service and sector j input such that $\beta^{\ell,i} + \sum_j \beta^{j,i} = 1$ for all i.

The composite occupation service is the constant elasticity of substitution (CES) aggregate defined as:

$$\ell_r^i(\kappa^i) = \left(\sum_{o \in \mathcal{O}} (\mu^i(o))^{1/\rho^i} \ell_r^i(o, \kappa^i)^{(\rho^i - 1)/\rho^i} \right)^{\rho^i/(\rho^i - 1)},$$

where $\ell^i(o, \kappa^i)$ is the input of occupation service o, $\rho^i > 0$ is the elasticity of substitution across occupations, and $\mu^i(o) \geq 0$ is a sector-specific exogenous demand shifter for occupation service o. This demand shifter captures the occupational intensity of the sector, e.g., manufacturing sectors will depend more on manual jobs than cognitive jobs.

We assume that the efficiency of producing good κ^i is a realization of a Fréchet distributed random variable with a cumulative distribution function:

$$a_r^i(\kappa^i) \sim G_r^{a,i}(a) = \exp(-T_r^i a^{-\theta^i}), \quad \theta^i > 1.$$

in which T_r^i governs the average productivity of sector i at location $r \in \mathcal{R} \cup ROW$. This parameter captures the regional heterogeneity in sectoral composition, e.g., Aichi with its auto-sector orientation will have higher average productivity in that sector.

The unit cost of producing intermediate good κ^i is given by $c_r^i / a_r^i(\kappa^i)$ where c_r^i is the cost of an input bundle:

$$c_r^i = C^i (p_r^{\ell,i})^{\beta^{\ell,i}} \prod_{j \in \mathcal{I}} (P_r^j)^{\beta^{j,i}}, \tag{3}$$

where $P_r^{\ell,i}$ is the price of the composite occupational services, and C^i is a constant. $P_r^{\ell,i}$ is the corresponding CES price index defined as:

$$P_r^{\ell,i} = \left(\sum_{o \in \mathcal{O}} \mu^i(o) \left(p_r(o)\right)^{1-\rho^i} \right)^{1/(1-\rho^i)}, \tag{4}$$

where $p_r(o)$ is the price of occupational service o at location r. We assume that intermediate good producers are perfectly competitive and price at marginal costs.

Final Good Producers

A perfectly competitive final good producer in each sector aggregates intermediate goods to form the sectoral final good. The final good producer in sector i at location $r \in \mathcal{R} \cup ROW$ purchases intermediate good κ^i from the lowest-cost suppliers across locations and combinesthrough the CES aggregator:

$$Q_r^i = \left[\int_{\kappa^i \in [0,1]} q_r^i(\kappa^i)^{(\sigma^i - 1)/\sigma^i} d\kappa^i \right]^{\sigma^i/(\sigma^i - 1)},$$

where $q_r^i(\kappa^i)$ is the demand for intermediate goods κ^i from the lowest-cost supplier and $\sigma_k > 0$ is an elasticity of substitution across intermediate goods. Final goods are used by local intermediate good producers or consumed by local workers according to the resource constraint. The corresponding dual price index is:

$$P_r^i = \left[\int_{\kappa^i \in [0,1]} p_r^i(\kappa^i)^{1-\sigma^i} d\kappa^i \right]^{1/(1-\sigma^i)}. \tag{5}$$

We assume that the final goods are non-tradable.

2.1 Equilibrium

Final Good Price Indices and Expenditure Shares

We assume that trade in intermediate goods is costly, and that there are standard iceberg trade costs. One unit of an intermediate good in sector i shipped from location m to location r requires producing $\tau_{mr}^i \geq 1$ units and $\tau_{mm}^i = 1$ for all $m \neq r \in \mathcal{R} \cup ROW$. A final good producer in sector i sources each intermediate good κ^i from the lowest-cost supplier after taking into account the trade costs. Therefore, the price of intermediate good κ^i in sector i at the destination location r is:

$$p_r^i(\kappa^i) = \min_{m \in \mathcal{R} \cup ROW} \left\{ \frac{c_m^i \tau_{mr}^i}{a_m^i(\kappa^i)} \right\}.$$

By taking advantage of the property of the Fréchet distribution, we can determine the price index of final good i at location r:

$$P_r^i = \Gamma^i \left(\sum_{m \in \mathcal{R} \cup ROW} T_m^i (c_m^i \tau_{mr}^i)^{-\theta^i} \right)^{-1/\theta^i}, \tag{6}$$

where $\Gamma^i = \Gamma\left(\frac{-\theta^i + 1 - \sigma^i}{\theta^i}\right)^{1/(1-\sigma^i)}$ and $\Gamma(\cdot)$ is the Gamma function. Furthermore, we can express location r's share of expenditure on good i from location m as:

$$\pi_{mr}^i = \frac{T_m^i (c_m^i \tau_{mr}^i)^{-\theta^i}}{\sum_{m' \in \mathcal{R} \cup ROW} T_{m'}^i (c_{m'}^i \tau_{m'r}^i)^{-\theta^i}}. \tag{7}$$

We label π_{mr}^i as the bilateral trade share. The bilateral trade share of goods sourced from region m is increasing in the average productivity T_m^i and decreasing in the cost of input bundle c_m^i and trade cost τ^i_{mr}.

Worker's Occupational Choice

Let $w_r(k,s,o)$ be the wage per efficiency unit of group (k,s) worker when worked in occupation o at location $r \in \mathcal{R}$. With perfect competition, the profit maximization yields:

$$w_r(k,s,o) = S(k,s,o)p_r(o),$$

implying that the marginal cost is equal to marginal revenue of hiring an additional unit of efficiency labor.

Given the occupational wage $w_r(k,s,o)$, each worker $z \in \mathcal{Z}_r(k,s)$ in location r chooses the occupation that maximizes her wage income, $\varepsilon(z,o)w_r(k,s,o)$. Since $\varepsilon(z,o)$ is Fréchet distributed, the probability that a randomly sampled worker $z \in \mathcal{Z}_r(k,s)$ chooses occupation o is given by:

$$\varphi_r(k,s,o) = \frac{[S(k,s,o)p_r(o)]^\zeta}{\sum_{o' \in \mathcal{O}} [S(k,s,o')p_r(o')]^\zeta}. \tag{8}$$

This probability is increasing in worker group- and occupation-specific efficiency $S(k,s,o)$ and the price of occupational service $p_r(o)$. Therefore, conditional on task prices, the higher share of group (k,s) workers in occupation o implies that they have a comparative advantage in occupation o.

Let $\text{Wage}_r(k,s,o)$ be the average wage of group (k,s) worker in occupation o at location $r\{R\}$, which is the integral of $\varepsilon(z,o)w_r(k,s,o)$ across workers in o at location r. The average wage can then be expressed as:

$$\begin{aligned}
\text{Wage}_r(k,s,o) &= \int_{z \in \{\mathcal{Z}_r(k,s) | \text{choose } o\}} \varepsilon(z,o) w_r(k,s,o) dG^\varepsilon(\varepsilon) \\
&= \tilde{\Gamma} S(k,s,o) p_r(o) \left(\varphi_r(k,s,o)\right)^{-1/\zeta}, \qquad (9)
\end{aligned}$$

where $\tilde{\Gamma} = \Gamma(1 - 1/\zeta)$. By substituting $\varphi_r(k,s,o)$ with the expression obtained in equation (8), we have:

$$\text{Wage}_r(k,s,o) = \text{Wage}_r(k,s) = \tilde{\Gamma}\left(\sum_{o\in\mathcal{O}} \left(S(k,s,o)p_r(o)\right)^{\zeta}\right)^{1/\zeta}. \tag{10}$$

This implies that the expected wage conditional on working in o is the same across all occupations. In our model, the more attractive occupation characteristics of o for group (k,s) workers, such as higher productivity $S(k,s,o)$ and higher price $p_r(o)$, directly raise the wage of a worker with a given idiosyncratic efficiency draw. This directly increases the expected wage for the occupation. Meanwhile, more attractive characteristics also attract workers with lower idiosyncratic efficiency draws, which lowers the expected wage. With a Fréchet distribution of efficiency, these two effects offset one another.

Worker's Location Choice

A worker in Japan $z \in \mathcal{Z}(k,s)$ determines the work location after taking into account the idiosyncratic preference shocks $b_r(z)$ across locations, but before knowing the idiosyncratic efficiency draws $\varepsilon(z,o)$ across occupations. Therefore, she will form an expectation of income at each destination. Her expected income, and therefore her expenditure, at location $r \in \mathcal{R}$ can be expressed as:

$$\mathbb{E}\left[E_r(k,s)\right] = \sum_{o\in\mathcal{O}} \varphi_r(k,s,o)\text{Wage}_r(k,s,o) = \text{Wage}_r(k,s).$$

The second equality follows from equation (10). Combined with the expression of the indirect utility in equation (2), the probability that a worker $z \in \mathcal{Z}(k,s)$ chooses to locate in the region $r \in \mathcal{R}$ is given by:

$$\psi_r(k,s) = \frac{B_r(k,s)\left(\text{Wage}_r(k,s)/P_r\right)^{\eta}}{\sum_{m\in\mathcal{R}} B_m(k,s)\left(\text{Wage}_m(k,s)/P_m\right)^{\eta}}, \tag{11}$$

This implies that location choice probability is increasing in average amenity, $B_r(k,s)$, and expected wage, $\text{Wage}_r(k,s)$, and decreasing in the consumption price index, P_r. The mass of group (k,s) workers at location $r \in \mathcal{R}$ is given by:

$$L_r(k,s) = \psi_r(k,s)L(k,s). \tag{12}$$

Market Clearing

Let $I_r(o)$ be total labor income in occcupation o at location $r \in \mathcal{R} \cup ROW$,

$$I_r(o) = \sum_{k\in\mathcal{K}, s\in\mathcal{S}} \text{Wage}_r(k,s)L_r(k,s,o) \tag{13}$$

where

$$L_r(k,s,o) = \varphi_r(k,s,o)L_r(k,s) \tag{14}$$

is the mass of group (k,s) workers who work in o. Then, the total household expenditure at domestic location r is given by:

$$E_r = \begin{cases} (1+\omega)\sum_{o\in\mathcal{O}} I_r(o) & \text{for } r \in \mathcal{R} \\ \sum_{o\in\mathcal{O}} I_r(o) - \omega \sum_{m\in\mathcal{R}} \sum_{o\in\mathcal{O}} I_r(o) & \text{for } r = ROW \end{cases} \tag{15}$$

To justify Japan's external trade deficit (or surplus), we consider the lump-sum transfer of income from the rest of the world to Japanese regions equivalent to the constant fraction ω of the regional value added. The total expenditure on good i at location r is given by:

$$X_r^i = \sum_{j\in\mathcal{I}} \beta^{i,j} Y_r^j + \alpha^i E_r, \tag{16}$$

where the first term on the right-hand side of the equation captures the expenditure by intermediate good producers of all sectors and the second term captures the expenditure by workers. Y_r^i is the gross output (total revenue) of sector j, which is:

$$Y_r^i = \sum_{m \in \mathcal{R}} \pi_{r,m}^i X_m^i. \tag{17}$$

Equation (16) and (17) implies that trade is bilaterally balanced.

The task market clearing condition implies:

$$I_r(o) = \sum_{i \in \mathcal{I}} \beta^{\ell,i} Y_r^i \frac{\mu^i(o) p_r(o)^{1-\rho^i}}{(P_r^{\ell,i})^{1-\rho^i}}. \tag{18}$$

The left-hand side of the equation (18) is the supply in value, and the right-hand side is the demand in value.

We now formally define the spatial general equilibrium of the model.

Definition 1 (Spatial General Equilibrium in Level) *Given $\{L(k,s)\}_{k,s}$ and other fundamentals $\Theta = \{\{B_r(k,s)\}_{k,s,r}, \{S(k,s,o)\}_{k,s,o}, \{\mu^i(o)\}_{i,o}, \{T_r^i\}_{i,r}, \{\tau_{mr}^i\}_{i,m,r}\}$, an equilibrium is a vector of wages $\{Wage_r(k,s)\}_{k,s,r}$, prices of final goods $\{P_r^i\}_{r,i}$ and task services $\{p_r(o)\}_{r,o}$, and allocations of workers across regions $\{L_r(k,s)\}_{k,s,r}$ and across tasks $\{L_r(k,s,o)\}_{k,s,r,o}$ that satisfy equilibrium conditions (3), (4), (5), (6), (7), (8), (10), (11), (12), (13), (14), (15), (16), (17), and (18) for all k, s, r, o, i.*

2.2 Equilibrium in Relative Changes

Using the model, we will conduct a counterfactual exercise to assess the impacts of an inflow of foreign workers on equilibrium outcomes, such as wages and employment. Let $\{L(k,s)\}_{k,s}$ be the factual number of workers (data) and $\{L'(k,s)\}_{k,s}$ be the counterfactual number. Keeping everything else unchanged, we will compare the equilibrium under $\{L(k,s)\}_{k,s}$ and the one under $\{L'(k,s)\}_{k,s}$. Instead of solving an equilibrium in level, we solve it for changes in wages, prices, and labor allocations after changing from $\{L(k,s)\}_{k,s}$ to $\{L'(k,s)\}_{k,s}$. We define it as an *equilibrium in relative changes* and we will employ the exact hat algebra *à la* Dekle et al. (2008). By doing so, we can exactly match the model to the data in a base year and identify the effects on equilibrium outcomes from the policy shocks. Furthermore, we can solve for the general equilibrium of the model without needing to estimate fundamental parameters that are difficult to estimate in the data.

For a generic variable x, the variable with a hat $\hat{x}$ denotes the relative change of the variable from x to x', i.e., $\hat{x} = x'/x$. We now define the equilibrium of the model under $\{L'(k,s)\}_{k,s}$ relative to $\{L(k,s)\}_{k,s}$:

Definition 2 (Spatial General Equilibrium in Relative Changes) *Let $\{Wage_r(k,s)\}_{k,s,r}$, $\{P_r^i\}_{r,i}$, $\{p_r(o)\}_{r,o}$, $\{L_r(k,s)\}_{r,k,s}$, and $\{L_r(k,s,o)\}_{r,k,s,o}$ be an equilibrium under $\{L(k,s)\}_{k,s}$ and Θ, and let $\{Wage'_r(k,s)\}_{r,k,s}$, $\{P_r'^i\}_{r,i}$, $\{p'_r(o)\}_{r,o}$, $\{L'_r(k,s)\}_{r,k,s}$, and $\{L'_r(k,s,o)\}_{r,k,s,o}$ be an equilibrium under $\{L'(k,s)\}_{k,s}$ and Θ'. Define $\{\hat{Wage}_r(k,s)\}_{r,k,s}$, $\{\hat{P}_r^i\}_{r,i}$, $\{\hat{p}_r(o)\}_{r,o}$, $\{\hat{L}_r(k,s)\}_{r,k,s}$, and $\{\hat{L}_r(k,s,o)\}_{r,k,s,o}$ as an equilibrium under $\{L'(k,s)\}_{k,s}$ and Θ' relative to $\{L(k,s)\}_{k,s}$ and Θ. Using the equilibrium conditions listed in Definition 1, the equilibrium conditions in relative changes satisfy:*

Consumer price index:

$$\hat{P}_r = \prod_{i \in \mathcal{I}} \left(\hat{P}_r^i\right)^{\alpha^i}. \tag{19}$$

Cost of input bundle:

$$\hat{c}_r^i = (\hat{P}_r^{\ell,i})^{\beta^{\ell,i}} \prod_{j \in \mathcal{I}} (\hat{P}_r^i)^{\beta^{j,i}}, \tag{20}$$

Price of composite task service:

$$\hat{P}_r^{\ell,i} = \left(\sum_{o \in \mathcal{O}} \hat{\mu}^i(o) \left(\hat{p}_r(o)\right)^{1-\rho^i} \frac{\mu^i(o) p_r(o)^{1-\rho^i}}{(P_r^{\ell,i})^{1-\rho^i}}\right)^{1/(1-\rho^i)}, \tag{21}$$

Sectoral price index:

$$\hat{P}_r^i = \left(\sum_{m \in \mathcal{R}} \hat{T}_m^i \left(\hat{c}_m^i \hat{\tau}_{m,r}^i\right)^{-\theta^i} \pi_{m,r}^i\right)^{-1/\theta^i}. \tag{22}$$

Bilateral trade share:

$$\hat{\pi}^i_{m,r} = \frac{\hat{T}^i_m \left(\hat{c}^i_m \hat{\tau}^i_{m,r}\right)^{-\theta^i}}{\sum_{m' \in \mathcal{R}} \hat{T}^i_{m'} \left(\hat{c}^i_{m'} \hat{\tau}^i_{m'r}\right)^{-\theta^i} \pi^i_{m',r}}. \tag{23}$$

task choice probability:

$$\hat{\varphi}_r(k,s,o) = \frac{\left(\hat{S}(k,s,o)\hat{p}_r(o)\right)^{\zeta}}{\sum_{o' \in \mathcal{O}} \left(\hat{S}(k,s,o')\hat{p}_r(o')\right)^{\zeta} \varphi_r(k,s,o)}. \tag{24}$$

Average wage:

$$\hat{Wage}_r(k,s) = \left(\sum_{o \in \mathcal{O}} \left(\hat{S}(k,s,o)\hat{p}_r(o)\right)^{\zeta} \varphi_r(k,s,o)\right)^{1/\zeta}. \tag{25}$$

Location choice probability:

$$\hat{\psi}_r(k,s) = \frac{\hat{B}_r(k,s)\left(\hat{Wage}_r(k,s)/\hat{P}_r\right)^{\eta}}{\sum_{r' \in \mathcal{R}} \hat{B}_{r'}(k,s)\left(\hat{Wage}_{r'}(k,s)/\hat{P}_{r'}\right)^{\eta} \psi_{r'}(k,s)}, \tag{26}$$

Regional allocation of workers:

$$\hat{L}_r = \sum_{k \in \mathcal{K} s \in \mathcal{S}} \hat{L}_r(k,s) \frac{L_r(k,s)}{\sum_{k' \in \mathcal{K} s' \in \mathcal{S}} L_r(k',s')}. \tag{27}$$

Total labor income by task:

$$\hat{I}_r(o) = \sum_{k \in \mathcal{K} s \in \mathcal{S}} \hat{Wage}_r(k,s,o)\hat{L}_r(k,s,o) \frac{Wage_r(k,s,o)L_r(k,s,o)}{\sum_{k' \in \mathcal{K} s' \in \mathcal{S}} Wage_r(k',s',o)L_{r'}(k',s',o)} \tag{28}$$

Task market clearing:

$$\hat{I}_r(o) = \sum_{i\in\mathcal{I}} \frac{\hat{Y}_r^i}{\hat{p}_r^{\ell,i}} \hat{\mu}^i(o)\hat{p}_r(o)^{1-\rho^i} \frac{\beta^{\ell i} Y_r^i \frac{\mu^i(o)p_r(o)^{1-\rho^i}}{(p_r^{\ell,i})^{1-\rho^i}}}{\sum_{i'\in\mathcal{I}} \beta^{\ell i'} Y_r^{i'} \frac{\mu^i(o)p_r(o)^{1-\rho^{i'}}}{(p_r^{\ell,i'})^{1-\rho^{i'}}}}. \tag{29}$$

Total household expenditure:

$$\hat{E}_r = \begin{cases} \sum_{o\in\mathcal{O}} \hat{I}_r(o) \frac{I_r(o)}{\sum_{o'\in\mathcal{O}} I_r(o')} & \textit{for } r \in \mathcal{R} \\ \sum_{o\in\mathcal{O}} \hat{I}_r(o) \frac{I_r(o)}{E_r} - \omega \sum_{m\in\mathcal{R}} \sum_{o\in\mathcal{O}} \hat{I}_m(o) \frac{I_m(o)}{E_r} & \textit{for } r = ROW \end{cases} \tag{30}$$

Total expenditure:

$$\hat{X}_r^i = \sum_{j\in\mathcal{J}} \hat{Y}_r^j \frac{\beta^{i,j} Y_r^j}{\sum_{j'\in\mathcal{J}} \beta^{i,j'} Y_r^{j'} + \alpha^i E_r} + \hat{E}_r \frac{\alpha^i E_r}{\sum_{j'\in\mathcal{J}} \beta^{i,j'} Y_r^{j'} + \alpha^i E_r}. \tag{31}$$

Gross output:

$$\hat{Y}_r^i = \sum_{m\in\mathcal{R}} \hat{\pi}_{r,m}^i \hat{X}_m^i \frac{\pi_{r,m}^i X_m^i}{\sum_{m'\in\mathcal{R}} \pi_{r,m'}^i X_{m'}^i}. \tag{32}$$

for all k, s, r, o, i.

By inspecting equilibrium conditions (19 through 32), we can see that solving an equilibrium in relative changes allows us to perform counterfactual experiments without estimating fundamentals such as the average regional amenity, occupational comparative advantage, production technology, and trade cost. Solving an equilibrium requires data on regional allocation ($L_r(k,s)$ and $\psi_r(k,s)$), occupational allocation ($L_r(k,s,o)$, $\varphi_r(k,s,o)$), bilateral trade share (π_{mr}^i), household expenditure (E_r), average wage ($\text{Wage}_r(k,s)$), and the expenditure share of each occupation in the total labor cost ($\frac{\mu^i(o)p_r(o)^{1-\rho^i}}{(p_r^{\ell,i})^{1-\rho^i}}$). We label them as "base year equilibrium outcomes," which we condition on in solving an equilibrium in relative changes. As described in the next section, all the base year equilibrium outcomes can be observed in the data for domestic regions in Japan. For the rest of the world, however, some of them, such as wages by worker group and occupational allocation, are not available. Therefore, in conducting counterfactual analysis, we let wages and prices of occupational services in the rest of the world be fixed.

In addition to the base year equilibrium outcomes, we need to calibrate the following structural parameters: the value-added share in production ($\beta^{\ell,i}$), the share of sectoral intermediate inputs (β^{ji}), the share of each sector in final demand (α^i), the dispersion parameters of regional amenity shocks (η), efficiency shocks across occupations (ζ), and production technology shocks (θ^i), and the elasticity of substitution across occupations(ρ^i). Except for the last four parameters, we can easily calibrate all parameters in the data using, for example, the input-output table. We need to estimate the three Fréchet dispersion parameters and the elasticity of substitution across occupations for each industry. We describe the calibration strategy in the following section.

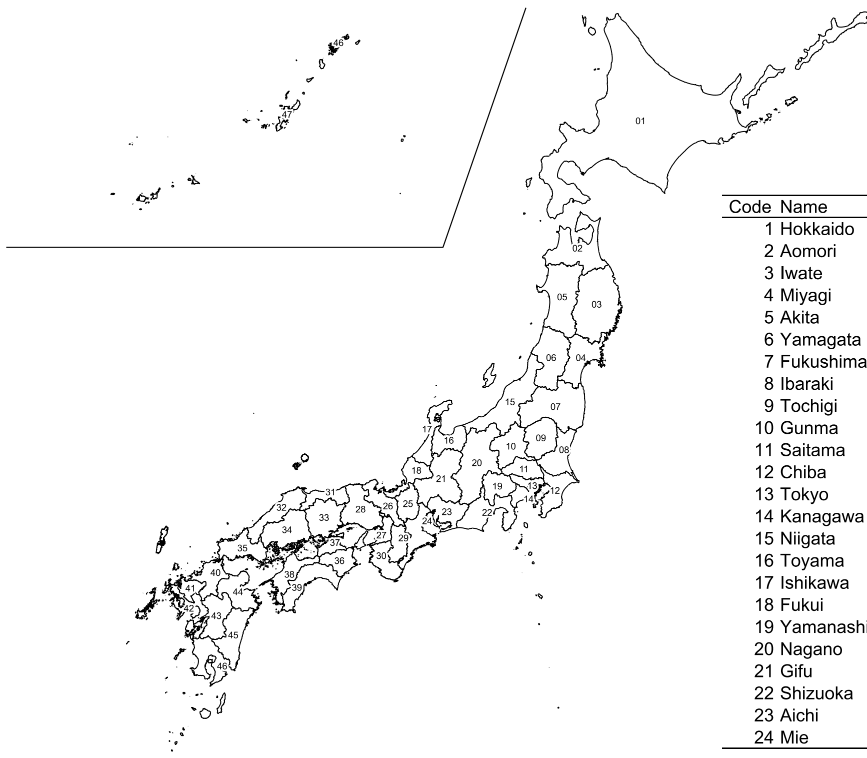
3 Quantification

We define our units of analysis in the quantification as follows: we consider 47 prefectures and the rest of the world. See Figure 1 for the list of prefectures and their geographic locations. Workers are classified by Japanese or foreign and other attributes. Domestic workers are grouped by education level (edu; high-education and low-education), gender (sex; male and female), and age groups (age; 15–29, 30–59, +60). High-education refers to a 4-year college degree or more (excluding junior college). Due to the limited number of sampled foreign workers in the data, we consider education level and gender as the foreign workers' attributes. There are in total 16 worker groups, i.e., 12 types for native and four types for foreign. In our notation, s is a vector of $\{edu, sex, age\}$ for domestic worker ($k = D$) and $\{edu, sex\}$ for foreign worker ($k = F$). We consider 24 occupations based on the Japan Standard Occupation Classification (Revision 1986). Table 1 shows the list of 24 occupations. Lastly, we consider six industries, manufacturing of food, metal, and machinery, other manufacturing, construction, and service. Sectoral classification is based on the Inter-Regional Input-Output Table compiled by Ministry of Economy, Trade, and Industry (2010). We rule out the primary sectors (agriculture, forestry, and fishery) and mining due to the data availability.

3.1 Data

We use the Japanese government micro-level data to construct the set of aggregate moments to estimate the structural parameters and the base year equilibrium outcomes. The first data set is the Basic Survey of Wage Structure (*Chingin Kōzō Kihon Tōkei Chōsa*) collected by the Ministry of Health, Labour, and Welfare (MHLW). The MHLW Wage Survey is an establishment-level survey

Figure 1: 47 Prefectures of Japan



Code	Name	Code	Name
1	Hokkaido	25	Shiga
2	Aomori	26	Kyoto
3	Iwate	27	Osaka
4	Miyagi	28	Hyogo
5	Akita	29	Nara
6	Yamagata	30	Wakayama
7	Fukushima	31	Tottori
8	Ibaraki	32	Shimane
9	Tochigi	33	Okayama
10	Gunma	34	Hiroshima
11	Saitama	35	Yamaguchi
12	Chiba	36	Tokushima
13	Tokyo	37	Kagawa
14	Kanagawa	38	Ehime
15	Niigata	39	Kochi
16	Toyama	40	Fukuoka
17	Ishikawa	41	Saga
18	Fukui	42	Nagasaki
19	Yamanashi	43	Kumamoto
20	Nagano	44	Oita
21	Gifu	45	Miyazaki
22	Shizuoka	46	Kagoshima
23	Aichi	47	Okinawa
24	Mie		

conducted annually, surveying more than one million workers in all sectors except primary ones. We can observe workers' attributes (such as gender, age, and highest education attained), work hours, and monthly wage. As of the 2019 survey, sampled foreign workers must report their residence status (visa category). In the 2020 survey, among 1,327,241 sampled workers, 14,603 (1.1%) workers were identified as foreign. We complement the MHLW Wage Survey with the Basic Survey of Employment Structure (*Shūgyō Kōzō Kihon Chōsa*) conducted by the Ministry of Internal Affairs and Communications (MIC). The MIC Employment Survey is a household-level survey conducted every five years. Individuals aged 15 and older report their employment status.

Both datasets have caveats in constructing the relevant aggregate moments. In the MHLW Wage Survey, sampled workers report the exact values of work hours and monthly wages. However, until 2019, workers reported their occupations only if they were itemized in the non-exhaustive occupation list. As a result, a substantial fraction of observations lacked occupational information. As of 2020, the occupation list has become exhaustive, and the occupation classification complies with the Japan Standard Occupational Classification. In estimating the structural parameters, however, we need to construct the occupation distribution and occupation expenditure share by sector and region over time. We therefore use the MIC Employment Survey, in which all workers report their

Table 1: List of Occupations

	Occupation name	Example
1	Engineer	*Chemical engineer, system consultant*
2	Medical technicians and healthcare	*Medical doctor, nurse*
3	Social welfare professional	*Childcare worker*
4	Teacher	*Teacher, professor*
5	Other professional and technical	*Legal professional, designer*
6	Administrative and managerial	*Director, manager*
7	Clerical	*General clerical, sales clerk*
8	Merchandise sales	*Retailer*
9	Quasi-sales	*Insurance sales*
10	Life-related service	*Hairdresser, launderer*
11	Food and drink preparatory	Chef
12	Food and drink service	*Waitron*
13	Other service	*Apartment management personnel*
14	Security	*Security staff*
15	Agriculture, forestry and fishery	*Farmer, fishing ship crew*
16	Transport and communication	*Railway and bus driver*
17	Mining	*Dam and tunnel excavation*
18	Ceramic/stone product, metal material, chemical product manufacturing	*Production and inspection of the products*
19	Metal product and machinery manufacturing	*Production and inspection of the products*
20	Food/beverage, and fiber/wooden/paper/rubber/leather product manufacturing and printing/bookbinding	*Production and inspection of the products*
21	Other manufacturing	*Painting*
22	Stationary engine and construction machinery operation and electric construction	*Power plant and crane operation*
23	Construction	*Carpenter*
24	Labor worker	*Janitor, packing*

occupations. A drawback of using the MIC Employment Survey is that, unlike the MHLW Wage Survey, individuals report their work days, hours, and annual income by choosing the bins instead of answering the exact values. Furthermore, we cannot identify the worker's nationality in the MIC Employment Survey.

We also use several other sources of data: price deflators (consumer price indices) are taken from the Retail Price Survey (Ministry of Internal Affairs and Communications, 2015) and Consumer Price Index (Ministry of Internal Affairs and Communications, 2020) conducted and compiled by the Ministry of Internal Affairs and Communications. The bilateral distance across prefectures is sourced from Geospatial Information Authority of Japan (n.d.). We also use the Inter-Regional Input-Output (IO) Table compiled by the Ministry of (Ministry of Economy, Trade, and Industry, 2010) to construct the inter-prefectural bilateral trade flow matrix. We will discuss the use of the IO table in detail below.

3.2 Calibration of Structural Parameters

Cobb-Douglas Coefficients in Production and Utility Functions

The value-added share in production ($\beta^{\ell,i}$), the share of intermediate inputs ($\beta^{j,i}$) by sector, and the sectoral share in final demand (α^i) are all calibrated from the World Input-Output Database (WIOD) (Timmer et al., 2015). We use the data for 2014, the latest year in the dataset. We assume that parameter values differ between Japan and the rest of the world, but they are same across domestic regions. The share of composite task services in the total production cost in each sector j, $\beta^{\ell,i}$, is calibrated from the value-added share. Primary sectors (i.e., agriculture, forestry, and fishery) are dropped in calibrating the parameter values.

Elasticity of Residential Choice

The remaining structural parameters to be calibrated are those governing the elasticities of residential choice (η), occupation choice (ζ), substitution across tasks (ρ^i), and interregional trade (θ^i). We outline how to construct the moment conditions to estimate those parameters. Then we show the estimation results.

We start by estimating the shape parameter of the Fréchet amenity shock, η. From here on, we index variables by time subscript t. For a generic variable x, let $\hat{x}_t$ be the relative change in variable x between any two consecutive periods t and $t' > t$, i.e, $\hat{x}_t = x_{t'}/x_t$.

From the equilibrium condition (11), we have:

$$\begin{aligned}\psi_{rt}(k,s) &= \frac{B_r(s)\left(\text{Wage}_{rt}(k,s)/P_{rt}\right)^{\eta}}{\sum_{r'\in\mathcal{R}} B_{r'}(k,s)\left(\text{Wage}_{r't}(s)/P_{r't}\right)^{\eta}} \\ &= \frac{B_r(k,s)\left(\text{Wage}_{rt}(k,s)/P_{rt}\right)^{\eta}}{\Upsilon_t(s)}\end{aligned}$$

where $\Upsilon_t(s)$ is the "multilateral resistance" term. Taking logs, we have the following moment condition:

$$\begin{aligned}\log(\psi_{rt}(k,s)) &= \eta\log(\text{Wage}_{rt}(k,s)/P_{rt}) + \log(B_r(k,s)) - \log(\Upsilon_t(k,s)) + \nu^{\eta}_{rt}(k,s) \\ &= \eta\log(\text{Wage}_{rt}(k,s)/P_{rt}) + \delta^{\eta}_r(k,s) - \delta^{\eta}_t(k,s) + \nu^{\eta}_{rt}(k,s) \qquad (33)\end{aligned}$$

where region-type fixed effects $\delta_r^\eta(k,s)$ capture the unobserved amenity $\log(B_r(k,s))$ and the time-type fixed effects $\delta_t^\eta(k,s)$ capture the unobserved multilateral resistance term $\Upsilon_t(s)$. In the estimation below, we also include region-year fixed effects to control for the regional shocks, which are common to all worker groups.

Any unobserved shocks to location choice probability may affect the average wages. If there is a positive shock to the region that attracts more workers to reside there, the average wages may get lower due to the larger labor supply. In this case, the parameter estimates under the OLS may be downward biased. To address the potential endogeneity, we construct an instrument to control for the potential endogeneity. Following Tombe and Zhu (2019), we construct a Bartik-style expected income as follows:

$$\text{ExpWage}_{r,t}(k,s) = \sum_i \lambda_{rt}(k,s)^i \text{Wage}_t^i(k,s)$$

where $\lambda_{rt}(k,s)^i$ is the fraction of type (k,s) workers in sector i and $\text{Wage}_t^i(k,s)$ is the average wage of type (k,s) workers in sector i nationwide.

Location choice probabilities and average wages by region, worker type, and industry are constructed using the MIC Employment Survey from 1997 to 2017. In this survey, we cannot identify an individual's nationality. Therefore, we use gender, education level, and age to define a labor type. Furthermore, given that the workers are less likely to move after the age of 60, we drop those workers from the sample in estimating the parameter. As mentioned above, in the Employment Survey, individuals report their annual work days, weekly work hours, and annual income by choosing the bins instead of answering the exact values. For example, in the 2017 Survey, there are 12 bins for weekly working hours: less than 15 hours, 15-19 hours, ..., and more than 74 hours per week. We use the intermediate value of each bin's range except for the first and last bins, e.g., we use 17 hours for the 15-19 hours/week bin. For the first and last bins, we use the upper and lower bounds of the bins, i.e., we use 14 and 75 hours/week for the first and the last bins, respectively.[9]

In order to measure the location choice probabilities, we compute the mass of workers by region and worker type based on the work hours.[10] We recover the hourly wage using the information on annual income, annual workdays, and weekly work hours. We then compute the average wages

[9] Since the ranges of the bins may differ across survey years (the surveys of later years have more disaggregated bins), we redefine the bins to be consistent over time.

[10] We use the sample weight associated with each observation to construct the aggregate work hours for each worker group and region.

Table 2: Residential Choice Elasticity (IV)

	OLS	IV
ln(Real Wage)	0.148	0.644
	(0.056)	(0.322)
Type-Region FE	YES	YES
Type-Year FE	YES	YES
First Stage		
ln(Exp Wage)		0.747
		(0.109)
F-statistics		22.08
Observations	1504	1504

Standard errors in parentheses

for each worker group and region. Average wages are deflated using the consumer price index (CPI).[11]

Table 2 summarizes the estimation results. The point estimate of η under OLS is lower than the IV estimate, which aligns with the discussion above. The point estimate under IV is 0.644, which we use for the baseline parameter value. For comparison, Tombe and Zhu (2019) find that the elasticity is 1.8 for Chinese provinces, and Fajgelbaum et al. (2019) find that it is 1.5 for the U.S. states (depending on specification). Our point estimates are below what those studies obtained.

3.3 Occupation Choice Elasticity and Elasticities of Substitution

We calibrate the shape parameter of the Fréchet efficiency shock ζ, which governs the elasticity of occupation choice, from Burstein et al. (2019), and take value 1.8. We estimate the elasticity of substitution across occupations for each industry, ρ^i, using the Japanese data. First, we assume that $S_t(k, s, o)$ can be decomposed into three components:

$$S_t(k, s, o) = S_t(k, s) \times S_t(o) \times S(k, s, o),$$

where the first two components are time-variant, and the last one is time-invariant. Then, we can express:

[11] We use the cross-sectional CPI at a prefecture level in 2015 (the national average is set to 100) and the time-series CPI for each prefecture from 1992 to 2017 (CPI in 2020 is normalized to 100) to construct the panel of CPI that can be compared across prefectures and over time.

$$\hat{S}_t(k,s,o) = \hat{S}_t(k,s) \times \hat{S}_t(o). \tag{34}$$

Let us define the transformed occupation price as the product of the occupation price $p_{r,t}(o)$ and the occupation-specific efficiency shifter $S_t(o)$, i.e., $q_{r,t}(o) = p_{r,t}(o)S_t(o)$.

From the first-order condition of an intermediate good producer, we can express the relative change in total expenditure on occupation service o in sector i as:

$$\hat{I}^i_{rt}(o) = \hat{Y}^i_{rt}\hat{\mu}^i(o)\left(\frac{\hat{p}^{\ell,i}_{r,t}}{\hat{p}_{r,t}(o)}\right)^{\rho^i-1}.$$

Let $s^i_t \equiv \mu^i(o)S_t(o)^{\rho^i-1}$ be a composite occupation shifter. Then, we can rewrite equation (34) as:

$$\begin{aligned}
\hat{I}^i_{rt}(o) &= \hat{Y}^i_{rt}\hat{\mu}^i(o)S_t(o)^{\rho^i-1}\left(\frac{\hat{p}^{\ell,i}_{r,t}}{\hat{p}_{r,t}(o)S_t(o)}\right)^{\rho^i-1} \\
&= \hat{Y}^i_{rt}s^i_t(o)\left(\frac{\hat{p}^{\ell,i}_{r,t}}{\hat{q}_{r,t}(o)}\right)^{\rho^i-1} \\
&= \hat{Y}^i_{rt}s^i_t(o)\hat{p}^{\ell,i}_{r,t}\left(\frac{\hat{q}_{r,t}(o)}{\hat{q}_{r,t}(o)}\right)^{\rho^i-1} \\
&= \hat{Y}^i_{rt}s^i_t(o)\hat{p}^{\ell,i}_{r,t}\left(\hat{q}_{r,t}(o')\right)^{1-\rho^i}\left(\left(\frac{\hat{q}_{r,t}(o')}{\hat{q}_{r,t}(o)}\right)^{\zeta}\right)^{\frac{1}{\zeta}(\rho^i-1)}
\end{aligned}$$

where $\hat{q}_{r,t}(o)$ is the transformed occupation price defined above. Now, let $v_{r,t}(o',o) = (\hat{q}_{r,t}(o)/\hat{q}_{r,t}(o'))^{\zeta}$ be the relative transformed occupation price of o. Then, from equation (24), we can show that the relative occupation price to the power of ζ can be expressed using the relative change in occupation choice probabilities:

$$\hat{v}_{r,t}(o,o') \equiv \left(\frac{\hat{q}_{r,t}(o)}{\hat{q}_{r,t}(o')}\right)^{\zeta} = \frac{\hat{\varphi}_{r,t}(k,s,o)}{\hat{\varphi}_{r,t}(k,s,o')} \tag{35}$$

Table 3: Estimates of ρ^i

	Point estimate	Standard Error
Elasticity of substitution ρ^i		
Food	0.976	0.070
Metal	1.044	0.066
Machinery	1.023	0.067
Other manuf	1.032	0.055
Construction	0.955	0.051
Service	1.007	0.018

As $\frac{\hat{\varphi}_{r,t}(k,s,o)}{\hat{\varphi}_{r,t}(k,s,o')}$ is observable in the data, so is $\hat{v}_{rt}(o,o')$. If we take logs, we get:

$$\begin{aligned}\log\left(\hat{I}^i_{rt}(o)\right) =& \log\left(\hat{s}^i_{rt}(o)\right) + \log\left(\hat{Y}^i_{rt}\left(\hat{p}^{\ell i}_{r}\right)^{\rho^i-1}\left(\hat{q}_{rt}(o')\right)^{1-\rho^i}\right) + \frac{1}{\zeta}(1-\rho^i)\log\left(v_{r,t}(o,o')\right)\\ =& \frac{1}{\zeta}(1-\rho^i)\log\left(v_{r,t}(o,o')\right) + \delta^{\rho^i}_{rt} + \nu^{\rho^i}_{rt}(o)\end{aligned}$$

where $\delta^{\rho^i}_{rt} = \log\left(\hat{Y}^i_{rt}\left(\hat{p}^{\ell i}_{rt}\right)^{\rho^i-1}\left(\hat{q}_{rt}(o')\right)^{1-\rho^i}\right)$ is the time-region fixed effect and $\nu^{\rho^i}_{rt}(o) = \log\left(\hat{s}^i_{rt}(o)\right) + \vartheta^{\rho^i}_{r,t}(o)$ is the composite of unobserved change in occupation shifter and measurement error.

Since the higher growth of the occupation shifter may lead to the higher growth of the occupation price, the unobserved term $\nu^{\rho^i}_{rt}(o)$ may be positively correlated with the occupation price $\hat{q}_{rt}(o)$. To address this potential endogeneity, we construct the following instrument:

$$\chi^{\rho}_{rt} = \sum_{r'\neq r}\lambda_{rr'}\left(\frac{\hat{q}_{rt}(o)}{\hat{q}_{rt}(o')}\right)^{\zeta}, \tag{36}$$

where $\lambda_{rr'} = \frac{1/\text{dist}_{rr'}}{\sum_{r''}1/\text{dist}_{rr''}}$ is a weight based on the bilateral distance between r and r' as defined above. This is a distance-weighted average of the occupation price (to the power of ζ).

We estimate ρ^is with the two-stage least squares. We use the data from the MIC Employment Survey on four time periods: 1997–2002, 2002–2007, 2007–2012, 2012–2017. We restrict the samples to those aged between 15 and 59.

Table 3 summarizes the results. The point estimates suggest that occupational expenditure shares are almost constant, implying the Cobb-Douglas aggregator.

Table 4: Base Year Equilibrium Outcomes

	Description	Source
$\text{Wage}_r(k,s)$	Average wage	MHLW Wage Survey
$L_r(k,s,o)$	Number of workers	MHLW Wage Survey
$\text{Share}_r^i(o)$	Average occupation expenditure share	MHLW Wage Survey
π_{rm}^i	Bilateral trade share	Imputed

Trade Elasticity

Lastly, for the trade elasticity θ^i, we calibrate the values from Caliendo and Parro (2015). As our sectoral classification is more aggregated, we use the simple average of the point estimates across sub-sectors within each sector. We also refer to the results by Eckert (2019) showing that the distance elasticity of trade of the service sector has been getting close to that of the manufacturing sector over the past decades in the U.S. We set $\theta = 4.5$ for the service sector.

3.4 Base Year Equilibrium Outcomes

Our base year is 2020, i.e., we solve an equilibrium in relative changes, conditioning on the equilibrium outcomes in 2020. We construct the base year equilibrium variables as summarized in Table 4. We compute average wages at the worker type and region levels, the mass of workers at the worker type, region, and occupation levels, and occupational expenditure shares for each sector using the MHLW Wage Survey 2020. In the Wage Survey, temporary workers are not required to report their education attainment. Sampled workers with missing education information account for approximately 11% of the observations. More importantly, among sampled foreign workers, education is missing for 34% of the samples. To impute the missing education, we first assume that workers below 22 are low-education, since 22 is the age at which students graduate from the 4-year colleges. Given the nature of each visa classification, we assume that foreign workers who are admitted under the visa categories of Professor, Highly Skilled Professionals, Education, Engineer, and Specialist in Humanities and International Services are high-education. Those admitted under the Technical Intern Trainee Program are assumed to be low-education. This leaves 62% of sampled foreign workers with missing education. We drop the rest of the observations from the sample[12].

[12] Among the sampled foreign workers that are dropped from the analysis, 77% of them have the residence based on the civil status, such as Permanent Residents

Wages and Occupation Expenditure Shares

Average wages by region and worker type, $\text{Wage}_r(k, s)$, are computed based on the hourly wages. Individual hourly wage is computed by summing up the scheduled wage and the bonus.[13] Average wages are then computed as follows:

$$\text{Wage}_r^{\text{Data}}(k, s) = \frac{\sum_{z \in \mathcal{Z}_r^{\text{Data}}(k,s)} \omega_r(k, s, z) h_r^{\text{Data}}(k, s, z) w_r^{\text{Data}}(k, s, z)}{\sum_{z \in \mathcal{Z}_r^{\text{Data}}(k,s)} \omega_r(k, s, z) h_r^{\text{Data}}(k, s, z)}$$

where $w_r^{\text{Data}}(k, s, z)$ is the hourly wage of worker z, $h_r^{\text{Data}}(k, s, z)$ is the monthly work hour, and $\omega_r(k, s, z)$ is the corresponding sample weight. As we now have the mass of workers and the average wages in hand, we can compute the value added by region according to equations (13).

Mass of Workers (Location and Occupation Choice Probabilities)

We construct the mass of workers by aggregating (monthly) work hours for each region, worker group, and occupation aggregate, $L_r(k, s, o)$.[14] In the Wage Survey 2020, the mass of foreign workers accounts for 1.4% of total workers in Japan. This is below the number based on the Foreign Employment Report (Ministry of Health, Labour, and Welfare, 2019) which counts the universe of foreign workers in Japan. The discrepancy suggests that foreign workers are underrepresented in the MHLW Wage Survey. We blow up the mass of foreign workers by a constant factor of 1.94, keeping the regional, occupational, and worker group compositions fixed as in the Wage Survey data, to match the fraction of foreign workers to 2.6%.

We compute the location choice probability in the base year as:

$$\psi_r^{\text{Data}}(k, s) = \frac{\sum_o L_r^{\text{Data}}(k, s, o)}{\sum_{r'} \sum_{o'} L_{r'}^{\text{Data}}(k, s, o')}.$$

Figure 2 compares the geographic distribution of low-education males for domestic (aged 30–59) and foreign workers (all ages) in the base year 2020.[15] The number in the figure shows the fraction

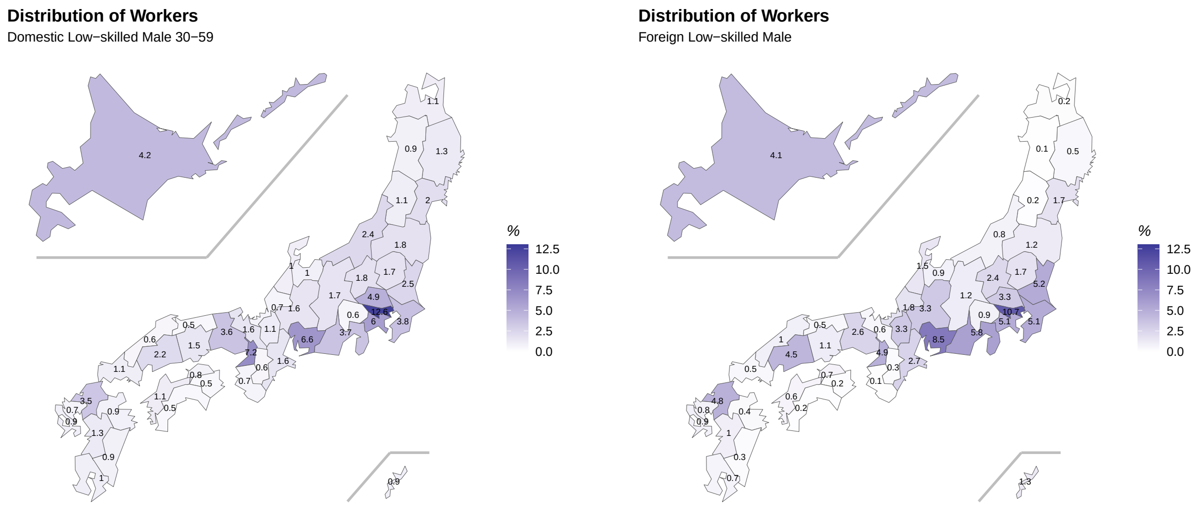
[13] We compute the scheduled wage and the bonus on an hourly basis. We divide the monthly schedule wage by monthly work hours (including overtime work hours) to get the hourly scheduled wage. The hourly bonus is calculated by dividing the annual bonus by the annual work hours.

[14] We confirmed that the correlation coefficient between the work-hour-based measure and headcount-based measure is 0.99.

[15] For the other types of workers, see Appendix B.

Figure 2: Geographic Distribution of Low-Education Male 30-59 (2020)

(a) Domestic (b) Foreign



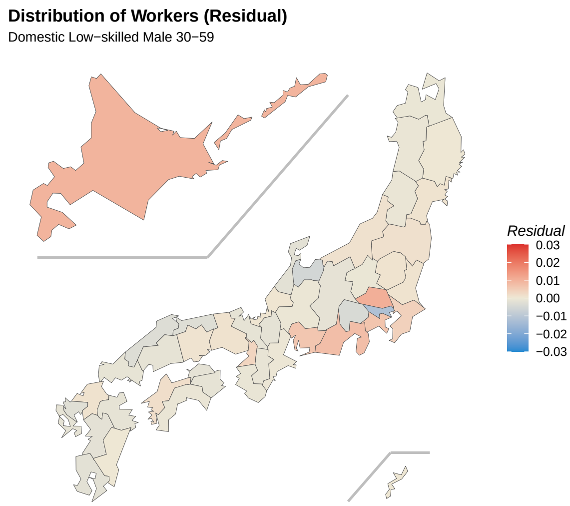
Note: Number in the figure shows the fraction of workers in a given type residing in each region, $\psi_r(k, s)$.

of workers of a given type residing in each location, i.e., $\psi_r(k, s)$. For domestic workers, Tokyo accounts for the largest share (12.5%) followed by Osaka (7.2%) and Aichi (6.6%). Those are three major urban areas in Japan. For foreign workers, Tokyo ranks first (10.7%), followed by the two prefectures in the Tokai area, Aichi(8.5%) and Shizuoka (5.8%). Shizuoka accounts for only 3.7% of domestic workers and Osaka accounts for 4.9% of foreign workers. In order to highlight the heterogeneous distribution of domestic and foreign workers across space, we regress $\psi_r(k, s)$ on real wages (using the average wage constructed above denominated by the consumer price index, $\text{Wage}_r(k, s)$), sectoral composition (sectoral share of employment across all worker types), and the size of the local economy measured by the overall population distribution (fraction of workers of all types residing in each region). Figure 3 shows the residualized geographic distribution of low-education males for domestic and foreign workers. Regions that are colored red (blue) indicate they accommodate (less) more workers. Panel (b) show that there remains a substantial variation in the geographic distribution of foreign workers, which is not explained by the difference in real income, sectoral composition, and the size of the economy. According to the model, the residual suggests the worker type-specific local amenities. Moreover, the higher concentration of foreign workers in certain regions relative to domestic workers, such as Aichi and Shizuoka, implies that foreign employment policy will have strong regional implications.

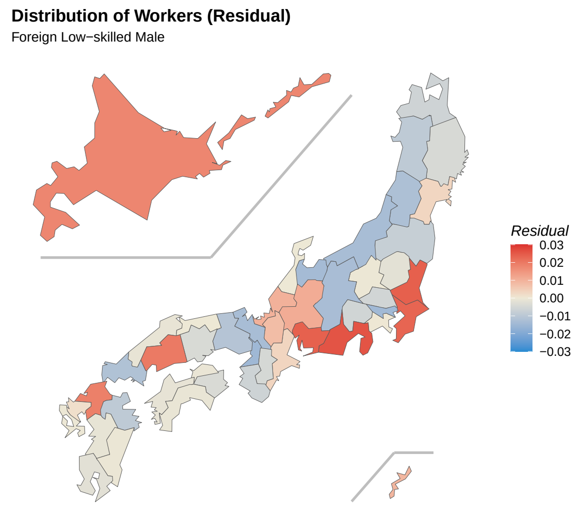
We construct the occupation choice probability $\varphi_r(k, s, o)$ as follows:

Figure 3: Residualized Geographic Distribution of Low-Education Male 30-59 (2020)

(a) Domestic



(b) Foreign

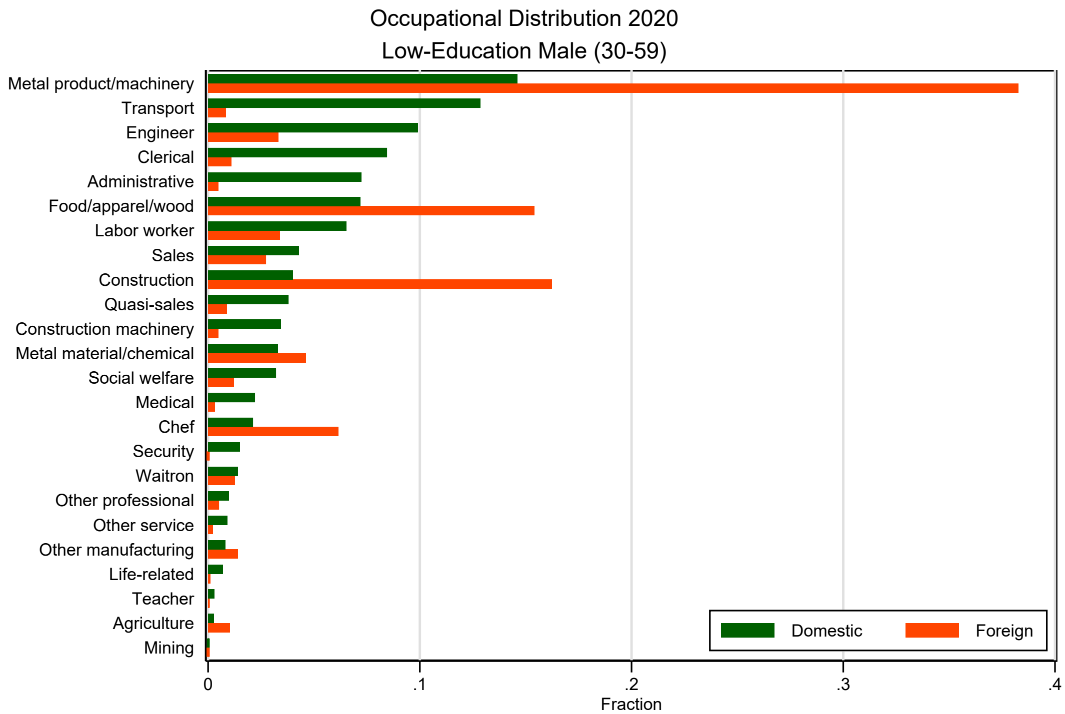


Note: Figure shows the residuals of OLS regression of geographic distribution of workers.

$$\varphi_r^{\text{Data}}(k,s,o) = \frac{L_r^{\text{Data}}(k,s,o)}{\sum_{o'} L_r^{\text{Data}}(k,s,o')}.$$

While occupation choice probabilities are defined at the worker type and region levels, Figures 4 and 5, respectively, compare the occupational distribution of low- and high-education males between domestic (aged 30–59) and foreign workers (all ages) across all regions. The number in the figure indicates the fraction of workers who work in each occupation. We see that the patterns of occupation sorting are substantially different between domestic and foreign workers after conditioning on education level and gender. For low-education domestic males, 15% engage in Metal Product/Machinery Manufacturing, followed by Transport (13%) and Engineer (10%). For foreign workers, Metal Product/Machinery Manufacturing accounts for 38%, followed by Construction (16%) and Food/Apparel/Wood Manufacturing (15%). Transport and Engineer occupations comprises only 1% and 3%, respectively. A heterogeneous occupational distribution is also evident for high-education males. Clerical (18%), Engineer (18%), and Administrative (16%) are the top three occupations for domestic workers, while Metal Product/Machinery Manufacturing (20%), Food/Apparel/Wood Manufacturing (16%), and Construction (13%) occupations are ranked first to third for foreign workers. Our theoretical framework attributes the different patterns of occupation sorting to the different patterns of occupational comparative advantage. Furthermore, this

Figure 4: Occupational Distribution of Low-Education Male



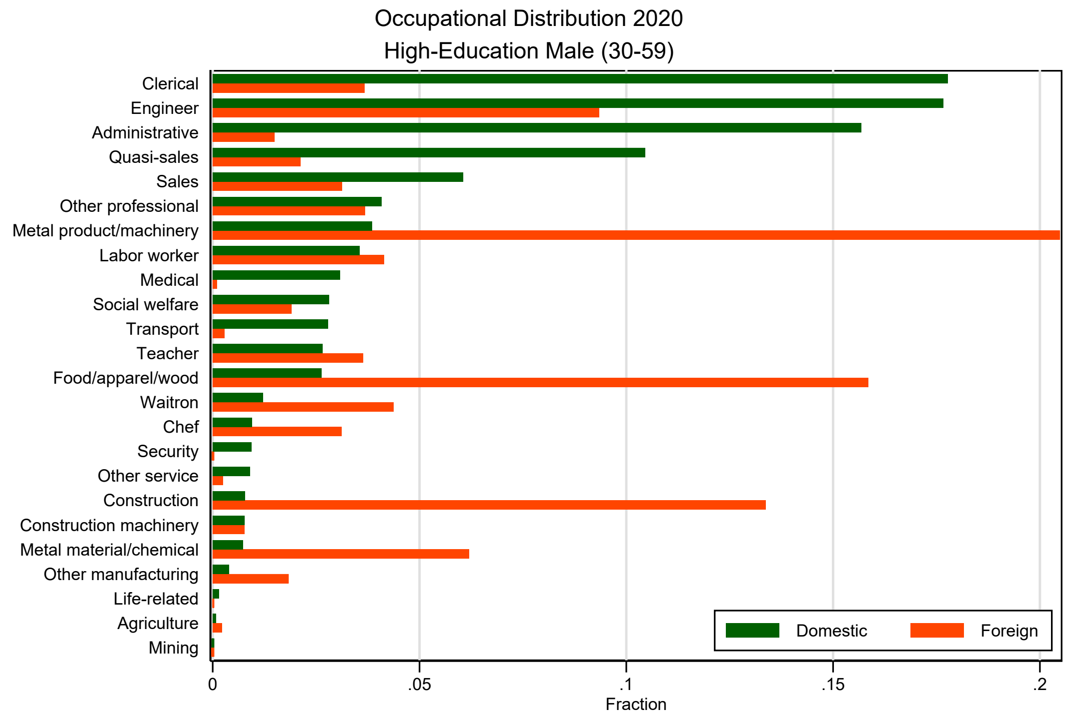
Note: workers of all ages are included for the foreign samples.
Source: MHLW Wage Survey (2020)

governs the extent to which foreign workers and domestic workers compete head-to-head in the labor market.

In order to provide a possible hint about the heterogeneous sorting of domestic and foreign workers, in Appendix C, we classify occupations into the four task-based aggregates in the spirit of Acemoglu and Autor (2011). We measure the task contents of occupations in two dimensions, namely manual vs. cognitive and routine vs. non-routine. We find that foreign workers, relative to domestic workers, are more likely to engage in routine tasks than non-routine tasks conditional on education level. High-education workers, relative to low-education, are more likely to engage in cognitive tasks than manual tasks.

We also find that the distribution of foreign low-education workers is concentrated in a few occupations. The top three occupations, Metal Product/Machinery Manufacturing, Construction, and Food/Apparel/Wood Manufacturing, account for almost 70%. Given that the manufacturing occupations can be seen as specific factors in certain industries, the concentration of foreign workers in those occupations may lead to their retention to certain locations. In contrast, domestic high-education workers (compared with domestic low-education and foreign high-education)

Figure 5: Occupational Distribution of High-Education Male



Note: workers of all ages are included for the foreign samples.
Source: MHLW Wage Survey (2020)

concentrate in more generic occupations, e.g., Clerical, Engineer, and Administrative occupations, which will be used in many sectors (we will show the evidence below). Therefore, we expect that they are more likely to relocate across regions in response to shocks.

Occupation Expenditure Shares

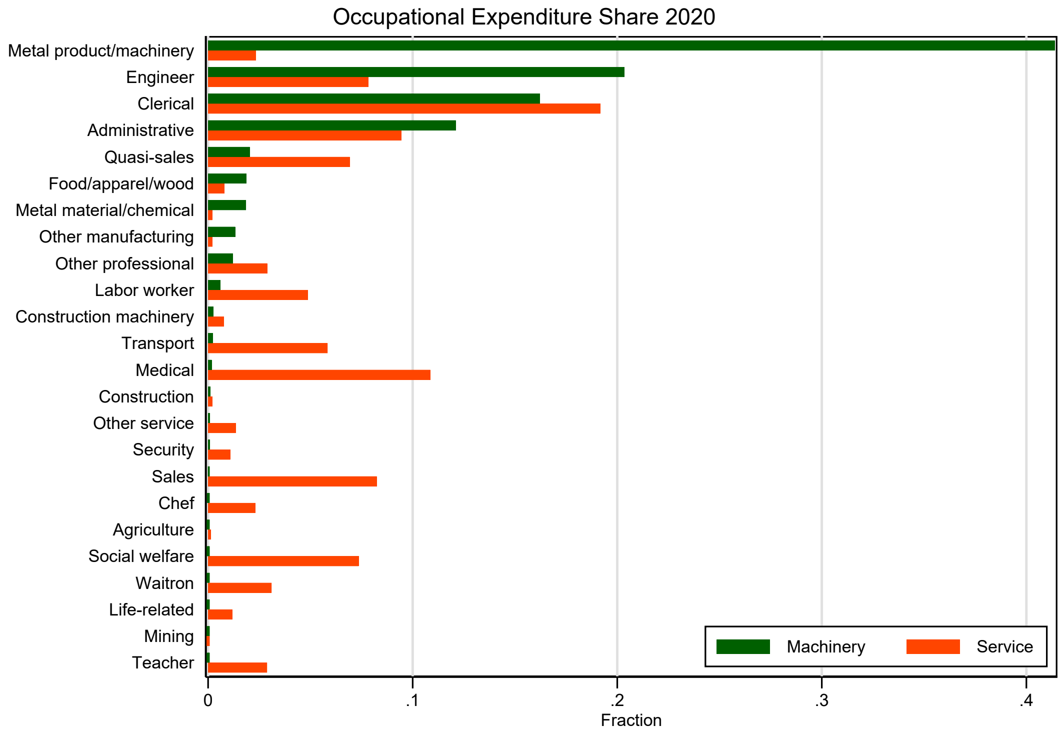
We compute the occupational expenditure shares in total labor cost for each sector as:

$$\text{Share}_r^{i,\text{Data}}(o) = \frac{\sum_{z \in \mathcal{Z}_r^i(o)} h_r^{\text{Data}}(o,z) w_r^{\text{Data}}(o,z)}{\sum_{o' \in \mathcal{O}} \sum_{z \in \mathcal{Z}_r^i(o')} w_r^{\text{Data}}(o',z) h_r^{\text{Data}}(o',z)}$$

where $\mathcal{Z}_r^i(o)$ is the set of workers in sector i engaging in occupation o at location r, $w_r^{\text{Data}}(o,z)$ is worker z's hourly wage (defined above), and $h_r^{\text{Data}}(o,z)$ is the monthly work hours. When aggregating the wage bills, we use the sample weights associated with each sampled worker.

Table 6 shows the occupational expenditure share for the two selected sectors, Manufacturing

Figure 6: Occupational Expenditure Share: Machinery Manufacturing and Service



Source: MHLW Wage Survey (2020)

of Machinery and Service. We see that the expenditure share on the Metal Product/Machinery manufacturing occupation is over 40% for the Machinery sector and 2% for Service. The clerical occupation share is highest in the Service sector (19%) among 24 occupations, but its share in the Machinery sector (12%) is not as different from the Metal/Product Machinery occupation. The Administrative occupation is also used by the both sectors with a similar intensity (12% for Machinery and 9% for Service). The concentration of foreign low-skilled workers in the Metal Product/Machinery occupation suggests that foreign employment policy will have strong sectoral implications.

Inter-Prefectural Trade Flows

Lastly, the bilateral trade share π^i_{mr} is imputed in the spirit of Eckert (2019). For Japan, the Ministry of Economy, Trade, and Industry (2010) has compiled the Interregional Input-Output Table. However, in this table, prefectures are aggregated into nine regions, and the latest version was released in 2005. The aggregation of prefectures may obscure the important heterogeneity in sectoral productivity and amenities. We therefore impute the inter-prefectural trade flows as follows:

Step 1: construct the Head and Ries indices: Using the Interregional IO table (Ministry of Economy, Trade, and Industry, 2010), we first construct the Head and Ries indices (HRI) of bilateral trade costs (Head and Ries, 2001) for each sector. Let τ^j_{RM} be the bilateral trade cost (iceberg trade cost) from region R to region M. We can show that the trade cost, to the power of trade elasticity θ, can be expressed with the bilateral trade flows X as follows:

$$HRI_{RM} = \sqrt{\frac{X_{RM}}{X_{MM}}\frac{X_{MR}}{X_{RR}}} = \tau_{RM}^{-\theta} (= \tau_{MR}^{-\theta})$$

Here we assume that $\tau_{RR} = 1$ and $\tau_{RM} = \tau_{MR}$. Following Wrona (2018), we regress the HRI on bilateral distance, adjacency dummies, and same island dummies for each sector;

$$\ln HRI^j_{RM} = \alpha^j_0 + \alpha^j_1 \ln \text{dist}_{RM} + \alpha^j_2 \text{adj}_{RM} + \alpha^j_3 \text{island}_{RM} + \varepsilon^j_{RM}$$

where dist_{RM} is bilateral distance, adj_{RM} is adjacency dummy that takes 1 if region R and M are adjacent, and island_{RM} is the same island dummy that takes 1 if $R = M$. To construct the inter-regional bilateral distance, we computed the population-weighted average distance between prefectures as follows:

$$\text{dist}_{RM} = \sum_{r\in R, m\in M} \frac{L_r L_m \text{dist}_{r,m}}{\sum_{r'\in R, m'\in M} L_{r'} L_{m'}}$$

where r and m, respectively, are the indices of prefecture within region R and M. Then, using the coefficient estimates in the previous step, we predict the HRI across prefectures.

$$\ln H\hat{R}I^j_{rm} = \hat{\alpha}^j_0 + \hat{\alpha}^j_1 \ln \text{dist}_{rm} + \hat{\alpha}^j_2 \text{adj}_{rm} + \hat{\alpha}^j_3 \text{island}_{rm}$$

Step 2: compile the national level IO table without agriculture and mining: Based on the national-level IO table compiled by Timmer et al. (2015), we construct the IO table without primary sectors. When we drop agriculture sectors, the identity of the IO table (i.e., gross output on the sales side and input side coincide) breaks. We modify the IO table so that primary sectors are ruled out and the identity still holds. This step generates the gross and net export to the rest of the world for each sector. Details are described in Appendix D.

Step 3: imputing the bilateral trade shares: Using the HRIs, national-level IO table with external trade, and the sectoral value-added for each prefecture, we impute the inter-prefectural bilateral trade shares in the spirit of Eckert (2019). The basic idea is to recover the bilateral trade shares that rationalize the data (external trade) and are consistent with the model. As the gross output and the total expenditure are recovered based on the model, the bilateral trade is balanced across domestic regions. The details of the imputation method are described in Appendix D.

After imputing the inter-prefectural trade shares, we recover the model-consistent base year total expenditure (X_r^i) and gross output (Y_r^i) across regions and sectors by solving the system of equations (16) and (17) given the total household expenditure (E_r) and the bilateral trade share (π_{mr}^i). The details are described in E.

4 Policy Counterfactuals

Using data for 2020 as the base year, we consider two counterfactual changes in the supply of foreign workers. The first policy counterfactual is to tighten Japan's foreign employment policy. We operationalize this change by eliminating foreign workers completely. This exercise allows us to evaluate the gains from foreign employment and see how the national economy would look if the government had kept the prohibitive immigration policy before the 1990s. Second, we then perform what turns out to be the more forward-looking exercise of asking what would happen if the economy further increased the amount of foreign employment.

We can examine counterfactuals according to different criteria. One is the aggregate welfare of domestic workers in Japan. In our framework, the aggregate welfare of each type of worker can be assessed as an ex-ante expected utility, i.e., expected utility before individuals observe the idiosyncratic preference shocks. Formally, it can be expressed as:

$$U(k,s) = \mathbb{E}\left[\max_r U_r(k,s)\right] = \Gamma\left(\frac{\eta-1}{\eta}\right)\left(\sum_r B_r(k,s)\left(\frac{\text{Wage}_r(k,s)}{P_r}\right)^{\eta}\right)^{1/\eta},$$

We further aggregate the welfare over domestic worker types in a utilitarian way, i.e.:

$$U_{D,Util} = \sum_s L(D,s)U(D,s)$$

and can express the change in social welfare as

$$\hat{U}_D = \sum_s \frac{L(D,s)U(D,s)}{\sum_{s'} L(D,s')U(D,s')} \hat{L}(D,s)\hat{U}(D,s) \tag{37}$$

where

$$\hat{U}(k,s) = \left(\sum_r \psi_r(k,s) \left(\frac{\hat{\text{Wage}}_r(k,s)}{\hat{P}_r} \right)^{\eta} \right)^{1/\eta}.$$

and L. In order to compute the aggregate welfare for each type in the base year, $U(k,s)$, we need price index P_r and average amenities $B_r(k,s)$ for each region, in addition to average wages $\text{Wages}_r(k,s)$. I use the consumer price index as a data counterpart of the regional price index. Then, we back out the amenities using the model inversion technique. For further details on model inversion, refer to Appendix F.

In the second counterfactual, we also consider minimum welfare change:

$$\hat{U}_{D,Min} = \min_s \hat{U}(D,s) \tag{38}$$

which gauges the welfare implications of the worst-off group of domestic workers.

Besides these welfare measures, we also consider the aggregate GDP ($\sum_{k,s} \text{Wage}_r(k,s)L_r(k,s)$) and sectoral value added ($\beta^{\ell,i}Y_r^i$) at both national and prefectural levels as well as real wages and employment across regions to assess the counterfactuals. Changes in GDP and sectoral value added are evaluated in a nominal term where the wages in the ROW are taken as numéraire, i.e., change in Japan's GDP can be evaluated relative to foreign GDP.

4.1 A Complete Elimination of Foreign Workers

In this scenario, we let $\hat{L}(F,s) = 0$ for all s, where s is a vector of attributes of foreign workers $\{edu, sex\}$. Table 5 summarizes what happens in a move to labor market autarky in terms of the utilitarian social welfare (first row), aggregate and sectoral value added, and external trade (second row and below).

Table 5: Change in Social Welfare and Value Added: Complete Elimination of Foreign Workers

	National			Regional Value Added				
	Welfare and VA	Export	Import	Min change		Median	Max change	
Utilitarian Welfare	-0.08							
Value Added								
All Sectors	-2.53	1.42	-1.57	-6.48	Aichi	-1.89	-1.21	Miyazaki
Manufacturing	-3.42	-4.60	-0.45	-12.27	Aichi	-2.51	0.59	Niigata
Food	-3.02	-2.14	-0.27	-7.58	Aichi	-2.30	-0.58	Miyazaki
Metal	-2.61	0.76	-2.76	-8.46	Aichi	-1.74	-0.35	Tokushima
Machinery	-2.52	0.45	-2.57	-7.65	Shimane	-1.40	0.04	Hokkaido
Other	-4.51	-6.18	1.96	-23.18	Aichi	-2.86	2.61	Niigata
Construction	-2.55	0.77	-2.84	-7.39	Saitama	-1.82	-0.13	Nara
Service	-2.34	3.48	-6.24	-4.70	Aichi	-1.91	-1.34	Kagoshima

Notes: All percentage changes are calculated as $\ln(x'/x) \times 100$ where x' is the outcome under counterfactual (labor market autarky, $L(F, s) = 0$ for all s) and x is the outcome in the base year 2020.

The first row reports the loss of social welfare, which is equal to 0.08%. This indicates a welfare gain from foreign employment, but the magnitude is less than 0.1%. We see rather more pronounced implications on output. GDP drops by 2.53% nationwide, where a 2.08% decline is due to the elimination of foreign workers itself and 0.45% is due to the decline in value added generated by domestic workers. The third row and below show the change in sectoral value added. We see that the manufacturing sector declines most (-3.42%), followed by the construction (-2.55%) and service sectors (-2.34%). This result is in line with the Rybczynski prediction as manufacturing and construction sectors are occupations into which foreign workers are more likely to sort, as confirmed in Figure 4 and 5. The change in external exports (column 3) shows a -4.60% drop in manufacturing exports and a 3.48% rise in service exports. The larger impact on the manufacturing sector supports the policymakers' assertion that foreign employment policy is an effective tool to address declining manufacturing.

The right half of Table 5 summarizes the changes in aggregate and sectoral value added across prefectures, displaying the minimum, median, and maximum changes. A decline in the aggregate output ranges from -6.48% in Aichi to -1.21% in Miyazaki. Across sectors, Aichi exhibits the most significant drop in value added for all sectors but Machinery and Construction. The largest drop in value added in Aichi can be attributed to the higher dependence of the regional economies on foreign employment in the base year. In 2020, foreign workers comprised 6.57% of total employment in Aichi. On the other hand, one of the least foreign-dependent prefectures, Miyazaki, where the foreign employment share is 0.82%, exhibits the least decline in value added. Across sectors, manufacturing output declines by 12.27% in Aichi, highlighting the substantial role of foreign employment in regional manufacturing production.

Table 6: Change in Welfare and Real Wages: A Complete Elimination of Foreign Workers

				Regional Real Wage				
			Welfare	Min		Median	Max	
Low-Edu	Male	15-29	0.90	-0.11	Aomori	0.60	2.69	Aichi
		30-59	0.46	-0.13	Aomori	0.33	1.67	Aichi
		60+	0.29	-0.22	Gifu	0.14	0.88	Aichi
	Female	15-29	0.00	-0.88	Gifu	-0.04	0.43	Okayama
		30-59	-0.19	-0.69	Gifu	-0.19	0.11	Shiga
		60+	0.06	-0.40	Toyama	0.00	0.54	Aichi
High-Edu	Male	15-29	-0.21	-0.93	Gifu	-0.20	0.17	Saga
		30-59	-0.29	-0.71	Gifu	-0.22	0.12	Fukui
		60+	-0.20	-0.75	Toyama	-0.17	0.13	Kumamoto
	Female	15-29	-0.35	-1.27	Gifu	-0.41	0.13	Saga
		30-59	-0.33	-1.00	Gifu	-0.34	0.18	Kumamoto
		60+	0.11	-0.75	Gifu	-0.08	1.36	Kumamoto

Notes: All percentage changes are calculated as $\ln(x'/x) \times 100$ where x' is the outcome under counterfactual (labor market autarky, $L(F, s) = 0$ for all s) and x is the outcome in the base year 2020.

Table 6 shows the impacts on aggregate welfare and real wages across different types of domestic workers. The table shows that, despite a social welfare gain from foreign employment, welfare implications differ qualitatively and quantitatively across worker types. The welfare impact ranges from -0.35% for high-education females aged 15–29 to 0.90% for low-education males aged between 15–29. In general, low-education workers gain, and high-education workers lose from completely eliminating foreign employment. The pattern of welfare implications across worker types can be explained by the patterns of occupation sorting. To make this point clear, Figure 7 summarizes the correlation of occupation choice probabilities, $\varphi(k, s, o)$, between domestic workers (rows in the table) and foreign workers (columns). A higher correlation implies that the given pair of domestic and foreign workers are more likely to sort into the same set of occupations and, therefore, more likely to compete head-to-head in the labor market. In the figure, for example, foreign workers (across all skill levels) and low-education males aged 15–29 exhibit the highest correlation of 0.73. On the other hand, foreign workers and high-education females aged 15–29 display the lowest correlation of -0.06. The correlation patterns of occupation sorting are consistent with the welfare implications across worker types, i.e., low-education males (high-education females) aged 15–29 gain most (least) from a move to labor market autarky.

While the magnitude of aggregate welfare implications is within $\pm 1\%$ for all types of domestic workers, we see a substantial variation in change in real wages across prefectures as shown in the right half of Table 6. Figure 8 shows the change in real wages across 47 prefectures for low-

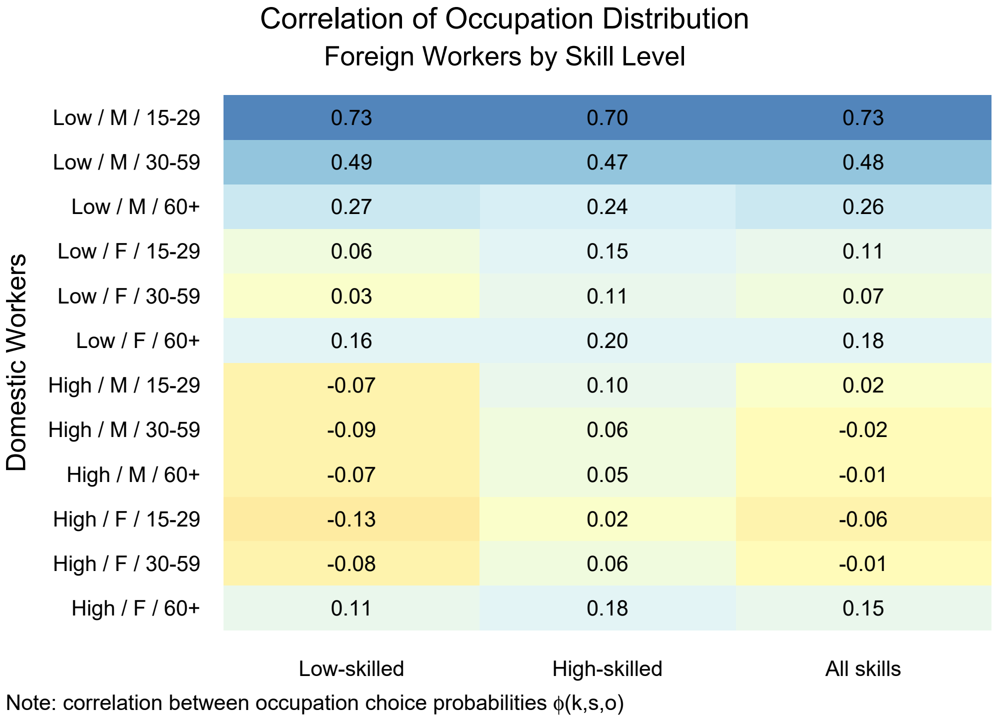


Figure 7: Correlation of Occupation Choice Probability

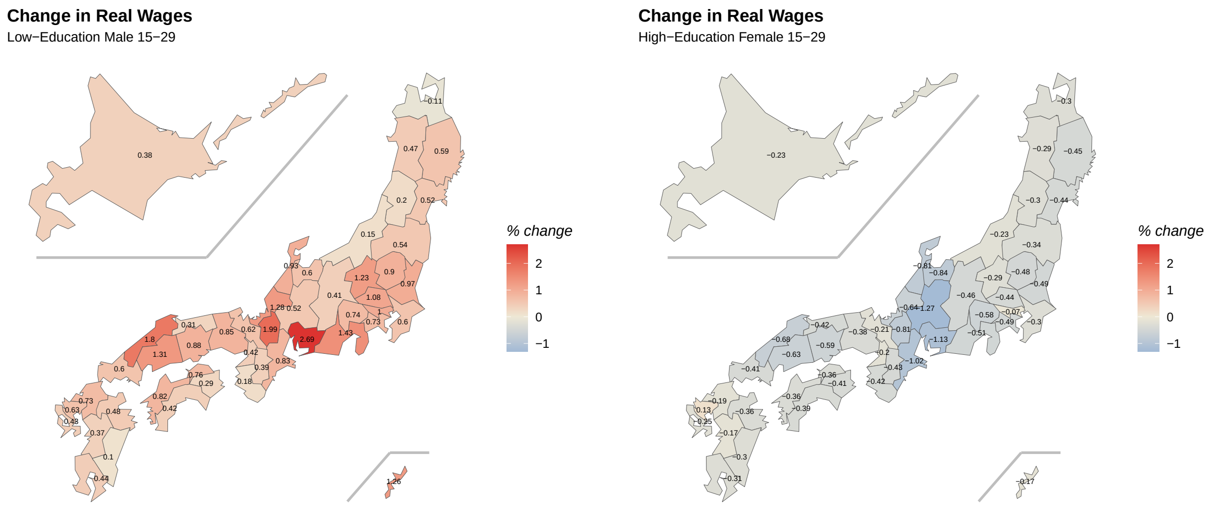
education males and high-education females aged 15–29. Real wages of low-education males *increase most* in Aichi by 2.69%, compared with a decline by 0.11% in Aomori.[16] Given that the share of foreign workers is highest in Aichi (6.57%) and the second lowest in Aomori (0.78%), the dependence of the regional economies on foreign employment may be a determinant of the real wage responses. However, the two neighboring prefectures of Aichi, Gifu and Mie, exhibit the *smaller increase* in real wages for low-education males $(0.52\%$ and $0.83\%)$, despite the fact that those two regions are the second (4.81%) and fifth (3.90%) most foreign-dependent.

This result can be interpreted through the inter-prefectural input-output linkage. Aichi, Gifu, and Mie are located in the Tokai area, known as the manufacturing center of the Japanese economy. According to the bilateral trade share matrix, Gifu and Mie depend most on the input sourced from Aichi. In the Other Manufacturing sector, for example, the expenditure shares of Gifu and Mie, which are spent on goods from Aichi, are 39.22% and 31.35%, respectively. When foreign workers are completely eliminated, the manufacturing sectors of Aichi shrink dramatically. This impact will propagate to the other regions through the inter-prefectural trade, but most to the two neighboring

[16] A 2.69% increase in real wages of Aichi can be further decomposed into a 1.80% increase in nominal wages and a 0.87% drop in price index. Analogously, a 0.11 decline in the real wages of Aomori can be decomposed into a 0.60% decline in nominal wages and a 0.49% decline in the price index.

Figure 8: Change in Real Wages: A Complete Elimination of Foreign Workers

(a) Low-Education Male 15–29 (b) High-Education Female 15–29



Note: Figure shows the residuals of OLS regression of geographic distribution of workers.

prefectures, driving down their local wages. Indeed, we find that domestic employment declines most in the Gifu (-0.31%) and Mie (-0.20%).

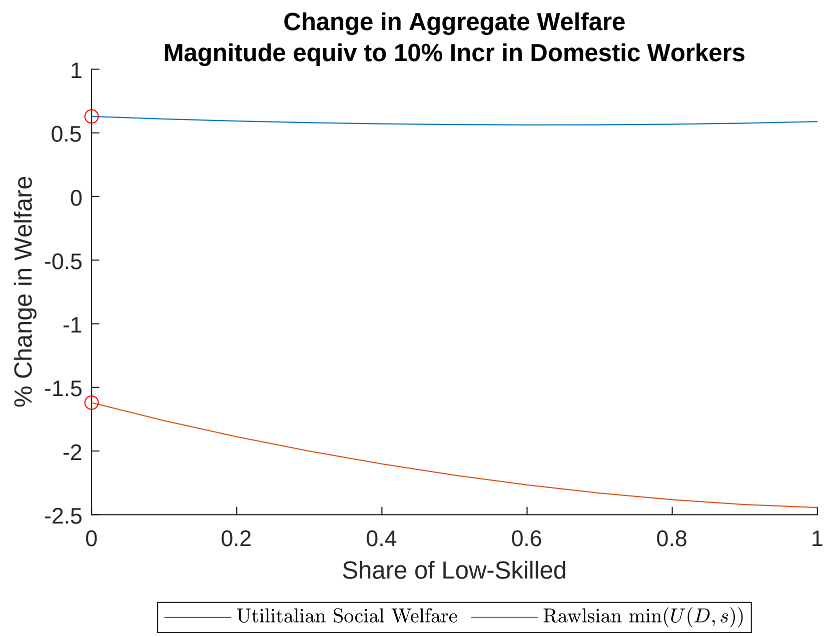
4.2 Increase in Foreign Workers

We next examine what would happen if the economy further expands the number of foreign workers. Here we consider an inflow of foreign workers equivalent to a 10% increase in the number of domestic workers. The working age population (15–64) in Japan has dropped by almost 10% since 1995. Therefore, this exercise can be seen as replicating the repopulation of Japan to get the labor force back to the peak level in 1995. In order to provide guidance for future employment policy, we consider the different high- and low-education compositions of incoming foreign workers. We denote by ΔL an increment of labor supply that is fixed throughout the exercise. Let x be the fraction of low-education foreign workers where $x \in [0,1]$. We consider the following shock under education composition x:

$$\hat{L}(F, edu, sex; x) = \hat{L}(F, edu; x) \text{ for all } sex$$

where

Figure 9: Change in Aggregate Welfare



$$\hat{L}(F, edu; x) \begin{cases} \frac{\sum_{sex} L(F,\text{Low},sex)+x\times\Delta L}{\sum_{sex} L(F,\text{Low},sex)} & \text{if } edu \text{ is Low} \\ \frac{\sum_{sex} L(F,\text{High},sex)+(1-x)\times\Delta L}{\sum_{sex} L(F,\text{High},sex)} & \text{if } edu \text{ is Low} \end{cases},$$

i.e., we constrain the incoming foreign workers to be exclusively high-education if $x = 0$ and exclusively low-education if $x = 1$.

We discretize the space of x into evenly spaced grids, $x \in \{0, 0.1, 0.2, ..., 0.9, 1\}$. For each x, we evaluated the change in social welfare with two alternative metrics, utilitarian welfare as in equation (37) and minimum welfare change as in equation (38). Figure 9 summarizes the change in welfare measures with different values of x (horizontal axis). The figure shows that utilitarian social welfare improves for any skill composition x. However, there is always welfare loss for at least one type of domestic worker, i.e., there is no Pareto-improving policy. The figure also shows that targeting foreign high-education workers ($x = 0$) yields the maximum welfare gain in both measures.[17]

[17]We performed the same exercise with a different magnitude of labor supply shocks (equivalent to a 1%, 5%, 15% and 20% increase in domestic workers). Regardless of the size, we find that targeting high-education foreign workers maximizes both welfare measures.

Table 7 summarizes the changes in utilitarian social welfare as well as aggregate and sectoral value added. For comparison, the table shows the welfare and value added implications under other policy scenarios. The third column shows the welfare and production implications of an inflow of foreign low-education workers. The last two columns consider the domestic policy alternatives that encourage domestic female and senior workers to enter the workforce, i.e., exogenously increase the number of female and senior workers.[18] These domestic policies are in line with the initiatives of the Japanese government to cope with the tight labor supply. The size of the labor supply shocks is identical across all policy scenarios, i.e., equivalent to a 10% increase in domestic workers.

The first two rows show the change in social welfare. Targeting foreign high-education workers increases the utilitarian social welfare by 0.63%, which is greater than when targeting low-education workers. Under the domestic policy alternatives, utilitarian social welfare rises much more because the increase in domestic workers, $\hat{L}(D,s) > 0$, drives up the social welfare by construction. In terms of minimum welfare change, foreign employment policy targeting high-education workers minimizes the welfare loss of the worst-off group. Aggregate national GDP increases by 9.62% by accepting foreign high-education workers, compared with 7.49% when targeting foreign low-education, 7.13% when encouraging females to enter the workforce and 7.91% when encouraging seniors to enter the workforce. The larger increase in value added is primarily driven by the higher productivity of foreign high-education workers, which is implied by the wages.

As in the previous counterfactual exercise, we find that foreign employment policy has striking sectoral implications with more considerable growth in manufacturing sectors than service sectors. Manufacturing value added increases by 12.55%, compared with a 9.01% increase in the service sector. Encouraging seniors to enter the workforce has qualitatively similar impacts on sectoral output to the foreign employment policy, but the across-sector variation is much smaller. An increase in female labor supply increases service output more than manufacturing output, but it does not generate heterogeneous production responses across sectors. The stronger sectoral implications of foreign employment policy are attributed to the fact that foreign workers are disproportionately employed in certain manufacturing occupations, as seen in Figure 4 and 5.

Table 8 shows the changes in aggregate welfare and regional real wages across worker types. For all but two low-education male groups, there is a welfare gain from an inflow of foreign high-education workers. The aggregate welfare of low-education males aged 15–20 and 30–59, respec-

[18] We keep the skill and age composition fixed when we increase the number of female workers and keep the gender and skill composition fixed when we increase the number of senior workers.

Table 7: Change in Social Welfare and Value Added: Increase in Labor Supply

	Foreign Employment		Domestic Employment	
	High-Education	Low-Education	Female	Senior
Welfare				
Utilitarian Welfare	0.63	0.59	8.93	7.31
Min welfare change	-1.62	-2.44	-2.24	-1.67
Value Added				
All Sectors	9.62	7.49	7.13	7.91
Manufacturing	12.55	10.54	6.86	8.27
Food	11.08	9.18	7.13	7.95
Metal	9.65	8.31	6.37	7.70
Machinery	9.44	7.93	6.14	7.51
Other	16.11	13.54	7.21	9.07
Construction	9.72	7.51	7.09	7.89
Service	9.01	6.87	7.19	7.84

Notes: All percentage changes are calculated as $\ln(x'/x) \times 100$ where x' is the outcome under counterfactual (increase in labor supply) and x is the outcome in the base year 2020.

tively, declines by 1.62% and 0.35% as they are more likely to sort into the same set of occupations as foreign high-education workers. Furthermore, within a worker type, there exists a substantial variation in changes in real wages across locations. For example, real wages of low-education males aged 15–29 in Aichi drop by 6.12% while in Aomori, it rises by 0.56%.

Which regions exhibit a larger decline or rise in real wages, and what are the implications of heterogeneous real wage responses across space? Panel (a) Figure 10 reports exposure to foreign employment in each prefecture, as measured by the change in foreign employment on the horizontal axis and the change in real wages (domestic males aged 30–59) on the vertical axis. The blue bubbles represent low-education workers, and the orange bubbles represent high-education workers. We further divide prefectures into manufacturing regions and service regions based on the base year sectoral composition. We label prefectures with an above median manufacturing share (share of manufacturing in total output) as manufacturing regions and the rest as service regions. Manufacturing regions exhibit larger variations in changes in real wages compared with service regions. Low-education workers residing in manufacturing regions tend to work in occupations that foreign workers are likely to sort into, i.e., blue-collar occupations. Therefore, the more the region is exposed to an inflow of foreign workers, the more they are hit negatively. An increase in the relative supply of blue-collar occupations drives up the wages of high-education workers who sort into white-collar occupations. In the service regions, on the other hand, wages will be less sensitive to exposure to foreign workers as the service sector is less intensive in occupations with greater proportion of foreign workers.

Table 8: Change in Welfare and Real Wages: Increase in Foreign High-Education

			Welfare	Real Wage						Std Dev
				Min		Median		Max		
Low-Edu	Male	15-29	-1.62	Aichi	-6.12	-0.97		Aomori	0.56	1.09
		30-59	-0.35	Aichi	-2.43	-0.16		Nagano	1.07	0.72
		60+	0.15	Hiroshima	-1.32	0.26		Gifu	1.87	0.71
	Female	15-29	0.28	Tokyo	-0.81	0.38		Gifu	3.43	0.78
		30-59	1.00	Yamagata	-0.05	0.92		Mie	3.39	0.68
		60+	0.30	Aichi	-1.48	0.40		Mie	2.78	0.77
High-Edu	Male	15-29	0.60	Osaka	-0.54	0.68		Gifu	3.76	0.80
		30-59	1.08	Osaka	0.00	0.79		Aichi	3.24	0.75
		60+	0.92	Saga	-0.42	0.70		Yamanashi	3.24	0.82
	Female	15-29	1.04	Tokyo	0.10	1.22		Gifu	4.39	0.98
		30-59	1.09	Nagasaki	-0.20	1.02		Mie	4.15	0.92
		60+	0.01	Saga	-1.88	0.33		Mie	4.18	1.05

Notes: All percentage changes are calculated as $\ln(x'/x) \times 100$ where x' is the outcome under counterfactual (increase in foreign high-education workers) and x is the outcome in the base year 2020. The last column shows the standard deviation of changes in real wages across prefectures.

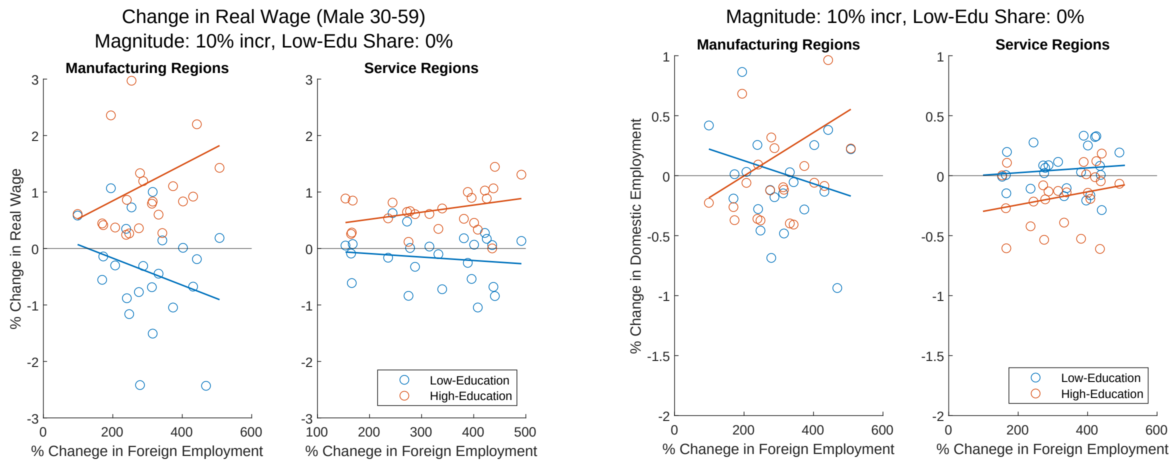
Panel (b) repeats the same exercise while taking the change in domestic employment on the vertical axis. Although the relationship is less tight, low-education workers in the manufacturing regions with greater foreign employment exposure tend to be driven out. As a result, there is a reallocation of low-education workers from the manufacturing regions to the service regions. The opposite pattern of regional reallocation is observed for high-education workers. However, employment responses (reallocation of workers across prefectures) are smaller than real wage responses in magnitude. This suggests that workers do not fully adjust to the shock by relocation, i.e., they do not move to less-affected regions. In other words, the Japanese labor market is more likely to be spatially segmented, which makes the local labor market responses more distinct across locations.

As implied by the above results, an inflow of foreign workers raises the skill premium of domestic workers. Figure 11 reports exposure to foreign employment in each prefecture on the horizontal axis and the change in skill premium on the vertical axis. We compute the skill premium as the average wage of high-education workers relative to one of the low-skilled workers. Each observation in the figure represents a prefecture. An increase in skill premium is more pronounced for males than females. Furthermore, the skill premium rises most for male workers aged between 15–29, who share more similar patterns of occupation sorting to foreign workers.

Lastly, Table 9 shows the change in occupational employment of domestic workers. The patterns of occupational reallocation are qualitatively similar between low-education and high-education workers. Domestic workers are driven out from foreign-intensive occupations, such as manufac-

Figure 10: Employment and Real Wage Responses: Increase in Foreign High-Education

(a) Real Wages　　　　(b) Domestic Employment



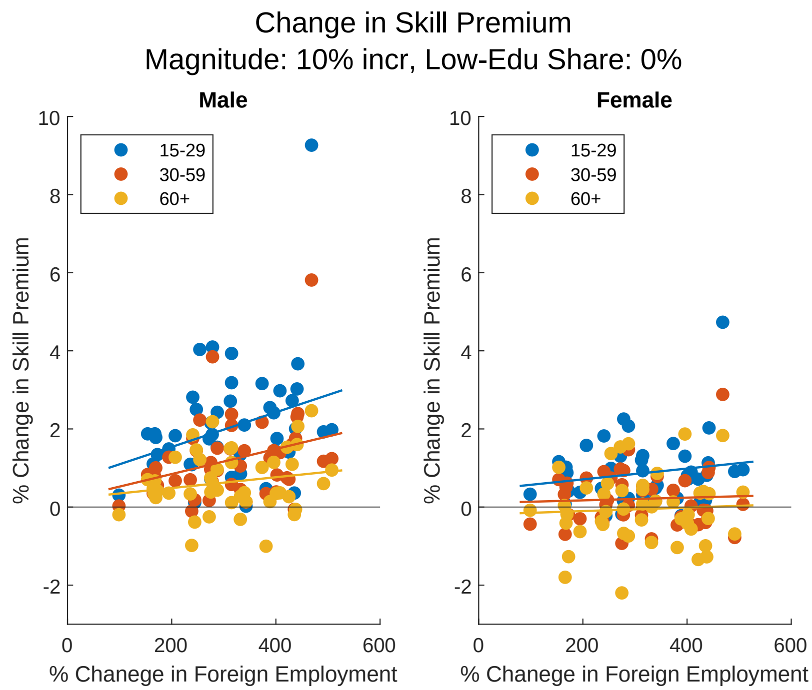
Note: bubbles represent prefectures. Horizontal axis measures % change in foreign employment. Vertical axis measures % change in real wages in panel (a) and % change in domestic employment in panel (b). All percentage changes are calculated as $\ln(x'/x) \times 100$ where x' is the outcome under counterfactual (increase in foreign high-education workers) and x is the outcome in the base year 2020.

turing and construction occupations. Compared with the change in regional employment, the reallocation of domestic workers across occupations is more pronounced in magnitude. This highlights the occupational reallocation as a more substantial margin of adjustment in response to an inflow of foreign workers.

5 Conclusion

This paper develops a spatial general equilibrium model to study the labor market and production implications of foreign employment. The model features multiple regions, labor groups, occupations, and sectors. Our model allows us to study how the occupational comparative advantage, regional heterogeneity in productivity and amenity, and sectoral heterogeneity in occupational intensity interact to determine the responses of wages, employment, and production to an inflow of foreign workers. We supply the model with data from the Japanese economy covering 47 regions, 24 occupations, and 6 sectors. We calibrate the structural parameters of the model and the base year equilibrium variables using the novel micro-level data. We conducted counterfactual exercises to evaluate the past and future immigration policy reforms. We found that in regions where foreign workers tend to gravitate, there was a substantial negative impact on the wages of low-education domestic workers. At a nationwide level, there was a minimal gain of social welfare.

Figure 11: Change in Skill Premium: Increase in Foreign High-Education



Note: Skill premium is measured by the wages of high-education workers of a given sex and age group relative to the wages of the counterpart low-education workers. All percentage changes are calculated as $\ln(x'/x) \times 100$ where x' is the outcome under counterfactual (increase in foreign high-education workers) and x is the outcome in the base year 2020.

We argued that these results suggest that the Japanese labor market is segmented spatially, particularly for low-education workers. We also highlighted the importance of the sectoral dimension in understanding the impact of foreign workers. Specifically, the skewed occupational distribution of foreign workers has pronounced implications on sectors that are intensive in occupations with a larger proportion of foreign workers and sectoral input-output linkage plays a key role in determining the regional impacts.

Table 9: Change in Occupational Employment: Increase in High-Education Foreign

	Education	
	Low	High
Engineer	2.41	-0.32
Medical	5.40	5.02
Social welfare	1.51	0.40
Teacher	-7.44	-9.65
Other professional	-5.73	-7.99
Administrative	6.84	5.10
Clerical	4.45	3.61
Sales	1.77	0.39
Quasi-sales	4.78	3.52
Life-related	5.46	4.22
Chef	-2.01	-4.50
Waitron	-6.96	-11.11
Other service	3.53	1.26
Security	7.07	6.09
Agriculture	12.76	2.09
Transport	7.45	5.45
Mining	11.80	11.34
Metal matreial/chemical	-5.22	-9.03
Metal product/machinery	-7.88	-11.45
Food/apparel/wood	-17.62	-20.74
Other manufacturing	-4.46	-7.99
Construction machinery	5.56	3.34
Construction	-12.82	-18.07
Labor work	0.61	-0.58

Notes: Table reports the change in occupational employment for domestic workers by education level. All percentage changes are calculated as $\ln(x'/x) \times 100$ where x' is the outcome under counterfactual (increase in high-education foreign) and x is the outcome in the base year 2020.

Appendices

A Sequence of Worker's Decisions

A.1 Suggestive Evidence

In our baseline model specification in the main text, we assume that a worker determines the location first and then chooses the task. We do not have direct evidence in the data that supports this timing assumption. However, the Employment Survey provides some suggestive evidence about workers' occupation and location decisions. Table A1 shows the fractions of workers who did or did not switch their occupations and/or locations in the last five years. The left panel is for male low-education workers and the right panel is for male high-education workers. An occupational switch is defined by the change of 2-digit occupation classification (Division of the Japan Standard Occupation Classification) in the last five years. A location switch is defined by the change of residential prefecture. For example, among low-education workers, 83.55% switched neither occupation nor location in the last five years. 5.21% of them switched their residential prefectures while staying in the same occupation.

From this table, we see that low-education workers are more likely to switch occupations while staying in the same prefecture (10.13%) while high-education workers are more likely to change locations while staying in the same prefectures (13.35%). This suggests that workers with different skills may have a different sequence of decisions. For example, we would assume that workers with higher academic degrees, such as M.D. and Ph.D., may fix the occupations first, such as medical doctor and faculty, and then search for the locations. On the other hand, low-education workers may have more flexibility in occupation choices. Given this, we will outline the model in which a worker determines the occupation first and then location second.

A.2 Modified Model

Environment

Consumer Preferences

Consumer preferences are the same as in the baseline model. Utility for workers $z \in \mathcal{Z}(k, s)$ residing in location r depend on goods consumption C_r and idiosyncratic amenity shock to the utility

Table A1: Occupation and Location Switches in the Last 5 Years

A. Male Low Education

		Location	
		Not moved	Moved
Occupation	Not Switched	83.55%	5.21%
	Switched	10.13%	1.11%

B. Male High Education

		Location	
		Not moved	Moved
Occupation	Not Switched	77.98%	13.35%
	Switched	7.19%	1.49%

Source: Basic Survey of Employment Structure 2002
Note: Numbers in the table indicate the fractions of workers who switched or not switched their occupations and/or locations in the last five years. We restrict the samples to those who are aged between 30 and 59 as of 2002 and are working in 2002 and 1997. Occupational switch is defined by the change of 2-digit occupation classification (Division of the Japan Standard Occupation Classification) in the last five years. Location switch is defined by the change of residential prefecture.

from residing in that location $b_r(z)$:

$$U_r(z) = b_r(z)C_r(z).$$

The idiosyncratic amenity shocks $b_r(z)$ are drawn i.i.d. across locations from a Fréchet distribution:

$$b_r(z) \sim G_r^b(b; k, s) = \exp(-B_r(k, s)b^{-\eta}), \quad \eta > 1,$$

The corresponding indirect utility function of worker z residing in location r is given by:

$$U_r(z) = \frac{E_r(z)}{P_r} b_r(z),$$

where $E_r(z)$ is nominal expenditure of worker z. Each worker chooses the location that offers the highest utility after taking into account the idiosyncratic preferences. The location choice is made *after* determining the task.

Task Production Units

Before making the location decisions, a worker makes task choide to maximize her *expected* real income, i.e.,

$$\max_{o \in \mathcal{O}} \mathbb{E}[\mathrm{rw}(k,s,o)]\varepsilon(z,o)$$

where $\mathbb{E}[\mathrm{rw}(k,s,o)]$ is *expected* real wage per efficiency unit and $\varepsilon(z,o)$ is idiosyncratic efficiency units of labor she can supply in task o. $\varepsilon(z,o)$ is assumed to be drawn i.i.d. across tasks from the Fréchet distribution:

$$\varepsilon(z,o) \sim G^{\varepsilon}(\varepsilon) = \exp(-\varepsilon^{-\zeta}), \quad \zeta > 1.$$

Production functions of the task production units are the same as in the baseline model.

Intermediate Good Producers and Final Good Producers

Production side of the model is as same as the baseline model presented in the main text.

Equilibrium

Final Good Price Indices and and Expenditure Shares

As before, the price index of final good i at location r is given by :

$$P_r^i = \Gamma^i \left(\sum_m T_m^i (c_m^i \tau_{mr}^i)^{-\theta^i} \right)^{-1/\theta^i},$$

and we can express location r's share of expenditure on good i from location m (i.e., bilateral trade share) as:

$$\pi_{mr}^i = \frac{T_m^i (c_m^i \tau_{mr}^i)^{-\theta^i}}{\sum_{m' \in \mathcal{R}} T_{m'}^i (c_{m'}^i \tau_{m'r}^i)^{-\theta^i}}.$$

Worker's Location Choice

A worker determines the location after making a task decisions. Consider a type (k, s) worker $z \in \mathcal{Z}(k, s, o)$ who chose task o. She will choose the location that maximizes the utility after taking into account the idiosyncratic preference shocks $b(z)$ across locations. Her real wage income in the destination location r is $w_r(k, s, o)\varepsilon(z, o)$ where $w_r(k, s, o)$ is wage per effieicny unit. Since $\varepsilon(z, o)$ is independet of locations, the probability that a worker $z \in \mathcal{Z}(k, s, o)$ chooses to locate in region r is given by:

$$\psi_r(k, s, o) = \frac{B_r(k, s) \left(w_r(k, s, o)/P_r\right)^\eta}{\sum_{m \in \mathcal{R}} B_m(k, s) \left(w_m(k, s, o)/P_m\right)^\eta}, \tag{A1}$$

Mass of group (k, s) workers at location r working in task o is given by:

$$L_r(k, s, o) = \psi_r(k, s, o) L(k, s, o). \tag{A2}$$

where $L(k, s, o)$ is the mass of type (k, s) workers who choose task o, which we define below.

Worker's Task Choice

A worker makes ocupation decision before choosing location. Therefore, in determining the task, she will form an expectation on real wage (per efficiency unit) across potential tasks. The Expected real wage is given by:

$$\mathbb{E}[\mathrm{rw}(k, s, o)]) = \sum_r \psi_r(k, s, o) \frac{w_r(k, s, o)}{P_r} \tag{A3}$$

After drawing the idiosyncratic efficiency shocks across tasks $\varepsilon(z, o)$, she will choose the task to maximize the expected real wage income, $\mathbb{E}[\mathrm{rw}(k, s, o)]\varepsilon(z, o)$. By taking advantage of the property of Fréchet distribution, we can express the probability that a type (k, s) worker to choose task o as:

$$\varphi(k, s, o) = \frac{(\mathbb{E}[\mathrm{rw}(k, s, o)])^\zeta}{\sum_{o'} (\mathbb{E}[\mathrm{rw}(k, s, o')])^\zeta} \tag{A4}$$

Mass of workers who choose task o is then:

$$L(k, s, o) = \varphi(k, s, o) L(k, s) \tag{A5}$$

With perfect competition, the profit maximization of the task production unit yields:

$$w_r(k, s, o) = S(k, s, o) p_r(o). \tag{A6}$$

Now, let $\bar{\iota}(k, s, o)$ be the average expected real income of type (k, s) workers who choose task o. This is the expectation of $\mathbb{E}[\mathrm{rw}(k, s, o)]\varepsilon(z, o)$ conditionl on worker z having chosen task o. As $\varepsilon(z, o)$ is Fréchet distributed, we have analytical expression such as:

$$\begin{aligned}\bar{\iota}(k, s, o) &= \int_{z \in \{z | z \text{ chooses } o\}} \varepsilon(z, o) \mathbb{E}[\mathrm{rw}(k, s, o')] dG^{\varepsilon}(\varepsilon) \\ &= \tilde{\Gamma} \left(\sum_{o'} \mathbb{E}[\mathrm{rw}(k, s, o')])^{\zeta} \right)^{1/\zeta} = \bar{\iota}(k, s) \text{ for all } o \end{aligned} \tag{A7}$$

where $\tilde{\Gamma}$ is constant. As in the baseline model, the average real income conditional on working in task o is the same across all tasks. Task with higher expected real wage $\mathbb{E}[\mathrm{rw}(k, s, o)]$ directly raises the average expected real income of a worker with a given idiosyncratic efficiency draw. This directly increases the average expected real income in the task. Meanwhile, more attractive task also attracts workers with lower idiosyncratic efficiency draws, which lowers the average expected real income. With a Fréchet distribution of efficiency, these two effects exactly offset one another.

Markets Clearing

Using the result in equation (A7), we can compute the average efficiency units of labor conditional on workers having chosen the best task:

$$\overline{\varepsilon}(k, s, o) = \int_{z \in \{z | z \text{ chooses } o\}} \varepsilon(z, o) dG^{\varepsilon}(\varepsilon)$$

$$= \frac{1}{\mathbb{E}[\text{rw}(k,s,o)]} \int_{z \in \{z | z \text{ chooses } o\}} \varepsilon(z,o) \mathbb{E}[\text{rw}(k,s,o')] dG^{\varepsilon}(\varepsilon)$$
$$= \frac{\bar{\iota}(k,s)}{\mathbb{E}[\text{rw}(k,s,o)]} \tag{A8}$$

Since the tasks with relatively higher expected real wage tend to attract workers with lower idiosyncratice efficiency draws, the conditional average of efficiency units of labor will be lower. Then, we can now express task market clearing as:

$$\sum_{k,s} \overbrace{\underbrace{\underbrace{L(k,s)\varphi(k,s,o)}_{\text{mass of workers in } o} \psi_r(k,s,o)}_{\text{mass of workers in } o \text{ at } r} \bar{\varepsilon}(k,s,o)}^{\text{agg efficiency units of labor in } o} w_r(k,s,o) = \sum_{i \in \mathcal{I}} \beta^{\ell,i} Y_r^i \underbrace{\frac{\mu^i(o) p_r(o)^{1-\rho^i}}{(p_r^{\ell,i})^{1-\rho^i}}}_{\text{Expenditure share of } o} \tag{A9}$$

where Y_r^i is gross output (total revenue) of sector i at location r. Left-hand side and right-hand side of the equation, respectively, are the supply and demand in value.

Total expenditure on good i at location r is given by:

$$X_r^i = \sum_{j \in \mathcal{I}} \beta^{i,j} Y_r^j + \alpha^i E_r, \tag{A10}$$

where E_r is the total household expenditure. Goss output Y_r^i is given by :

$$Y_r^i = \sum_{m \in \mathcal{R}} \pi_{r,m}^i X_m^i. \tag{A11}$$

Lastly, total household expenditure E_r is given by

$$E_r = \sum_{o} \sum_{k,s} \overbrace{\underbrace{\underbrace{L(k,s)\varphi(k,s,o)}_{\text{mass of workers in } o} \psi_r(k,s,o)}_{\text{mass of workers in } o \text{ at } r} \bar{\varepsilon}(k,s,o)}^{\text{agg efficiency units of labor in } o} \text{w}_r(k,s,o) \tag{A12}$$

We now define formally the spatial general equilibrium of the modified model.

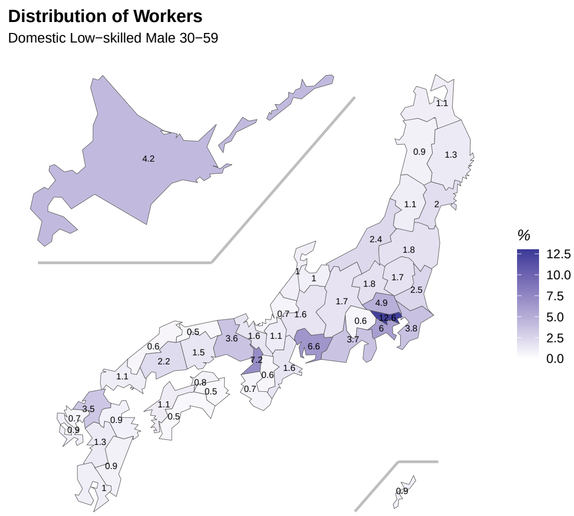
Definition 3 (Spatial General Equilibrium in Level: Modified Model) *Given $\{L(k,s)\}_{k,s}$ and other fundamentals $\Theta = \{\{B_r(k,s)\}_{r,k,s}, \{S(k,s,o)\}_{k,s,o}, \{\mu^i(o)\}_{i,o}, \{T_r^i\}_{r,i}, \{\tau_{mr}^i\}_{m,r,i}\}$, an equilibrium is a* *vector of wages* $\{w_r(k,s,o)\}_{r,k,s,o}$*, prices of final goods* $\{P_r^i\}_{r,i}$ *and task services* $\{p_r(o)\}_{r,o}$*, and allocations of workers across tasks* $\{L(k,s,o)\}_{k,s,o}$ *and across regions* $\{L_r(k,s,o)\}_{r,k,s,o}$ *that satisfy equilibrium conditions* (*3*), (*4*), (*5*), (*6*), (*7*), (*A1*), (*A2*), (*A3*), (*A4*), (*A5*), (*A6*), (*A8*), (*A9*), (*A10*), (*A11*), *and* (*A12*) *for all* r, k, s, o, i.

B Additional Figures for Baseyear Outcomes

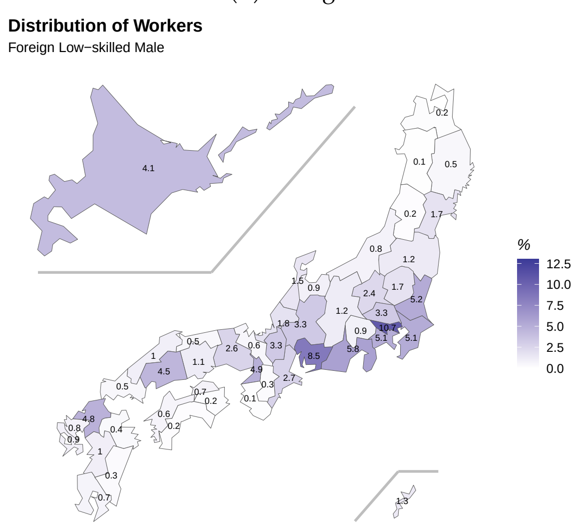
B.1 Geographic Distribution of Domestic and Foreign Workers

Figure B1: Geographic Distribution of Low-Education Male 30-59 (2020)

(a) Domestic



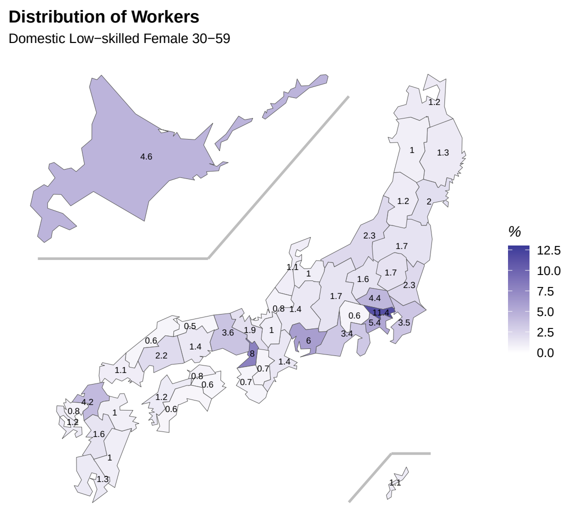
(b) Foreign



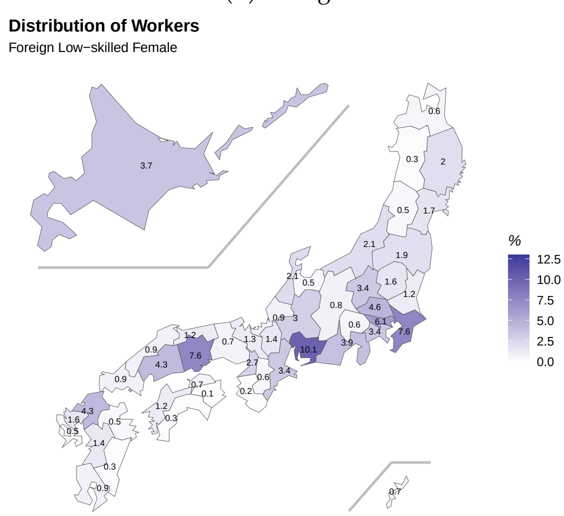
Note: Number in the figure shows the fraction of workers in a given type residing in each region.

Figure B2: Geographic Distribution of Low-Education Male 30-59 (2020)

(a) Domestic



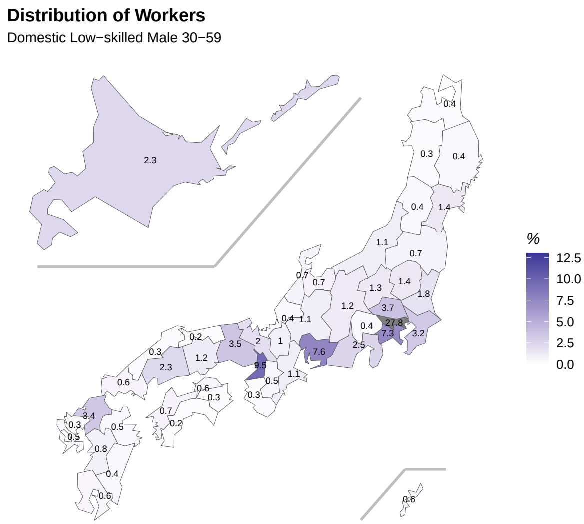
(b) Foreign



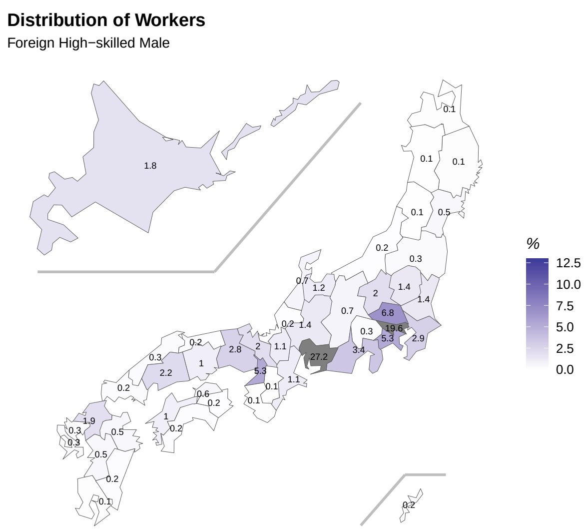
Note: Number in the figure shows the fraction of workers in a given type residing in each region.

Figure B3: Geographic Distribution of High-Education Male 30-59 (2020)

(a) Domestic



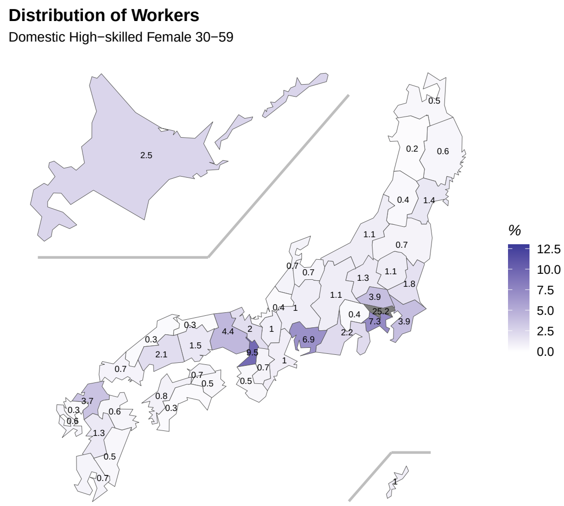
(b) Foreign



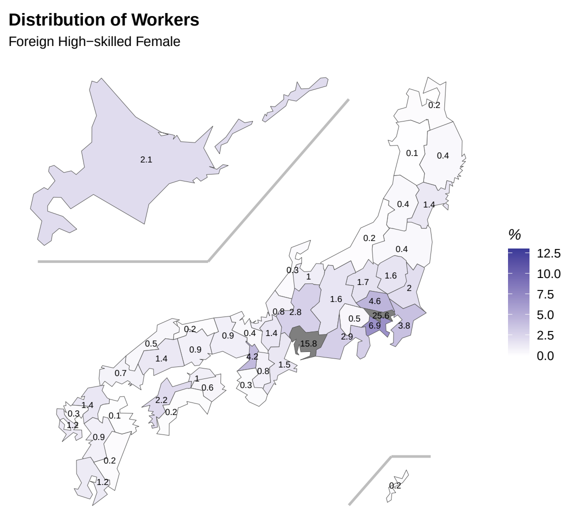
Note: Number in the figure shows the fraction of workers in a given type residing in each region.

Figure B4: Geographic Distribution of High-Education Male 30-59 (2020)

(a) Domestic



(b) Foreign



Note: Number in the figure shows the fraction of workers in a given type residing in each region.

C Task Contents of Occupations

C.1 Task-Based Aggregation of Occupations

In order to see the nature of occupations which domestic and foreign workers are more likely to sort into, we apply the task-based approach. Following Acemoglu and Autor (2011), we measure the task contents of occupations. We take advantage of the Japanese version of O-NET *jobtag*[19], which the Ministry of Labour, Health, and Labour launched in 2020. As the *jobtag* database is designed in the spirit of the original O*NET database of the U.S. Department of Labor, Employment and Training Administration[20], it has a very similar set of variables to the US O*NET data. Using the concordance table between *jobtag* occupation classification and the Japan Standard Occupation Classification provided by Komatsu and Mugiyama (2021), we measured the routine-ness and the cognitive-ness of each occupation. Acemoglu and Autor (2011) defined five task categories; non-routine analytical, non-routine interactive, routine cognitive, routine manual, and non-routine manual. We use the O*NET variables (and corresponding *jobtag* variables) associated with the first three tasks to measure the cognitive-ness (or manual-ness) of each occupation. Analogously we measure the routine-ness of the jobs using the variables associated with the second and last tasks. We normalize each task score to have zero mean and unit standard error, where we weight each observation (occupation) with the number of employees in each year[21]. We label the occupations with a cognitive-task score above zero as "cognitive" and below zero as "manual," and those with a routine-task score above zero as "routine" and below zero as "non-routine." See Figure C1 for the distribution of task scores for the year 2017. Table C1 illustrates the example of occupations in each task category.

Table C2 summarizes the distribution of domestic and foreign workers across four task-based occupation aggregates. It confirms that high-skilled workers are more likely to work in cognitive jobs. Comparing domestic and foreign workers, we see that domestic workers are more likely to work in non-routine jobs within cognitive- and manual jobs relative to foreign. This suggests that the patterns of comparative advantage differs between natives and foreign, conditional on skill level.

[19]Jobtag data: `https://shigoto.mhlw.go.jp/User/`

[20]O*NET OnLine: `https://www.onetonline.org/`

[21]For the years after 2007, the MIC Employment Survey records worker's occupation at the most disaggregated level (3-digit) with more than 200 occupations. However, for the years between 1992 and 2002, it uses a more aggregate level of occupation classification (numbers of occupations differ by years, ranging from 16 to 66). Occupation classification in the *jobtag* database, on the other hand, is even more disaggregated than the 3-digit Japan Standard Occupation Classification. Therefore, for those years in which occupations are coarsely classified in the MIC Employment Survey, we use the Census data of the closest years (for example, the 1990 Census for the year 1992) to measure the task scores for each occupation in the Census. And then, we compute the task scores for the aggregated occupations used in the Employment Survey

Figure C1: Aggregating Occupations Based on Task Contents

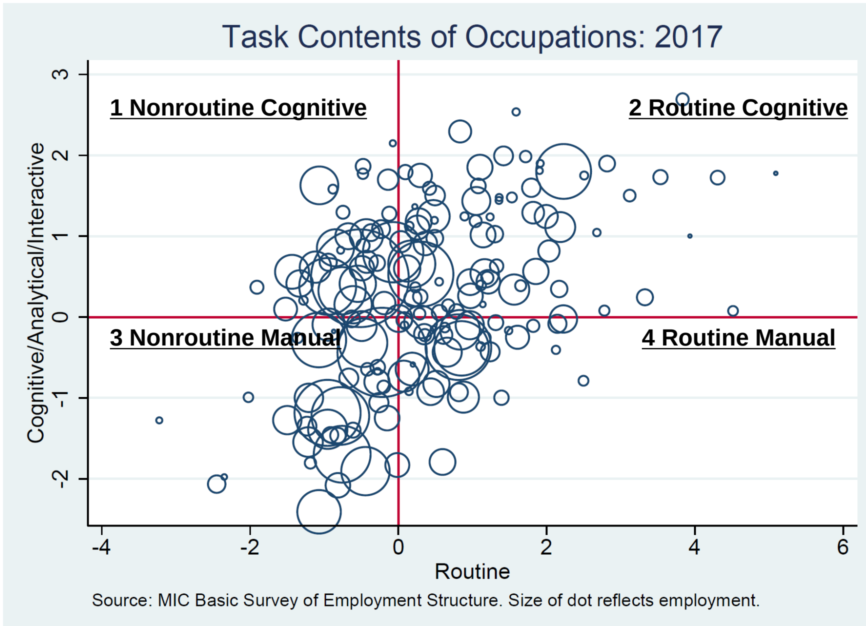


Table C1: Example of Occupations in Four Tasks (2017)

	Non-routine	**Routine**
Cognitive/Analytical/Interactive	Executive System consultant Judge Financial sales	Researcher Med doctor Optical products manufacturer Pilot
Manual	Metal press worker Food manufacturer Train conductor Construction worker	Shop seller Metal welding worker Automotive assembler Janitorial worker

as the weighted average where we use the number of employees in the Census as a weight.

Table C2: Task Distribution (2020)

	Japanese			Foreign		
	All	Low	High	All	Low	High
1 Non-routine cognitive	26.06%	21.69%	33.63%	10.26%	3.86%	15.09%
2 Routine cognitive	21.97%	20.96%	23.62%	20.34%	15.55%	23.74%
3 Non-routine manual	36.03%	37.34%	33.56%	30.64%	30.11%	31.12%
4 Routine manual	15.95%	20.00%	9.18%	38.76%	50.48%	30.04%

Note: the table shows the fraction of workers of a given type who work in each of four tasks.

D Imputation of Interregional Trade Flow

We will outline the imputing method of inter-prefectural IO table.

D.1 Constructing the IO Table without Primary Sectors

Table D1 shows the illustrative example of national IO table that consists of Japan. J and F refer to the country, Japan (J) and foreign (F). The Table consists of three sectors, agriculture (Agri), manufacturing (Manf), and Service (Serv). $M_{r,m}^{i,j}$ is the intermediate input from country r to m from sector i to$j$, VA^i is the value added in sector i, $FD_{r,m}^i$ is final demand of sector i in region m sourced from region r, and $GO_{sales}^i = GO_{inpur}^i$ is the gross output of sector i at sales side and input side.

Table D1: Illustrative Example of IO Table

	Source	Agri	Manf	Serv	FD	EXP	GO
Agri	J	$M_{J,J}^{A,A}$	$M_{J,J}^{A,M}$	$M_{J,J}^{A,S}$	$FD_{J,J}^{A}$	$FD_{J,F}^{A}$	GO_{sales}^{A}
Manf	J	$M_{J,J}^{M,A}$	$M_{J,J}^{M,M}$	$M_{J,J}^{M,S}$	$FD_{J,J}^{M}$	$FD_{J,F}^{M}$	GO_{sales}^{M}
Serv	J	$M_{J,J}^{S,A}$	$M_{J,J}^{S,M}$	$M_{J,J}^{S,S}$	$FD_{J,J}^{S}$	$FD_{J,F}^{S}$	GO_{sales}^{S}
Agri	F	$M_{F,J}^{A,A}$	$M_{F,J}^{A,M}$	$M_{F,J}^{A,S}$	$FD_{F,J}^{A}$		
Manf	F	$M_{F,J}^{M,A}$	$M_{F,J}^{M,M}$	$M_{F,J}^{M,S}$	$FD_{F,J}^{M}$		
Serv	F	$M_{F,J}^{S,A}$	$M_{F,J}^{S,M}$	$M_{F,J}^{S,S}$	$FD_{F,J}^{S}$		
VA		VA_J^A	VA_J^M	VA_J^S			
GO		GO_{input}^A	GO_{input}^M	GO_{input}^S			

As we will rule out agriculture (and mining) in the quantitative exercise, we need to compile the IO without agriculture which still holds the identity, sum of each column coincides with sum of row. First, we will compute the level of income transfer to justify the trade deficit (or surplus) in the data. let $\alpha^i = \frac{FD_{JJ}^i + FD_{FJ}^i}{\sum_{j \neq A} FD_{JJ}^j + FD_{FJ}^j}$ be the sector i's share of expenditure in final demand and let $\gamma^{i,j}$ be the share of intermediate input i in production of j. We then compute the level of subsidy (tax) ω that justify the observed trade deficit (or surplus)

$$\underbrace{\sum_{k \neq A} GO_{sales}^k}_{\text{total revenue}} = \underbrace{\sum_{k \neq A} \alpha^k \left(\left(\sum_{k' \neq A} VA^j \right) \times (1+\omega) \right)}_{\text{total final demand expenditure}} + \underbrace{\sum_{k \neq A} \sum_{k' \neq A} \gamma^{k,k'} GO_{sales}^j}_{\text{expenditure as intermediate inputs}}$$

We then repeat the following steps:

1. Compute the expenditure share of final demand on sector i sourced from r

$$\alpha^i_{r,J} = \frac{FD^i_{r,J}}{\sum_{j\neq A}\left(FD^j_{J,J} + FD^j_{F,J}\right)} \text{ for } r = J, F$$

where final demand is the sum of final consumption by household and government, and gross fixed capital formation.

2. Compute value added share of sector i

$$\beta^{\ell,i} = \frac{VA^i}{\sum_{r\in\{J,F\}}\sum_{j\in\{A,M,S\}} M^{j,i}_{rJ} + VA^i}$$

Note that we take into account the intermediate input from agriculture too.

3. Compute the intermediate input share,

$$\gamma^{ij}_{r,J} = \left(\frac{M^{i,j}_{r,J}}{\sum_{r\in\{J,F\}}\sum_{j\neq A} M^{i,j}_{r,J}}\right) \times (1 - \beta^{\ell,j}) \text{ for } r = J, F \text{ and } i, j = M, S$$

4. Compute the gross output (sales side) excluding sales to agricultural sector

$$\tilde{GO}^i_{sales} = \sum_{j\neq A} M^{i,j}_{JJ} + FD^i_{J,J} + FD^i_{J,F} \text{ for } i = M, S$$

5. Using the value added share and sales-side gross output obtained above, compute the value added

$$\tilde{VA}^j = \beta^{\ell,j}\tilde{GO}^j_{sales} \text{ for } j = M, S$$

6. Analogously compute the intermediate inputs

$$\tilde{M}^{i,j}_{r,J} = \gamma^{i,j}_{r,J}\tilde{GO}^j_{sales} \text{ for } r = J, F \text{ and } i, j = M, S$$

7. Compute the final demand sourced domestically

$$\tilde{FD}^i_{J,J} = \alpha^i_{J,J}\left(\sum_{j\neq A}\tilde{VA}^j \times (1+\omega)\right)$$

8. Compute the gross output for both sales and input sides

$$\tilde{GO}^{i}_{sales} = \sum_{j} \tilde{M}^{i,j}_{JJ} + \tilde{FD}^{k}_{J,J} + FD^{i}_{J,F}$$
$$\tilde{GO}^{i}_{input} = \sum_{r\in\{J,F\}} \sum_{k'\neq A} M^{i,j}_{r,J} + \tilde{VA}^{i}$$

9. Repeat steps 3–9 until $\tilde{GO}^{i}_{sales}$ coincides with $\tilde{GO}^{i}_{input}$ for each $i \neq A$

D.2 Impute the Bilateral Trade Shares across Prefectures

This subsection illustrates the algorithm to impute the bilateral trade shares across prefectures. Using the MHLW Wage Survey data, for each sector i, compute the value added share of each prefecture

$$\frac{VA^{i}_{r}}{\sum_{r'} VA^{i}_{r'}}$$

Using the value added $\tilde{VA}^{i}$ from the (modified) IO table obtained in the previous section, we compute the sectoral VA across prefectures as

$$\tilde{VA}^{i}_{r} = \tilde{VA}^{i}$$

Suppose that the Cobb-Douglas parameters in utility and production functions are same across prefectures. Then, we can construct the total revenue Y^{i}_{r} and expenditure X^{i}_{r} by:

$$Y^{i}_{r} = \frac{1}{\beta^{\ell,i}} \tilde{VA}^{i}_{r}$$
$$X^{i}_{r} = \alpha^{i} \left(\sum_{j} \tilde{VA}^{j}_{r} \times (1+\omega) \right) + \sum_{k'} \gamma^{i,j} Y^{j}_{r}$$

Now, $\{Y^{i}_{r}\}^{r}_{k}$ and $\{X^{i}_{r}\}^{i}_{r}$ are data. For each sector, we have:

$$\sum_{r \in \mathcal{R} \cup ROW} Y_r^i = \sum_{r \in \mathcal{R} \cup ROW} X_r^i$$

From the market clearing condition, we have

$$Y_r^i = \sum_{m \in \mathcal{R} \cup ROW} \pi_{rm}^k X_{r'}^i$$

where π_{rm}^i is expenditure share of sector i that is sourced from region r to m. In the EK model, we can express the trade share as:

$$\pi_{rm}^i = \frac{T_r^i (c_r^i)^{-\theta^i} (\tau_{rm}^i)^{-\theta^i}}{\sum_{r'} T_{r'}^i (c_{r'}^i)^{-\theta^i} (\tau_{r'm}^i)^{-\theta^i}} \equiv \frac{\lambda_r \kappa_{rm}^i}{\sum_{r'} \lambda_{r'} \kappa_{r'm}^i} \tag{D1}$$

where C_r^i is the cost of input bundle. Let $\lambda_r^i = T_r^i (c_r^i)^{-\theta^i}$ be the origin fixed effect and $\kappa_{rm}^i = (\tau_{rm}^i)^{-\theta^i}$ be the sector and region pair specific trade friction. This coincides with the Head-Ries index, which we constructed based on the Inter-Regional IO Table of Japan. Here, we invoke the Lemma from Eckert (2019):

Lemma 1 (Eckert, 2019) *Consider a mapping of the form:*

$$A_r = \sum_m \frac{\lambda_r \kappa_{rm}}{\sum_{r'} \lambda_{r'} \kappa_{r'm}} B_m \tag{D2}$$

For any strictly positive vectors $\{A_r\} \gg 0$ and $\{B_i\} \gg 0$, such that $\sum_r A_r = \sum_r B_r$ and any strictly positive matrix $\kappa \gg 0$, there exists a unique (to scale), strictly positive vector $\{\lambda_i\} \gg 0$.

In our context, $\{A_r\} = \{Y_r^i\} \gg 0$, $\{B_r\} = \{X_r^i\} \gg 0$, and $\sum_r Y_r^i = \sum_r X_r^i$ holds. Furtherore, $\kappa_{rm}^i = (\tau_{rm}^i)^{-\theta}$ is strictly positive as $\tau_{rm}^i \geq 1$ and $\theta^i > 0$. Lemma suggests that we can find a unique (to scale) strictly positive vector $\{\lambda_i^i\}$ rationalizing the data. We then go over the following steps to impute the bilateral trade shares that rationalizes the external trade value of Japan observed in the IO table.

1. Guess a vector $\{\lambda_r^i\}$ of dimension $R + 1$ that sums to 1.

2. Solve for λ^i_{ROW} in terms of observed ROW exports (to Japan):

$$
\begin{aligned}
EXP^i_{ROW} &= \sum_{r\in\mathcal{R}} X^i_r \frac{\lambda^i_{ROW}\kappa^i_{ROW\,r}}{\sum_{r'\in\mathcal{R}\cup ROW}\lambda^i_{r'}\kappa^i_{r'r}} \\
\Rightarrow\ \lambda^i_{ROW} &= \frac{EXP^i_{ROW}}{\sum_{r\in\mathcal{R}} X^i_r \frac{\kappa^i_{ROW\,r}}{\sum_{r'\in\mathcal{R}\cup ROW}\lambda^i_{r'}\kappa^i_{r'r}}}
\end{aligned}
$$

3. Solve for X^i_{ROW} in terms of observed ROW imports (from domestic regions):

$$
\begin{aligned}
IMP^i_{ROW} &= \sum_{r\in\mathcal{R}} X^i_{ROW} \frac{\lambda^i_r\kappa^i_{r\,ROW}}{\sum_{r'\in\mathcal{R}}\lambda^i_{r'}\kappa^i_{r'\,ROW}+\lambda^i_{ROW}\kappa^i_{ROW,ROW}} \\
\Rightarrow\ X^i_{ROW} &= \frac{IMP^i_{ROW}}{\sum_{r\in\mathcal{R}} \frac{\lambda^i_r\kappa^i_{r\,ROW}}{\sum_{r'\in\mathcal{R}}\lambda^i_{r'}\kappa^i_{r'\,ROW}+\lambda^i_{ROW}\kappa^i_{ROW,ROW}}}
\end{aligned}
$$

4. Using the results in the previous steps, compute

$$
\begin{aligned}
Y^i_{ROW} = &\sum_{r\in\mathcal{R}} X_r \frac{\lambda^i_{ROW}\kappa^i_{ROW\,r}}{\sum_{r'\in\mathcal{R}}\lambda^i_{r'}\kappa^i_{r'r}+\lambda^i_{ROW}\kappa^i_{ROW\,r}} \\
&+ {}^iX_{ROW}\frac{\lambda^i_{ROW}\kappa^i_{ROW,ROW}}{\sum_{r'\in\mathcal{R}}\lambda^i_{r'}\kappa^i_{r'\,ROW}+\lambda^i_{ROW}\kappa^i_{ROW,ROW}}
\end{aligned}
$$

5. Using the results in previous steps, update $\{\lambda^i_r\}_{r\in\mathcal{R}}$

$$
\begin{aligned}
Y^i_r &= \sum_{r'\in\mathcal{R}} X^i_{r'} \frac{\lambda^i_r\kappa^i_{rr'}}{\sum_{r''\in\mathcal{R}\cup ROW}\lambda^i_{r''}\kappa^i_{r''r'}} + X^i_{ROW}\frac{\lambda^i_r\kappa^i_{r\,ROW}}{\sum_{r''\in\mathcal{R}\cup ROW}\lambda^i_{r''}\kappa^i_{r''\,ROW}} \\
\Rightarrow\ \lambda^i_r &= \frac{Y^i_r}{\sum_{r'\in\mathcal{R}} X^i_{r'}\frac{\kappa^i_{rr'}}{\sum_{r''\in\mathcal{R}\cup ROW}\lambda^i_{r''}\kappa^i_{r''r'}} + X^i_{ROW}\frac{\kappa^i_{r\,ROW}}{\sum_{r''\in\mathcal{R}\cup ROW}\lambda^i_{r''}\kappa^i_{r''\,ROW}}}
\end{aligned}
$$

6. Now we have updated all elements of $\{\lambda_r\}^i_{r\in\mathcal{R}\cup ROW}$. Ensure the normalization holds and then go back to step 2. Repeat those steps until the vector $\{\lambda^i_r\}$ is converged.

Figure D1 and D2 show the bilateral trade shares for machinery and service, respectively. The figure shows the higher expenditure shares on machinery coming from regions such as Aichi and Shizuoka in the Tokai region, the manufacturing cluster of the Japanese economy. We also confirm the higher own trade shares (diagonal elements) for the service sector, implying higher trade costs compared with the manufacturing sectors.

Figure D1: Bilateral Trade Shares (Machinery)

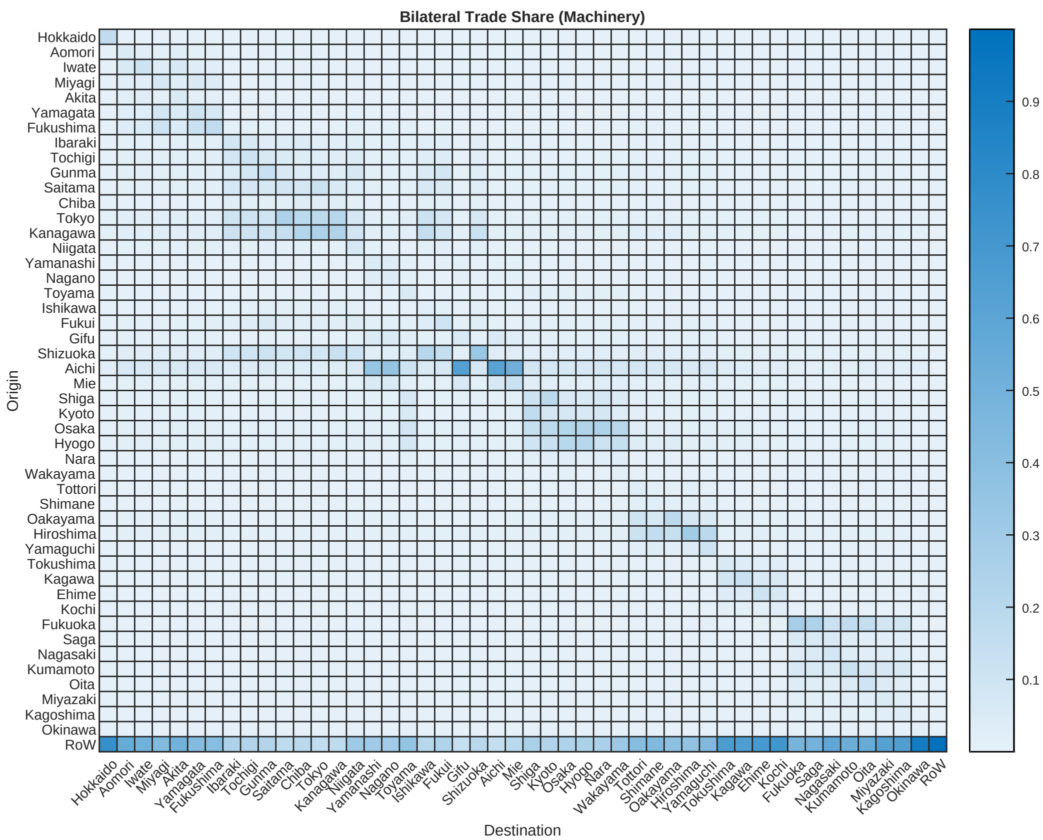
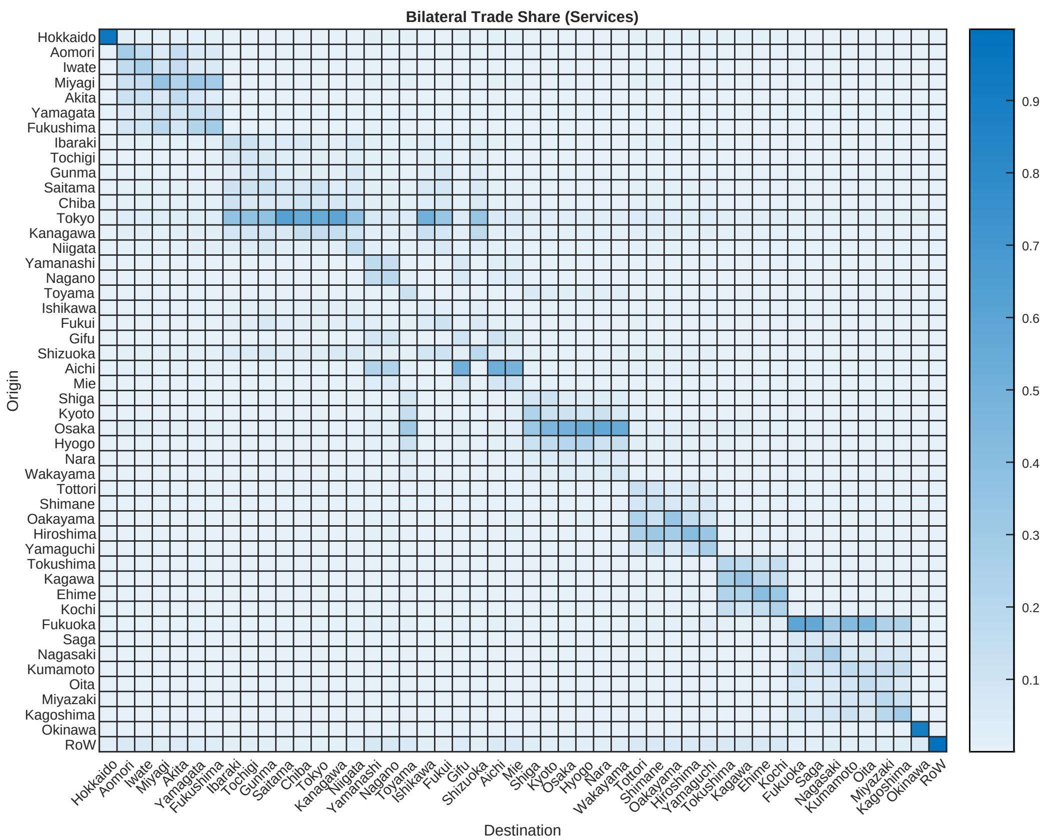


Figure D2: Aggregating Occupations Based on Task Contents



E Constructing Gross Output and Total Expenditure

In this section, we will describe the how to construct gross output (Y_r^i) and total expenditure (X_r^i) which are model-consistent. We start with constructing the regional value added in the base year:

$$VA_r^{Data} = \sum_{k,s} \text{Wage}_r^{Data}(k,s) L_r^{Data}(k,s) \tag{E1}$$

Using the sectoral expenditure shares in final consumption, α_{JPN}^i for Japan and α_{ROW}^i, calibrated from the IO table, we have total household expenditure:

$$HE_r^i = \begin{cases} \alpha_{JPN}^i \times (VA_r^{Data} \times (1 + \omega^{Data})) & \text{for } r \in \mathcal{R} \\ \alpha_{ROW}^i \times (VA_r^{Data} - \sum_{m \in \mathcal{R}} VA_m^{Data} \times \omega^{Data}) & \text{for } r = ROW \end{cases}$$

where we assume a constant share, ω^{Data}, of regional value added is transferred from the rest of the world workers in Japan to justify the Japan's external trade deficit in the data. Given the shares of labor and intermediate input, β_{JPN}^{ij} and β_{ROW}^{ij}, which is calibrated from the IO table, and the interregional trade shares π_{rm}^i which is imputed as described in Appendix D, we can solve the following system of equations for $\{X_r^i, Y_r^i\}_{r \in \mathcal{R} \cup ROW}^i$

$$X_r^i = \begin{cases} HE_r^i + \sum_j \beta_{JPN}^{ij} Y_r^j & \text{for } r \in \mathcal{R} \\ HE_r^i + \sum_j \beta_{ROW}^{ij} Y_r^j & \text{for } r = ROW \end{cases} \tag{E2}$$

$$Y_r^i = \sum_{m \in \mathcal{R} \cup ROW} \pi_{rm}^i X_m^i \tag{E3}$$

We can recover the model implied value added as:

$$VA_r^{i,Implied} = \begin{cases} \beta_{JPN}^{\ell,i} Y_r^{i,Implied} & \text{for } r \in \mathcal{R} \\ \beta_{ROW}^{\ell,i} Y_r^{i,Implied} & \text{for } r = ROW \end{cases}$$

which does not necessarily coincide with the data counterpart in (E1). Therefore, we adjust regional average wage $\text{Wage}_r(k,s)$ by constant factor ς_r such that

$$\widetilde{VA}^{Data} = \sum_{k,s} \underbrace{\left(\varsigma_r \times \text{Wage}_r^{Data}(k,s)\right)}_{\widetilde{\text{Wage}}_r^{Data}(k,s)} L_r^{Data}(k,s) = \sum_i VA_r^{i,Implied}$$

F Model Inversion to Back Out Local Amenities

We back out the average local amenities for each type of workers, $B_r(k,s)$, using the model-inversion technique. Probability that a randomly sampled worker of worker type (k,s) chooses to reside in region r is given by

$$\psi_r(k,s) = \frac{B_r(k,s)\left(\text{Wage}_r(k,s)/P_r\right)^\eta}{\sum_{r'} B_{r'}(k,s)\left(\text{Wage}_{r'}(k,s)/P_{r'}\right)^\eta}$$

We can observe the regional distribution of workers $\psi_r(k,s)$, average wages $\text{Wage}_r(k,s)$, and price index (CPI) P_r in the data and the location choice elasticity η is known. Let $v_r(s,s) = B_r(k,s)\left(\text{Wage}_r(k,s)/P_r\right)^\eta$ and we can rewrite:

$$\psi_r(k,s) = \frac{v_r(k,s)}{\sum_{r'} v_{r'}(k,s)} \;\Leftrightarrow\; v_r(k,s) = \sum_{r'}\left(v_{r'}(k,s)\psi_r(k,s)\right)$$

In matrix, we can write

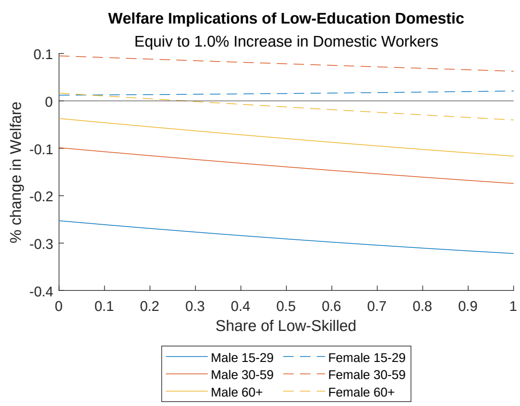
$$\begin{bmatrix} v_1(k,s) \\ v_2(k,s) \\ \vdots \\ v_R(k,s) \end{bmatrix} = \begin{bmatrix} \psi_1(k,s) & \psi_1(k,s) & \dots & \psi_1(k,s) \\ \psi_2(k,s) & \psi_2(k,s) & \dots & \psi_2(k,s) \\ \vdots & & & \\ \psi_R(k,s) & \psi_R(k,s) & \dots & \psi_R(k,s) \end{bmatrix} \begin{bmatrix} v_1(k,s) \\ v_2(k,s) \\ \vdots \\ v_R(k,s) \end{bmatrix}$$

From the Perron-Frobenius theorem, there exits one positive eigenvector $\mathbf{v}(k,s) = [v_1(k,s),...,v_R(k,s)]'$ up to normalization for each (k,s). Then, we can back out $B_r(k,s) = v_r(k,s)/\left(\text{Wage}_r(k,s)/P_r\right)^\eta$.

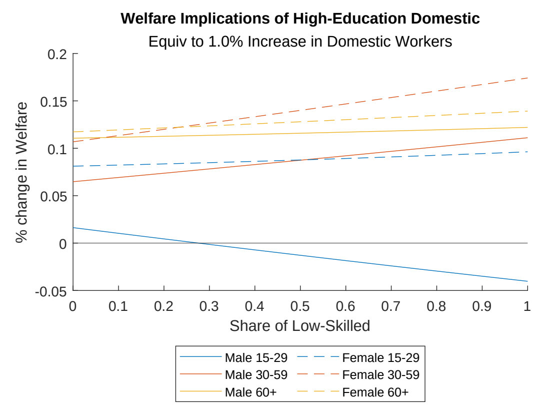
G Additional Tables and Figures for Counterfactuals

G.1 Welfare Implications: Different Magnitude of the Shocks

In this section, we demonstrate the welfare impacts of the exogenous increase in foreign workers with different magnitude. We consider the labor supply shock which is equivalent to a 1%, 10%, and 20% increase in the number of domestic workers. Figures G1, G2, and G3 show the change in aggregate welfare of each type of domestic workers. Horizontal axis is the share of low-education workers in the incoming foreign workers. Right panels (a) show the welfare changes of low-education domestic workers and left panels (b) show the ones of high-education domestic workers.

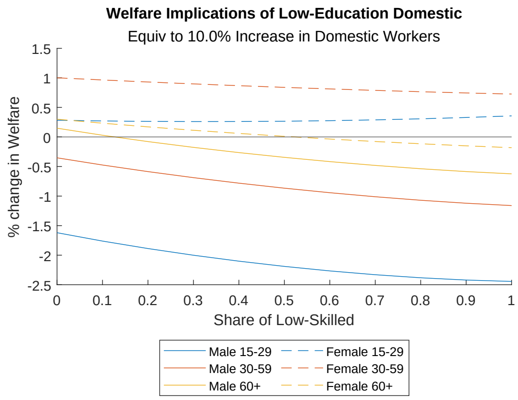


(a) Low-Skilled

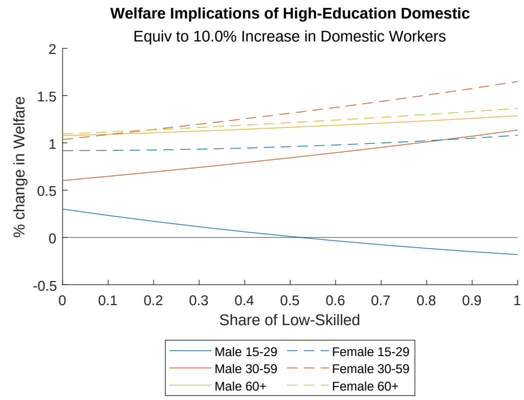


(b) Low-Skilled

Figure G1: 1% increase in Domestic Workers

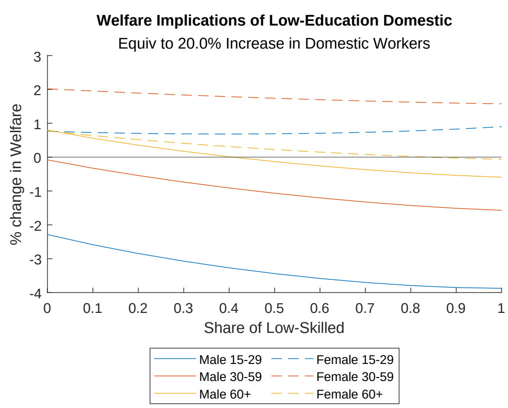


(a) Low-Skilled

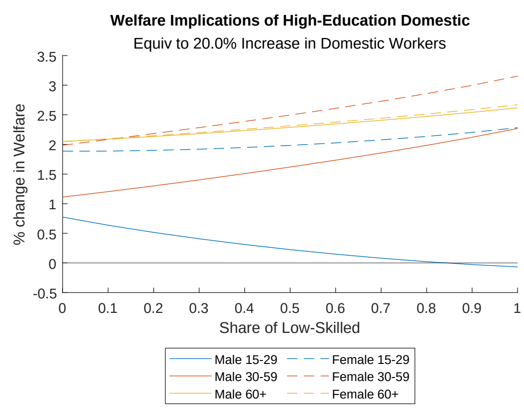


(b) Low-Skilled

Figure G2: 10% increase in Domestic Workers



(a) Low-Skilled



(b) Low-Skilled

Figure G3: 20% increase in Domestic Workers

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