Labor Market and Production Implications of Foreign Employment: Quantitative Evidence from Japan *

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(**Job Market Paper**)

October 23, 2022

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Abstract

With falling fertility and aging demography in advanced economies, there is increasing interest in accepting foreign workers to cope with the tight labor supply. Japan, where the labor shortage has become the central economic concern, has also expanded foreign employment significantly over the last three decades. We develop a quantitative spatial model to evaluate the consequences of accepting foreign workers on wages, employment, and production of local economies, which have been of interest in the policy debate. Our model features three crucial aspects (occupation, region, and sector) that interact with each other to determine the local labor market and production responses to an inflow of foreign workers. We quantify the model using the novel micro-level data and conduct policy counterfactual exercises. We find that foreign employment has quantitatively significant implications on production, while the impacts on wages of natives are minimal in magnitude. We also find that accepting foreign workers has dramatic economic implications in certain locations, while the policy alternatives targeting domestic workers (e.g., encouraging the elderly and females to the workforce) do not generate heterogeneous impacts across locations.

Keywords: occupational comparative advantage, spatial general equilibrium, foreign workers
JEL Classification: F14, F16, F22, F66

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 with falling fertility and aging demography, in particular, net migration has played a 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 residing in 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.

Japan, one of the most aged economies, has 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 Measure limited work visas in Japan strictly 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 expanded foreign employment and diversified the types of foreign workers. As of 2020, the number of foreign workers exceeds 1.7 million, consisting 2.6% of total workers. Regarding skill composition, approximately 40% of foreign workers do not have a 4-year college degree.

Meanwhile, foreign employment has been controversial in the policy discussion. The manufacturing sector, facing a severer labor shortage, has voiced that accepting foreign workers would be essential to maintaining domestic production. The Manufacturing Bureau at the Ministry of Economy, Industry, and Trade highlighted in 2018 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.

[1] The United Nations Department of Economic and Social Affairs estimates that almost 281 million people live in a country other than their country of birth, labeled as international migrants, in 2020. 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

For example, an article from the *Japan Times* on March 20, 2020, says that *"A textile manufacturer in Fukui said ... the arrivals of five 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 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, *"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 result 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 the 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 to the local economies. We use the model to evaluate the labor market and production implications of immigration policies, which target workers of a specific skill level. We compare the immigration policies with the other policy alternatives targeting domestic workers. Our model has three crucial aspects that interact with each other to determine the local labor market and production implications of foreign workers. We feature the comparative advantage of foreign relative to native across occupations (tasks), 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 in understanding foreign workers' spatial and occupational distributions and, therefore, in 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 two prefectures, Shizuoka (15%) and Mie

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

(6%). Those three prefectures, called *Tokai Three Prefectures*, embrace almost half of the Brazilians, 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. First, 64% of Brazilians engaged in production occupations (e.g., assembling) in 2020, compared with just 13% of native workers. This suggests the comparative advantage of Brazilians in production occupations relative to natives. Second, the Tokai region the manufacturing cluster of the Japanese economy centered around the auto industry.[6] Those two facts suggest 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. Furthermore, some local features may offer better amenities for Brazilian workers; e.g., some public schools provide language support for foreign kids.

Do Brazilian workers harm the wages of natives? The answer will depend crucially on the pattern of occupational comparative advantages of Brazilians relative to natives. If Brazilians sort into occupations where natives are less likely to work, they will not be the direct competitors. Thus, the occupational sorting of workers may mitigate the direct negative impacts on natives' wages. The host economy may rather benefit from the deepening division of labor. In support of this view, Yokkaichi City, a major industrial city in Mie, emphasized in 2007 the role of Brazilian workers as a vital source of labor for local manufacturing production.[7] However, aggregate impacts may also depend on how natives relocate their locations and occupations.

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 (tasks) 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.

[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.

(2019, 2020). Here, relative wage difference adopts the occupational comparative advantage. Third, the multi-region and multi-sector Eaton and Kortum (2002) model of trade with input-output linkage, *à la* Caliendo and Parro (2015), highlights the heterogeneous sectoral productivity across regions. The sectoral aspect is crucial in examining the channel through which an inflow of foreign workers has differential impacts across regions.

We take the model to the data for the Japanese economy with 47 prefectures, four task-based occupation aggregates, and seven sectors. We take advantage of the novel micro-level data from Japanese Government Statistics, the Basic Survey of Wage Structure. From 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 allocation of workers across regions and occupations for foreign and native workers.

Our counterfactual exercises examine the welfare, wage, employment, and production responses to an inflow of foreign workers. We consider three immigration policy scenarios (an increase in foreign low-skilled, high-skilled, and both low- and high-skilled) and compare the results with the policy alternatives targeting domestic workers. The labor supply shocks under those policy scenarios are all equivalent to a 10% increase in the supply of domestic workers. Our key finding is as follows: foreign employment has quantitatively significant implications on production, while the impacts on wages of natives are minimal in magnitude. Sectoral outputs rise by approximately 7% in Japan. In a certain immigration policy scenario, some regions (such as Aichi) exhibit more than 20% increase in manufacturing output. On the other hand, aggregate welfare implications are within the range of less than $\pm 0.5\%$, and the change in real wages across regions ranges from -3 to 2%. Furthermore, we find that accepting foreign workers has dramatic implications on production and the labor market in certain locations. In contrast, the policies targeting domestic workers, i.e., encouraging the elderly and females to the workforce, do not generate heterogeneous impacts across locations.

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 a national level, regional level, sectoral level, and occupational level (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 (tasks) based on comparative advantage, which governs the impacts on wages and employment. We also provide novel evidence for Japan's case, where the lack of comprehensive data on foreign workers has limited the quantitative studies. As 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 differ depending on region and sectors.

We also believe that Japan offers an ideal setting for studying 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 happened in the last three decades. Therefore, the assimilation of foreign workers in skills and preferences and the generational status of foreign workers would 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 aged advanced economies. For instance, the US Census Bureau projects that the older adults ratio 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 which 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) that developed a general equilibrium framework with the Fréchet-Roy model of occupation sorting. This paper extends their studies by embedding the 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 concludes.

2 A Quantitative Spatial General Equilibrium Model

We develop a quantifiable spatial general equilibrium model that features workers sorting into locations and occupations (tasks) *à la* Roy (1951). The model has a finite number of domestic regions 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 relative to one another. Labor is the only primary factor of production. There is a continuum of workers indexed by z. Workers are classified 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). Set of workers in group (k, s) in each country is given by $\mathcal{Z}(k, s)$ for Japan and $\mathcal{Z}_{ROW}(k, s)$ for the rest of the world, which have the mass by $L(k, s)$ and $L_{ROW}(k, s)$. The set of workers in each country is exogenous in the model. A worker in Japan is mobile across domestic locations and determines 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 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 consumption of bundle of final goods of all sectors (C_r^i) in a Cobb-Douglas fashion:

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

[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.

where α^i is the share of expenditure on 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 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 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 occupation 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 occupation 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 advantage 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 the occupation choice of workers in the rest of the world.

Intermediate Good Producers

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 $\kappa^i \in [0,1]$. Production of each κ^i requires two types of inputs; composites of occupation 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., auto sector-oriented Aichi will have higher average productivity in that sector.

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 occupation 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 occupation 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 goods 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 least cost suppliers across locations and combine through 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 least 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 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 least 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, the price index of final good i at location r is:

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

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 on 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_{mr}^i.

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 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 occupation 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:

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

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, 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). Combining 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. 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.

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 match exactly 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:

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

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.

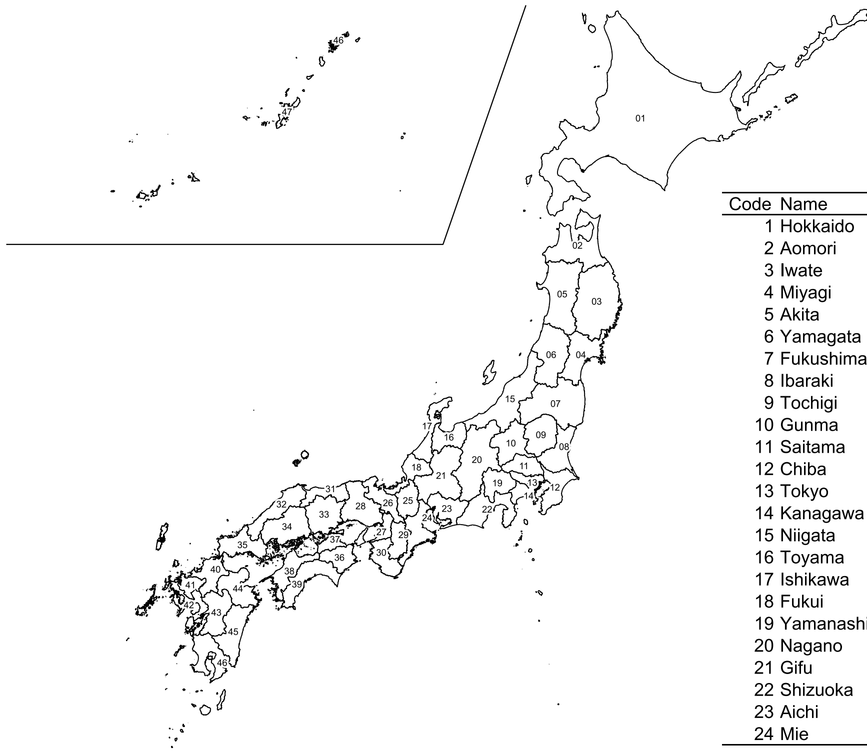
From inspecting equilibrium conditions (19 through 32), we can see that solving an equilibrium in relative changes allows us to perform counterfactual experiments without estimating fundamentals such as average regional amenity, occupational comparative advantage, production technology, and trade cost. Solving an equilibrium needs 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 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 price of occupation service 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 shock (η), efficiency shock 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. Labor types are defined by nationality (Japanese and foreign), an education level (low-skilled and high-skilled), gender (male and female), and age groups (15–29, 30–59, +60). We label a worker as high-skilled if s/he has a 4-year college degree or more (excluding junior college) and label them as low-skilled otherwise. Due to the limited number of sampled foreign workers in the data, we drop ages from the foreign workers' attributes, i.e., we consider education level and gender as foreign workers' attributes. There are in total 16 worker groups, i.e., 12 types for native and four types for foreign. We consider four task-based occupation aggregates, routine cognitive, non-routine cognitive, routine manual, and non-routine manual. We will discuss the aggregation of occupations in detail below. Lastly, we consider seven industries, mining, 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 due to the data availability.

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		

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 conducted by the Ministry of Health, Labour, and Welfare (*Chingin Kōzō Kihon Tōkei Chōsa*). The MHLW Wage Survey is an establishment-level survey conducted annually. More than one million workers in all sectors but primary sectors are surveyed. We can observe the work's attributes (such as gender, age, and highest education attained), work hours, and monthly wage. From 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 conducted by the Ministry of Internal Affairs and Communications (*Shūgyō Kōzō Kihon Chōsa*). The MIC Employment Survey is a household-level survey conducted every five years. Individuals who are 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, which helps compute data counterpart of the average wages. However, until 2019, workers report their occupations only if they are itemized in the non-exhaustive list of occupations. As a result, a substantial fraction of observations missed the occupational information. From 2020, the occupation list became exhaustive, and the occupation classification complies with the Japan Standard Occupational Classification. In estimating the structural parameters, however, we need to construct the occupational distribution and occupation expenditure shares by sector over time. We, therefore, use the MIC Employment Survey, in which all workers report their 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 data: price deflators (consumer price indices) are sourced 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 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 Task-Based Aggregation of Occupations

In our model framework, workers sort into occupations based on their underlying occupational comparative advantage and prices of occupations. When a group of native workers (e.g., low-skilled male aged between 30–59) has a similar pattern of comparative advantage to a group of foreign workers (e.g., low-skilled male), they are more likely to sort into the same set of occupations and, thus, compete head-to-head. The empirical counterpart of the occupation should be defined in a way that it captures an underlying heterogeneity of comparative advantage of foreign relative to native. For example, suppose we consider two broad occupations, white- and blue-collar jobs. Given that high-skilled workers generally have a comparative advantage in the white-collar job, we expect that accepting foreign high-skilled may impact most on domestic high-skilled. However, when domestic and foreign high-skilled engage in different sub-occupations within the white-collar, e.g., natives do more interaction-intensive job while the foreign do less interaction-intensive job due to the language barrier, they will not be direct competitors.

We apply the task-based approach to aggregate occupations. Following Acemoglu and Autor (2011), we measure the task contents of occupations. We take advantage of the Japanese version of O-NET *jobtag*[9], 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[10], 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[11]. 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 2 for the distribution of task scores for the year 2017. Table 1 illustrates the example of occupations in each task category.

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

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

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

Figure 2: Aggregating Occupations Based on Task Contents

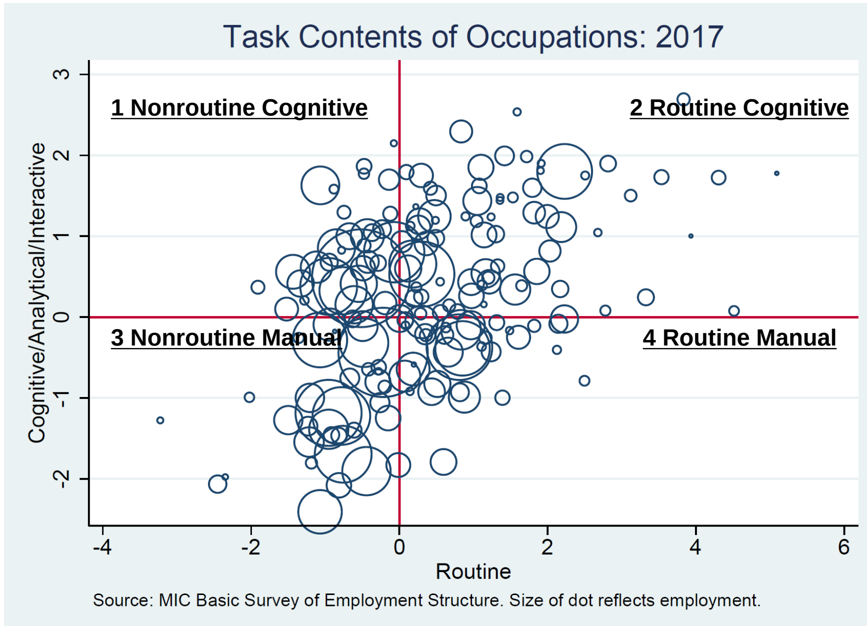


Table 1: Example of Occupations in Four Tasks (2017)

	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

3.3 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. 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 which govern 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. The estimation is in progress and the results presented in this manuscript are preliminary.

We start with estimating the shape parameter of the Fréchet amenity shock, η. From now 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 "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 $\delta^{\eta}_r(k,s)$ capture the unobserved amenity $\log(B_r(k,s))$ and the time-type fixed effects $\delta^{\eta}_t(k,s)$ 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 distance weighted average wage of neighboring regions:

$$\text{dwWage}(k,s)_{rt} = \sum_{r' \neq r} \lambda_{rr'} \text{Wage}(k,s)_{r't}, \tag{34}$$

where $\lambda_{rr'} = \frac{1/\text{dist}_{rr'}}{\sum_{r''} 1/\text{dist}_{rr''}}$ is a weight based on the bilateral distance between regions r and r'. A region whose neighbors have high wages will tend to have a high wage, but the neighbor's wage will be exogenous to a given region's shocks to residential choice.

Location choice probabilities and average wages by region and worker type are constructed using the MIC Employment Survey from 1992 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 age 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.[12]

In order to measure the location choice probabilities, we compute the mass of workers by region and worker type based on the annual work hours.[13] We recover the hourly wage using the information on annual income, annual workdays, and weekly work hours. We then compute the average wages for each worker group and region. Average wages are deflated using the consumer price index (CPI).[14]

Table 2 summarizes the estimation results. The point estimate of η under OLS is lower than

[12]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.

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

[14]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.

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

the IV estimate, which aligns with the discussion above. The point estimate under IV is 0.544, 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.

3.4 Occupation Choice Elasticity and Elasticities of Substitution

We next estimate the shape parameter of the Fréchet efficiency shock ζ, which governs the elasticity of occupation choice. To obtain the moment condition, following Burstein et al. (2019), 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:

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

Let us define the transformed occupation price as the product of occupation price $p_{r,t}(o)$ and occupation-specific efficiency shifter $S_t(o)$, i.e., $q_{r,t}(o) = p_{r,t}(o)S_t(o)$. Using this transformed price, we rewrite the change in average wage as:

$$
\begin{aligned}
\hat{\text{Wage}}_{r,t}(k,s) &= \left(\sum_o \left(\hat{S}_t(k,s,o)\hat{p}_{r,t}(o)\right)^{\zeta} \varphi_{r,t}(k,s,o)\right)^{1/\zeta} \\
&= \left(\sum_o \left(\hat{S}_t(k,s)\underbrace{\hat{S}_t(o)\hat{p}_{r,t}(o)}_{\hat{q}_{r,t}(o)}\right)^{\zeta} \varphi_{r,t}(k,s,o)\right)^{1/\zeta} \\
&= \hat{S}_t(k,s)\left(\sum_o \left(\hat{q}_{r,t}(o)\right)^{\zeta} \varphi_{r,t}(k,s,o)\right)^{1/\zeta}.
\end{aligned}
$$

Multiply and divide by the transformed occupation price of the reference occupation o', $\hat{q}_{r,t}(o')$, we get:

$$
\begin{aligned}
\hat{\text{Wage}}_{r,t}(k,s) &= \hat{S}_t(k,s)\left(\sum_o \left(\hat{q}_{r,t}(o)/\hat{q}_{r,t}(o')\right)^{\zeta} \varphi_{r,t}(k,s,o)\right)^{1/\zeta} \hat{q}_{r,t}(o') \\
&= \hat{S}_t(k,s)\left(\hat{u}_{r,t}(k,s)\right)^{1/\zeta} \hat{q}_{r,t}(o') \qquad (35)
\end{aligned}
$$

where

$$
\hat{u}_{r,t}(s) = \sum_o \left(\frac{\hat{q}_{r,t}(o)}{\hat{q}_{r,t}(o')}\right)^{\zeta} \varphi_{r,t}(k,s,o),
$$

is weighted average occupation price (to the power of ζ) where the weight is the occupation choice probability. 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:

$$
\hat{v}_{r,t}(o,o') \equiv \left(\frac{\hat{q}_{r,t}(o)}{\hat{q}_{r,t}(o')}\right)^{\zeta} = \frac{\hat{\varphi}_{r,t}(k,s,o)}{\hat{\varphi}_{r,t}(k,s,o')} \qquad (36)
$$

Therefore, $\hat{u}_{r,t}(s)$ is observable in the data. Taking logs of equation (35), we get

$$\log\left(\hat{\text{Wage}}_{r,t}(k,s)\right) = \frac{1}{\zeta}\log\left(\hat{u}_{r,t}(k,s)\right) + \log\left(\hat{q}_{r,t}(o')\right) + \log\left(\hat{S}_t(k,s)\right)$$
$$= \frac{1}{\zeta}\log\left(\hat{u}_{r,t}(k,s)\right) + \delta^{\zeta}_{rt} + \nu^{\zeta}_{rt}(k,s)$$

where $\delta^{\zeta}_{rt} = \log\left(\hat{q}_{r,t}(o')\right)$ is time-region fixed effects (same across all labor types), $\nu^{\zeta}_{t}(k,s) = \log\left(\hat{S}_t(k,s)\right) + \vartheta^{\zeta}_{r,t}(k,s)$ is the composite of unobserved change in labor-type-specific productivity and measurement error. ζ can be estimated via nonlinear least squares (NLS) regression, but the NLS estimates may be potentially biased due to the endogeneity. Recall optimality condition of the occupation production unit, i.e., $\hat{w}_{r,t}(k,s,o) = \hat{p}_{r,t}(o)\hat{S}_t(k,s)\hat{S}_t(o)$. Higher growth in labor type-specific productivity will lead to lower growth in the occupation price (given the wage per efficiency unit). As a result, the unobserved term $\nu^{\zeta}_{r,t}(k,s)$ and the regressor $(\hat{u}_{r,t}(k,s))$ may be negatively correlated and thus the NLS estimate would be downward biased.

To address the endogeneity, we construct the following instrument:

$$\chi^{\zeta}_{r,t}(k,s) = \sum_{o}\left(\frac{\hat{q}_{r,t}(o)}{\hat{q}_{r,t}(o')}\right)^{\zeta}\frac{\sum_{k,s}L_{r,t_0}(k,s)\varphi_{r,t_0}(k,s,o)}{\sum_{o'}\sum_{k,s}L_{r,t_0}(k,s)\varphi_{r,t_0}(k,s,o')}$$

where $\frac{\sum_{k,s}L_{r,t_0}(k,s)\varphi_{r,t_0}(k,s,o)}{\sum_{o'}\sum_{k,s}L_{r,t_0}(k,s)\varphi_{r,t_0}(k,s,o')}$ is the occupation choice probability for o across all labor types in the initial period (1992).

Using this instrument, we construct the moment condition:

$$\mathbb{E}_{k,s,r,t}\left[\left(y^{\zeta}_{r,t}(k,s) - \frac{1}{\zeta}x^{\zeta}_{r,t}(k,s)\right)\times z^{\zeta}_{r,t}(k,s)\right] = 0 \tag{37}$$

where $y^{\zeta}_{r,t}(k,s)$ is the OLS residual of a regression that projects the set of dependent variables $\hat{\text{Wage}}_{r,t}(k,s)$ on a set of region-year fixed effects, $x^{\zeta}_{r,t}(k,s)$ is the OLS residual of a regression that projects the set of endogenous independent variables $(\hat{u}_{r,t}(k,s))$ on a set of region-year fixed effects, and $z^{\zeta}_{r,t}(k,s)$ is the OLS residual of a regression that projects the set of instruments $\chi^{\zeta}_{r,t}(k,s)$ on a set of region-year fixed effects.

We now construct the second set of moment conditions to identify the elasticities of substitution across occupations for each industry ρ^i. 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 have:

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

where $\hat{q}_{r,t}(o)$ is the transformed occupation price defined above. Note that $v_{r,t}(o,o') = \left(\frac{\hat{q}_{r,t}(o)}{\hat{q}_{r,t}(o')}\right)^{\zeta}$ is observable in the data, as shown in equation (36). Take logs and 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 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, 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:

$$\chi^{\rho}_{rt} = \sum_{r' \neq r} \lambda_{rr'} \left(\frac{\hat{q}_{rt}(o)}{\hat{q}_{rt}(o')} \right)^{\zeta}, \tag{38}$$

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).

Using this instrument, we construct the second set of moment conditions:

$$\mathbb{E}_{o,r,t} \left[\left(y^{\rho^i}_{r,t}(o) - (1-\rho^i)\frac{1}{\zeta} x^{\rho^i}_{r,t}(o) \right) \times z^{\rho}_{r,t}(o) \right] = 0 \tag{39}$$

where $y^{\rho^i}_{r,t}(o)$ is the OLS residual of a regression that projects the set of dependent variables $\log\left(\hat{I}^i_{rt}(o)\right)$ on a set of region-year fixed effects, $x^{\rho}_{r,t}(o)$ is the OLS residual of a regression that projects the set of endogenous independent variables $(\hat{v}_{r,t}(o))$ on a set of region-year fixed effects, and $z^{\rho}_{r,t}(o)$ is the OLS residual of a regression that projects the set of instruments χ^{ρ}_{rt} on a set of region-year fixed effects.

We estimate ζ and ρ^is jointly using the sample analogue of the moment conditions in equations (39) and (37). Those moment conditions exactly identify the parameters.

In order to construct the sample analogs, we use the data from the MIC Employment Survey on five time periods: 1992–1997, 1997–2002, 2002–2007, 2007–2012, 2012–2017. We restrict the samples to those who are aged between 30 and 59.

Table 3 summarizes the result. Note that the results are very preliminary. We obtain a point estimate of ζ to 5.128 (standard error equal to 1.111), and a point estimate of ρ ranges from 0.472 to 1.250. However, the standard errors of the estimate for ρ^i are large for some i and they are not as precisely estimated as ζ. See Appendix C for the further details.

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 (distance-)elasticity of trade of the service sector is getting close to one of the manufacturing

Table 3: Estimates of ζ and ρ^i

	Point estimate	Standard Error
Elasticity of task choice ζ		
	5.128	1.111
Elasticity of substitution ρ^i		
Mining	0.974	2.533
Food	0.995	0.710
Metal	1.250	0.830
Machinery	1.071	0.820
Other manuf	1.050	0.565
Construction	0.472	1.289
Service	1.001	0.024

sectors over the past decades in the U.S. We set $\theta = 4.5$ for the service sector.

3.5 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. For each worker group and domestic region, we computed the mass of workers, regional and occupational distributions, and average wages 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-skilled, provided that 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-skilled. Those admitted under the Technical Intern Trainee Program are assumed to be low-skilled. This imputes 62% of sampled foreign workers with missing education. We drop the rest of the observations from the sample[15].

[15] 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

Table 4: Base Year Equilibrium Outcomes

	Description	Source
$\psi_r(s)$	Location choice probability	MHLW Wage Survey
$\varphi_r(s,o)$	Task choice probability	MHLW Wage Survey
π^i_{rm}	Bilateral trade share	Imputed
$L_r(s,o)$	Number of workers	MHLW Wage Survey
$\text{Share}^i_r(o)$	Average Tas expenditure share	MHLW Wage Survey

Location and Occupation Choice Probabilities

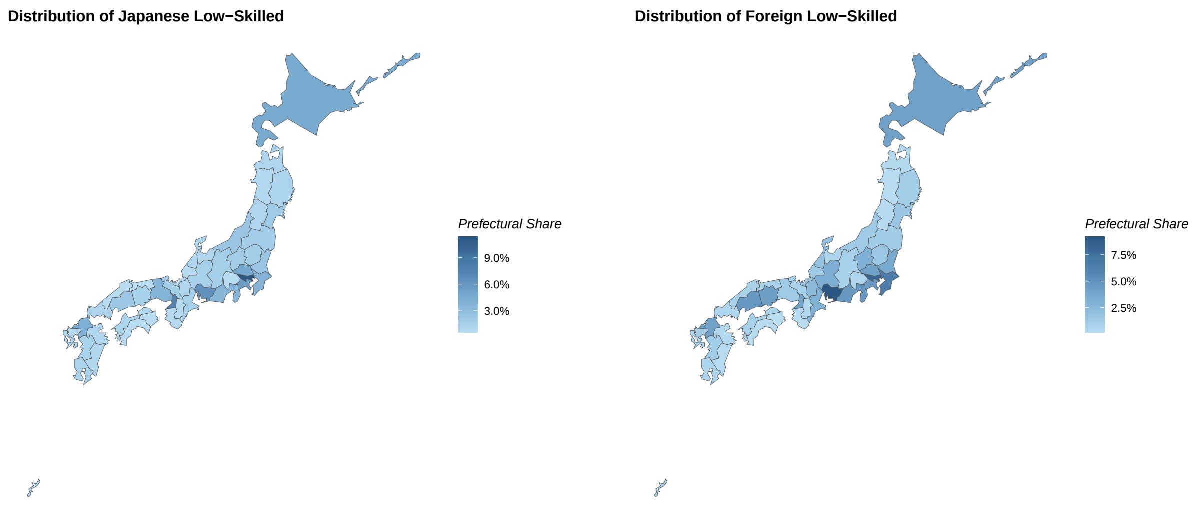
We construct the mass of workers by aggregating (monthly) work hours for each region, worker group, and occupation aggregate, $L_r(k,s,o)$.[16] In the Wage Survey 2020, the mass of foreign workers accounts for 1.4% of total workers in Japan. This is below the number based on the Foreign Employment Report (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, 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 3 and 4, respectively, compare the geographic distributions of low- and high-skilled workers between native and foreign. Numbers in the figure indicate the fraction of workers of a given type who reside in each region, i.e., location choice probability. For low-skilled native, Tokyo accounts the largest share (11.4%), followed by Osaka (7.4%) and Aichi (6.4%). Those regions are three major urban areas in Japan. For low-skilled foreign, however, Aichi accounts the largest share (9.2%), followed by Tokyo (8.3%) and Chiba (6.5%). As described in the introduction, the dominance of the manufacturing sector (auto industry, in particular) in Aichi may explain the high concentration of foreign low-skilled. Shizuoka (4.7%) and Hiroshima (4.6%), other auto-sector-oriented regions, are ranked at fourth and fifth places, compared with 10th

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



(a) Japanese Low-Skilled

(b) Foreign Low-Skilled

Figure 3: Geographic Distribution of Low-Skilled (2020)

and 13th for the distribution of Japanese low-skilled. For high-skilled native, Tokyo accounts 25.6%, followed by Osaka (9.3%) and Aichi (7.6%). For foreign high-skilled, Aichi (23.1%) again outweighs Tokyo (22.9%), followed by Kanagawa (5.7%) and Osaka (4.9%).

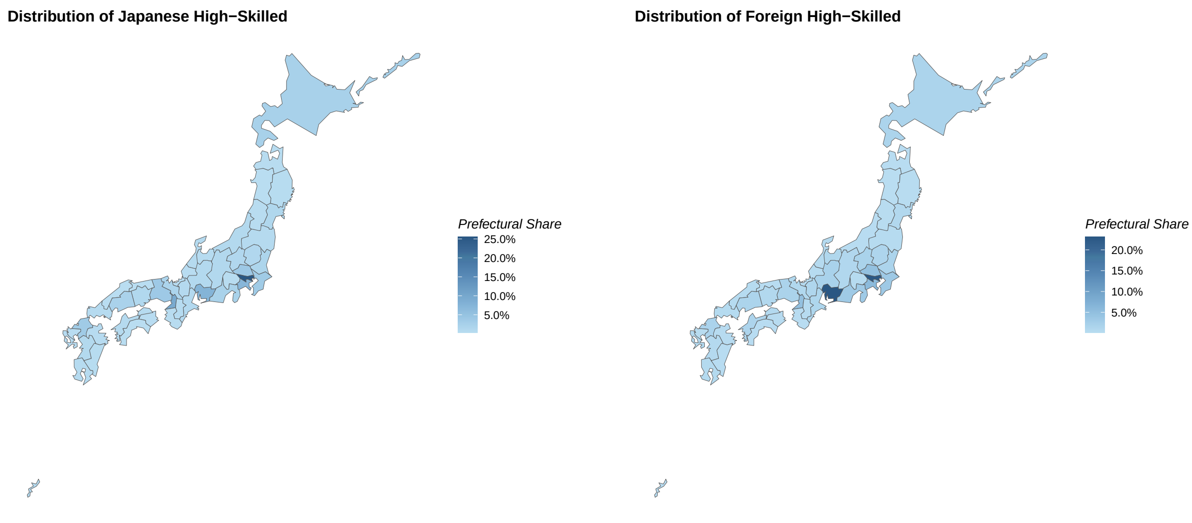
Analogously, the occupation choice probability $\varphi_r(k,s,o)$ is computed as:

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

Table 5 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.

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



(a) Japanese High-Skilled

(b) Foreign High-Skilled

Figure 4: Geographic Distribution of High-Skilled (2020)

Table 5: Task Distribution (2017)

	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.

bonus.[17] 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. Having the mass of workers and the average wages in hands, we can compute the value added by region according to equations (13).

To compute the expenditure share of each occupation in total labor cost, we first compute

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

Table 6: Task Expenditure Shares

	Metal	Machinery	Service
Nonroutine Cognitive	15%	32%	27%
Routine Cognitive	23%	11%	23%
Nonrutine Manual	23%	33%	43%
Routine Manual	40%	24%	7%

the expenditure share at establishment f in sector i as:

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

where $\mathcal{Z}_r(f,o)$ is the set of workers in establishment f engaging in occupation o, $w_r^{\text{Data}}(o,z)$ is worker z's hourly wage (defined above) and $h_r^{\text{Data}}(o,z)$ is the monthly work hours. We then compute the average expenditure share at the industry and occupation level as a weighted average of establishment-level expenditure share, using the sample weight associated with each sampled establishment. Table 6 summarizes the average task expenditure in selected industries. The table confirms that the manufacturing sectors are more manual-job-intensive than the service sector. Nevertheless, within manufacturing, the metal sector is more routine-intensive while the machinery sector is more non-routine-intensive. The heterogeneity in the occupational intensity across sectors, in conjunction with heterogeneous sectoral composition across regions, will imply that the influx of foreign workers has different impacts across regions as regions will attract different types of workers.

Inter-Prefectural Trade Flows

Lastly, the bilateral trade share π_{mr}^i is imputed in the spirit of Eckert (2019). For Japan, 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. 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 indice: 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:

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

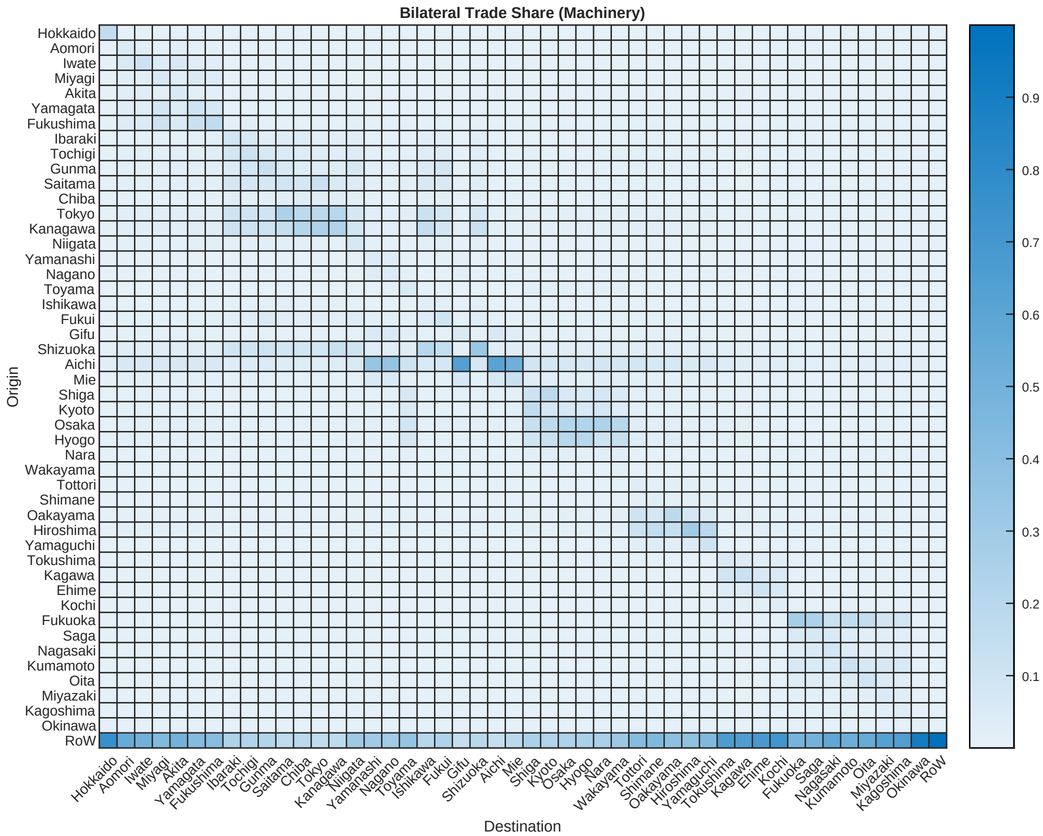
where r and m, respectively, are the indices of prefecture within region R and M. Then, using the coefficient estimates in the previous step, predict the HRI across prefectures.

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

Step 2: compile the national level IO table without agriculture: 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) will break. 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.

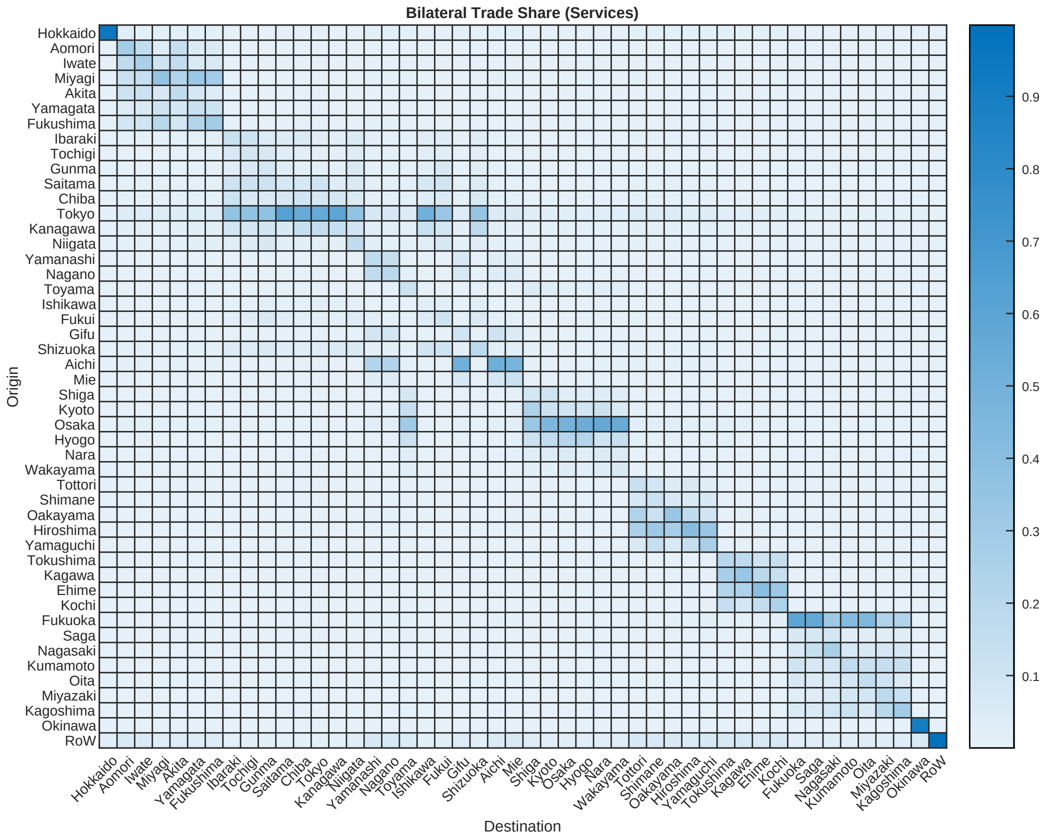
Step 3: imputing the bilateral trade shares: Using the HRIs, national-level IO table with ex-

Figure 5: Bilateral Trade Shares (Machinery)



ternal 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. The details of the imputation method are available upon request. In this step, we also recover the 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). As the gross output and the total expenditure are recovered based on the model, the bilateral trade is balanced across domestic regions. Figure 5 and 6 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 6: Aggregating Occupations Based on Task Contents



3.6 Policy Counterfactual

We conduct counterfactual exercises to examine the impacts of immigration policies and compare them with the alternative policies targeting domestic workers. Under all policy scenarios, we consider the labor supply shocks equivalent to a 10% increase in domestic workers relative to the base year 2020. We consider three immigration policies: increase in the number of foreign low-skilled (increase by approximately ninefold), foreign high-skilled (by sixfold), and both low- and high-skilled (by fourfold). For the first two scenarios, we keep the gender and age group compositions fixed as in the base year. For the last scenario, we keep the skill, gender, and age group compositions fixed. As policy alternatives to accepting foreign workers, we also consider an increase in the labor supply of domestic elderly workers (by 75%) and female workers (by 23%). Those policies are in line with the government initiatives to encourage elderly and female workers into workforce.

Change in Welfare

We begin by discussing the welfare implications. Aggregate welfare 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:

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

where $\Gamma(\cdot)$ is the gamma function. Using the "hat" notation, we can express the relative change in welfare as:

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

Table 7 summarizes the % change in aggregate welfare for each group of domestic workers under five different policy scenarios. For each group of workers, we underline the numbers to indicate the policy that yields the highest welfare gain (or least loss) among the three immigration policies; e.g., accepting foreign high-skilled is the most favorable for low-skilled male workers. The main results are fourfold. First, domestic low-skilled workers favor an inflow of foreign high-skilled and *vice versa*. The intuition is straightforward: native and foreign workers within the same skill level have more similar patterns of occupational comparative advantage and, therefore, may compete with each other directly. Second, despite the low-skilled male favoring the second policy scenario, their welfare declines in response to an inflow of foreign high-skilled. In Table 5, we saw that 37.3% of the low-skilled domestic workers engage in a routine manual job. The largest fraction of foreign high-skilled workers (31.1%) also engages in this occupation. Welfare loss of domestic low-skilled is driven by the sorting of foreign high-skilled and domestic low-skilled into the same occupation. Third, welfare gains or losses from the immigration shocks are at most 0.5%, implying quantitatively minimal impacts. Fourth, immigration policies would differ from the policy alternatives targeting domestic workers. An increase in the supply of elderly workers has more negligible welfare implications, potentially due to the lower productivity of the elderly compared to foreign workers. On the other hand,

Table 7: Welfare Implications

			Δ in Welfare (%)				
			Foreign			Domestic	
Skill	Sex	Age	(1) LS	(2) HS	(3) Mixed	(4) Elderly	(5) Female
Low	Male	15-29	-0.49	**-0.24**	-0.37	-0.13	0.00
		30-59	-0.34	**-0.13**	-0.24	-0.14	-0.02
		60-	-0.34	**-0.11**	-0.23	-0.20	-0.04
	Female	15-29	-0.03	**0.04**	-0.01	-0.09	-0.06
		30-59	0.06	**0.10**	0.07	-0.09	-0.07
		60-	-0.28	**-0.02**	-0.14	-0.22	-0.07
High	Male	15-29	**0.34**	0.09	0.18	0.06	-0.04
		30-59	**0.34**	0.14	0.21	0.06	-0.04
		60-	**0.15**	0.06	0.08	-0.07	-0.06
	Female	15-29	**0.40**	0.13	0.23	0.01	-0.07
		30-59	**0.26**	0.11	0.16	-0.05	-0.08
		60-	-0.31	**-0.10**	-0.20	-0.24	-0.08

an increase in the female labor supply will harm domestic workers more generally because they benefit less from the specialization.

Change in Real Wages

Table 8 summarizes the change in regional real wages for domestic male workers aged between 30 and 59. Figure 7 compares the real wage responses of low-skilled males (30–59) under the first and second policy scenarios. There are two key findings. First, skill-specific immigration policies have more heterogeneous implications across regions than alternative domestic policies. For example, the change in real wages ranges from -2.71% to 0.98% for low-skilled workers under the first immigration policy scenario, compared with the responses in real wages ranging from -0.57% to 0.24% when increasing the supply of the elderly workers. In other words, foreign employment policy may have a more dramatic impact on particular regions than other policies targeting domestic workers. This result is primarily driven by a significantly uneven distribution of foreign workers. Second, local real wage response differs both qualitatively and quantitatively across the different immigration policy scenarios. The two maps highlight that the impact on real wages of a given region can be positive (red on the map) under the first policy scenario but negative (blue) under the second scenario, and *vice versa*. This heterogeneous response is driven by the fact that foreign workers of different skill level sort into different regions, as we will see in the next.

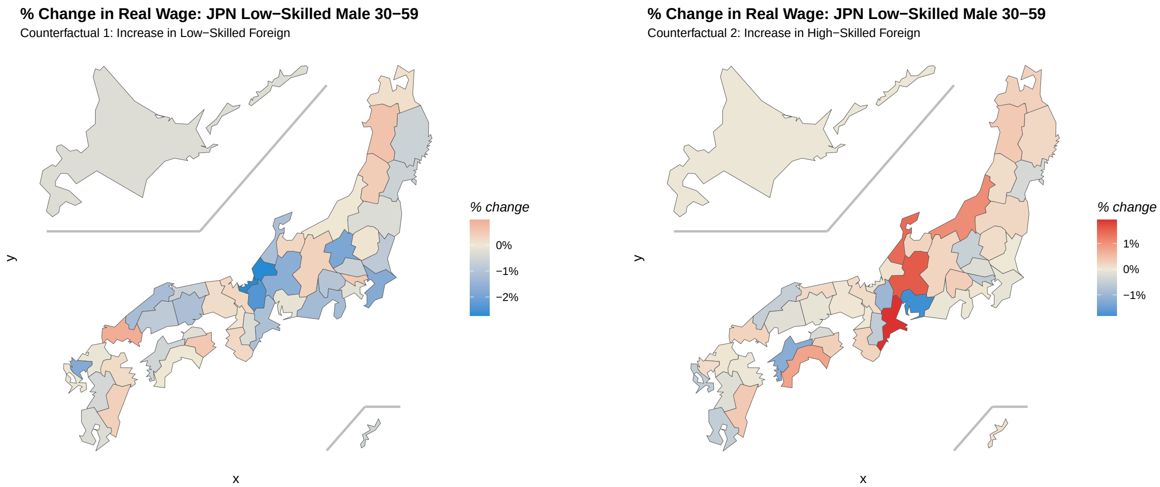
Table 8: Change in Regional Real Wage (Male 30–59): Summary Statistics

		Foreign			Domestic	
		(1) LS	(2) HS	(3) Mixed	(4) Elderly	(5) Female
Low-skilled	Min	-2.71	-1.81	-1.60	-0.57	-0.29
	Max	0.98	1.93	0.65	0.24	0.14
	Mean	-0.45	0.05	-0.19	-0.20	-0.05
	Median	-0.31	0.04	-0.16	-0.19	-0.03
	Std Dev	0.81	0.63	0.53	0.16	0.11
High-skilled	Min	-1.77	-1.05	-0.84	-0.39	-0.37
	Max	1.15	2.07	1.04	0.31	0.14
	Mean	0.14	0.33	0.23	-0.04	-0.09
	Median	0.30	0.23	0.24	-0.05	-0.08
	Std Dev	0.63	0.53	0.41	0.14	0.12
	N	47	47	47	47	47

Change in Regional Employment

Which regions attract more foreign workers, and does the influx of foreign workers trigger the reallocation of domestic workers across and within regions? Table 9 summarizes the change in foreign (F) and native (J) employment under three immigration policy scenarios. We list the top and bottom five regions in terms of foreign employment growth. The set of regions that attract more foreign workers differs across policy scenarios. In general, low-skilled are more likely to move to rural regions, while high-skilled are more likely to move to urban regions. For example, under the first policy scenario, Tokyo exhibits the smallest increase (187.49%) in foreign employment, and Niigata exhibits the largest increase (781.08%). Under the second policy, however, those two prefectures position completely in the opposite way: Tokyo gains the most (508.92%), and Niigata gains the least (92.72%). Under the third policy scenario, we see a much smaller variation in the change in foreign employment. The spatial sorting patterns generate the heterogeneous wage responses across policy scenarios scenarios we saw above.

The table also shows the change in domestic employment in the selected regions. Under the first two policy scenarios, the table shows that domestic workers are driven out (i.e., negative change in domestic employment) from the regions that attract more foreign workers. Under the third scenario, however, the larger inflow of foreign workers seems to accompany the inflow of domestic workers (i.e., crowding in). More importantly, we find that the reallocation of domestic workers across space is quantitatively insignificant, with a magnitude less than 1%.



(a) Low-Skilled

(b) Low-Skilled

Figure 7: Change in Real Wages for Low-Skilled Male aged 30–59

Table 9: Change in Foreign and Native Employment

	(1) LS			(2) HS			(3) Mixed		
		F	J		F	J		F	J
1	Tokyo	187.49	0.34	Niigata	92.72	0.58	Shimane	363.53	-0.17
2	Tokushima	192.95	0.35	Okinawa	139.47	0.06	Okayama	364.04	-0.13
3	Aichi	200.90	0.13	Saga	146.03	0.09	Fukui	367.43	-0.43
4	Ehime	269.48	-0.11	Iwate	148.34	0.14	Ehime	369.77	-0.28
5	Toyama	289.83	0.34	Okayama	157.43	0.04	Shiga	370.40	-0.67
43	Tottori	662.23	-0.04	Toyama	441.18	0.23	Miyazaki	378.83	0.28
44	Saga	688.87	-0.76	Ehime	442.00	-0.41	Akita	378.85	0.32
45	Iwate	695.21	-0.15	Aichi	496.71	-0.82	Niigata	379.12	0.41
46	Okinawa	712.29	-0.13	Tokushima	507.96	0.29	Mie	379.13	0.46
47	Niigata	781.08	0.15	Tokyo	508.92	-0.12	Yamaguchi	379.51	0.38

Note: the table lists the top and bottom five regions in terms of foreign employment growth.

We find quantitatively more pronounced adjustments across occupations within a region too. Table 10 summarizes the changes in occupational employment of native workers in the two selected regions, Mie and Aichi, which are the neighboring prefectures in the Tokai area. Under the second immigration policy, Mie exhibits the largest increase in domestic workers $(+1.10\%)$, and Aichi exhibits the largest decline (-0.82%). Under all immigration policy scenarios, domestic employment in the routine manual occupation declines, and domestic employment in cognitive occupation increases. A shift of domestic employment from the routine manual occupation is more significant under the first immigration policy scenario than in the second scenario. These results are in line with the comparative advantage of foreign workers,

Table 10: Change in Occupational Employment of Domestic Workers

	Foreign			Domestic	
Aichi	(1) LS	(2) HS	(3) Mixed	(4) Elderly	(5) Female
Non-routne Cognitive	8.15	7.83	7.97	7.50	9.21
Routine Cognitive	3.60	5.73	4.95	8.21	9.34
Non-routine Manual	-0.67	-5.65	-3.75	9.41	9.65
Routine Manual	-16.79	-12.03	-13.80	10.22	9.06
Mie					
Non-routne Cognitive	12.14	1.19	5.65	8.83	9.85
Routine Cognitive	0.75	2.58	1.93	10.13	9.74
Non-routine Manual	-3.41	3.83	0.78	11.72	10.07
Routine Manual	-12.43	-6.03	-8.59	10.89	9.58

Table 11: % Change in Sectoral Output

	Foreign			Domestic	
	(1) LS	(2) HS	(3) Mixed	(4) Elderly	(5) Female
Mining	5.47	7.50	6.67	9.64	9.65
Food	7.30	7.70	7.55	6.82	6.64
Metal	7.10	8.13	7.73	6.99	6.94
Machinery	7.04	8.52	7.93	6.90	6.97
Other manufacturing	7.37	7.87	7.65	7.79	7.85
Construction	6.71	7.48	7.18	6.82	6.76
Serviice	6.47	7.26	6.95	6.73	6.70

which is implied by the observed occupational distribution. We also find that the patterns of reallocation differ between the two regions. The reallocation of natives across occupations will depend on the extent to which foreign workers come to the location and its sectoral composition.

Change in Gross Output and Export

Lastly, we examine the change in sectoral output. Table 11 summarizes the % change in gross sectoral output at national level. Compared with the welfare implications, we find quantitatively more significant impacts on production. Among the three immigration policies, accepting foreign high-skilled workers yields the largest increase in sectoral production, driven by the potentially higher productivity of high-skilled than low-skilled. We also find significant variation in production responses across regions. Under the second immigration policy scenario, manufacturing production in Aichi grows by 24.19% while Niiga exhibits a decline in manufacturing by -1.03%.

Table 12: % Change in Sectoral Export

	Foreign			Domestic	
	(1) LS	(2) HS	(3) Mixed	(4) Elderly	(5) Female
Mining	0.86	-0.46	0.14	4.30	3.94
Food	4.96	2.16	3.32	1.62	1.04
Metal	2.77	1.74	2.20	2.22	1.84
Machinery	2.50	2.57	2.58	1.83	1.80
Other manufacturing	5.22	1.99	3.27	5.50	5.49
Construction	1.74	0.77	1.19	2.64	2.10
Serviice	-0.25	0.01	-0.08	2.15	2.29

Accepting foreign workers can enhance Japan's external competitiveness by lowering production costs. Table 12 summarizes the change in sectoral export at the national level. We find that the impacts on sectoral export differ across three immigration policies. For example, exports of food and other manufacturing products increase most by accepting foreign low-skilled. Comparing the foreign employment policies with the other alternatives, we find that the export of machinery (including automobiles) grows more by accepting foreign workers than by encouraging the elderly and females into the workforce.

4 Conclusion

This paper develops a spatial general equilibrium model to study the labor market and production implications of foreign workers in regional economies in Japan. 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 bring the model to the data for the Japanese economies with 47 regions, four task-based occupations, and seven sectors. We calibrate the structural parameters of the model and the base year equilibrium variables using the novel micro-level data. In the counterfactual experiments, we examine how welfare, local wages, employment, and production respond to the inflow of foreign high-skilled workers. Our key results are the following: accepting foreign workers has more heterogeneous impacts on the labor market across space than other policy alternatives. Compared with the quantitatively minor impacts on wages and employment, we confirmed more pronounced implications on production.

There are several remaining future research agendas: first, we assume that workers of different groups are perfect substitutes within each occupation due to the data availability. In the literature on labor economics, the elasticity of substitution between domestic and native workers has been the central object of interest. It would be worth confirming how the quantitative implications will be affected by allowing imperfect substitution of domestic and foreign workers. Second, in quantifying the model, we assume that trade is balanced across regions bilaterally, and we consider the closed economy by ruling out international trade. It would be worth studying whether allowing trade imbalances and external trade amplifies or reduces the impacts of counterfactual shocks. Incorporating external trade also allows us to examine the impacts of foreign employment on the competitiveness of Japan in the world economy. Lastly, in our quantification exercise, we did not calibrate the productivity, comparative advantage, and amenity parameters by taking advantage of exact hat algebra. Nevertheless, it would be worth identifying those parameters using the model inversion technique to discuss further the underlying determinants of the aggregate welfare implication and the local labor market response to accepting foreign workers.

Appendices

A Sequence of Worker's Decisions

A.1 Suggestive Evidences

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 support this timing assumption. Yet, the Employment Survey provides some suggestive evidence on workers' occupation and location decisions. Table A1 shows the fractions of workers who switched or not switched 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. 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 prefecture 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 the high-education workers are more likely to change the 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, 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.

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

A. Male Low Education				B. Male High Education			
		Location				Location	
		Not moved	Moved			Not moved	Moved
Occupation	Not Switched	83.55%	5.21%	Occupation	Not Switched	77.98%	13.35%
	Switched	10.13%	1.11%		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.

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 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:

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

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:

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

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:

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

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

$$
Y_r^i = \sum_{m\in\mathcal{R}} \pi_{r,m}^i X_m^i. \qquad \text{(A11)}
$$

Lastly, total household expenditure E_r is given by

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

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 Data

B.1 Occupation Classification

Table B1 lists the 24 occupations. We adopt the occupational classification used in the 2002 Employment Survey, based on the Japan Standard Occupation Classification (Revision 1986).

Table B1: 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	*Leagal 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*

C GMM Estimation

Let Θ be the vector of parameters $\Theta = [\zeta, \rho^1, ..., \rho^I]$. Suppose that the data consists of N observations with each observation consists of vectors $\mathbf{Y}^{\zeta}_{r,t} = [y^{\zeta}_{r,t}(k,s), x^{\zeta}_{r,t}(k,s), z^{\zeta}_{r,t}(k,s)]$ and $\mathbf{Y}^{\rho^i}_{r,t} = [y^{\zeta}_{r,t}(k,s), x^{\zeta}_{r,t}(k,s), z^{\zeta}_{r,t}(k,s)]$ for $i = 1, ..., I$. For the sake of presentation, let $I = 2$. The population moment conditions are:

$$\mathbf{m}(\Theta_0) = \mathbf{E}[\mathbf{g}(\mathbf{Y}_{r,t}, \Theta_0)] = \mathbb{E}\begin{bmatrix} g^{\zeta}(\mathbf{Y}^{\zeta}_{r,t}, \Theta_0) \\ g^{\rho^1}(\mathbf{Y}^{\rho^1}_{r,t}, \Theta_0) \\ g^{\rho^2}(\mathbf{Y}^{\rho^2}_{r,t}, \Theta_0) \end{bmatrix} = \mathbf{0}$$

where

$$g^{\zeta}(\mathbf{Y}^{\zeta}_{r,t}, \Theta) = \left(y^{\zeta}_{r,t}(k,s) - \frac{1}{\zeta}x^{\zeta}_{r,t}(k,s)\right) \times z^{\zeta}_{r,t}(k,s)$$
$$g^{\rho^i}(\mathbf{Y}^{\rho^i}_{r,t}, \Theta) = \left(y^{\rho^i}_{r,t}(o) - (1-\rho^i)\frac{1}{\zeta}x^{\rho^i}_{r,t}(o)\right) \times z^{\rho}_{r,t}(o) \ \text{ for } i = 1, 2$$

The sample moment conditions are

$$\hat{\mathbf{m}}(\Theta) = \frac{1}{N}\begin{bmatrix} \sum_{r,t} g^{\zeta}(\mathbf{Y}^{\zeta}_{r,t}, \Theta) \\ \sum_{r,t} g^{\rho^1}(\mathbf{Y}^{\rho^1}_{r,t}, \Theta) \\ \sum_{r,t} g^{\rho^2}(\mathbf{Y}^{\rho^2}_{r,t}, \Theta) \end{bmatrix}$$

Then the GMM estimator can be written as

$$\hat{\Theta} = \underset{\Theta}{\operatorname{argmin}}\, \hat{\mathbf{m}}(\Theta)'\mathbf{W}\hat{\mathbf{m}}(\Theta)$$

where **W** is a weighting matrix. We use the identity matrix as an intial weighting matrix. Then compute the variance-covariance matrix of the parameter estimates according to

$$\hat{\mathbf{V}} = \frac{1}{N}\left(\hat{\mathbf{G}}'\hat{\mathbf{S}}^{-1}\hat{\mathbf{G}}\right)^{-1}$$

with

$$\hat{\mathbf{G}} = \frac{1}{N}\sum_{r,t}\left.\frac{\partial \hat{\mathbf{g}}(\boldsymbol{\Theta})}{\partial \boldsymbol{\Theta}}\right|_{\boldsymbol{\Theta}=\hat{\boldsymbol{\Theta}}}$$

and

$$\hat{\mathbf{S}} = \frac{1}{N}\begin{bmatrix} \sum_{r,t} u^{\zeta}_{r,t}u^{\zeta}_{r,t} & \sum_{r,t} u^{\zeta}_{r,t}u^{\rho^1}_{r,t} & \sum_{r,t} u^{\zeta}_{r,t}u^{\rho^2}_{r,t} \\ \sum_{r,t} u^{\rho^1}_{r,t}u^{\zeta}_{r,t} & \sum_{r,t} u^{\rho^1}_{r,t}u^{\rho^1}_{r,t} & \sum_{r,t} u^{\rho^1}_{r,t}u^{\rho^2}_{r,t} \\ \sum_{r,t} u^{\rho^2}_{r,t}u^{\zeta}_{r,t} & \sum_{r,t} u^{\rho^2}_{r,t}u^{\rho^1}_{r,t} & \sum_{r,t} u^{\rho^2}_{r,t}u^{\rho^2}_{r,t} \end{bmatrix}$$

where

$$\begin{aligned} u^{\zeta}_{r,t} &= u^{\zeta}_{r,t}(\mathbf{Y}^{\zeta}_{r,t}, \hat{\boldsymbol{\Theta}}) = \left(y^{\zeta}_{r,t}(k,s) - \frac{1}{\hat{\zeta}}x^{\zeta}_{r,t}(k,s)\right) \times z^{\zeta}_{r,t}(k,s) \\ u^{\rho^i}_{r,t} &= u^{\rho^i}_{r,t}(\mathbf{Y}^{\rho^i}_{r,t}, \hat{\boldsymbol{\Theta}}) = \left(y^{\rho^i}_{r,t}(o) - (1-\hat{\rho}^i)\frac{1}{\hat{\zeta}}x^{\rho^i}_{r,t}(o)\right) \times z^{\rho^i}_{r,t}(o) \ \text{ for } i = 1,2 \end{aligned}$$

We then update the weighting matrix according to

$$\mathbf{W} = \hat{\boldsymbol{\Gamma}}^{-1}$$

where

$$\boldsymbol{\Gamma} = \frac{1}{N}\mathbf{u}'\mathbf{u}$$

with

$$\mathbf{u} = \begin{bmatrix} \vdots & \vdots & \vdots \\ u^{\zeta}_{r,t} - \overline{u}^{\zeta} & u^{\rho^1}_{r,t} - \overline{u}^{\rho^1} & u^{\rho^2}_{r,t} - \overline{u}^{\rho^2} \\ \vdots & \vdots & \vdots \end{bmatrix}$$

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