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

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Abstract

This paper examines the impact of foreign workers on regional economies, focusing on Japan, a country that has increasingly relied on foreign labor to address its shrinking native workforce. We develop a quantitative spatial general equilibrium model incorporating regional heterogeneity, occupational choice, and sectoral structure to evaluate the gains from foreign employment. Using newly available micro-data, we calibrate the model to the Japanese economy and conduct counterfactual analyses. Simulating a labor market autarky, we find an overall, albeit modest, welfare gain from existing levels of foreign employment. However, we document substantial regional heterogeneity in wage impacts, with low-skilled foreign workers having negative effects on low-skilled native wages in regions with high concentrations of these workers. The service sector exhibits a greater reliance on foreign labor than commonly recognized. We also find significant trade-offs between maximizing national GDP (favoring high-skilled immigration) and maximizing the welfare of the least benefited group (favoring a skill mix closer to the current one). Crucially, the optimal skill mix varies significantly across sectors, and interregional labor reallocation plays a key role in shaping the overall impacts. Our framework provides a valuable toolkit for analyzing the multifaceted impacts of immigration and informing policy decisions in advanced economies facing similar demographic challenges

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, facing declining fertility rates and aging populations, net migration has become increasingly important for maintaining population stability and supporting the labor force (United Nations, 2017; Peri, 2020). Japan, in particular, faces a rapidly shrinking native population, making the role of foreign employment a critical policy issue.

While Japan has historically been relatively closed to immigration, persistent labor shortages have driven a substantial increase in the number of foreign workers over the past three decades. Until the 1990s, the 1988 Sixth Basic Act on Employment Measures strictly limited work visas in Japan to skilled workers. Since then, the government has introduced new visa categories, expanding foreign employment opportunities and diversifying the skill composition of the foreign workforce. As of 2022, over 1.7 million foreign workers reside in Japan, comprising 2.7% of the total workforce.

This increasing reliance on foreign labor has fueled a vigorous policy debate. The manufacturing sector, facing particularly acute labor shortages, has strongly advocated for expanding foreign employment. In 2018, the Manufacturing Bureau at the Ministry of Economy, Industry, and Trade (METI) highlighted the crucial role of foreign workers in addressing the tight labor supply.[2] Anecdotal evidence during the COVID-19 pandemic further underscored this reliance, with regional manufacturers reporting significant disruptions due to restrictions on the entry of foreign workers.[3] For instance, a 2002 report to the Advisory Board on Foreign Employment warned of the risks of "contracting job opportunities and dampening wages of Japanese workers." The Japanese Trade Union Confederation also found in a 2018 survey that approximately 20% of workers expressed a hostile position towards accepting foreign workers, with 46% of those opposed citing potential negative impacts on native employment conditions.

Japan's relatively recent shift towards increased foreign employment provides a valuable opportunity to study the economic impacts of immigration in a setting less confounded by long-term assimilation processes and generational effects than countries with longer immigration histories,

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

[2] "Labor Shortage in Manufacturing and Employment of Foreign Workers," Ministry of Economy, Industry, and Trade, 2018 (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

[3] See, for example, "Japanese businesses hit by lack of Chinese trainees amid virus outbreak," *Japan Times*, March 20, 2020. https://www.japantimes.co.jp/news/2020/03/20/business/japan-businesses-hit-lack-chinese-trainees-amid-virus-outbreak/

such as the United States. Several key observations about the Japanese labor market also raise concerns about potential negative wage impacts from immigration. A preliminary reduced-form analysis reveals a negative correlation between foreign worker inflows and native wages at the occupational level, suggesting that immigration may exert downward pressure on wages in certain segments of the labor market. This concern is further amplified by the geographic and occupational distribution of foreign workers. Foreign workers in Japan are geographically concentrated, particularly in and around major urban areas like Tokyo and the industrial Tokai region, which can be considered "immigrant magnets" (Frey, 1996). For example, the Tokai region (comprising Aichi, Mie, and Shizuoka prefectures), a manufacturing cluster centered around the auto industry, hosts a disproportionately large share of Brazilian workers in Japan, despite accounting for a much smaller share of the native population. Moreover, even within the same skill and gender groups, foreign and native workers exhibit distinct occupational sorting patterns. Low-skilled foreign workers, for instance, are heavily concentrated in manufacturing occupations, a pattern particularly evident in the Tokai region. This combination of regional concentration and occupational segmentation suggests that the labor market effects of immigration may be highly localized and unevenly distributed.

To provide a comprehensive assessment of the overall gains from foreign employment and its production and labor market implications in Japan, we develop a quantitative spatial general equilibrium model that incorporates regional heterogeneity (47 prefectures), occupational choice (24 occupations), and sectoral structure (25 sectors). This framework allows us to analyze how workers, both native and foreign, sort across locations and occupations based on comparative advantage, and how these sorting patterns interact with regional productivity differences, intersectoral linkages, and worker mobility. We calibrate the model using newly available micro-data from the Japanese Basic Survey of Wage Structure, which provides detailed information on foreign workers' wages and visa status.

Using this calibrated model, we conduct counterfactual analyses to assess both past and potential future immigration policies. By simulating a labor market autarky, we find an overall welfare gain from foreign employment; while this gain is quantitatively modest, ranging from 0.07% to 0.14%. Across our counterfactual scenarios, we also find substantial regional heterogeneity in the wage impacts of immigration, with low-skilled foreign workers having negative effects on low-skilled native wages in regions with high concentrations of these workers, contrasting with more dispersed impacts predicted by models assuming higher internal labor mobility. The service sector exhibits a greater reliance on foreign labor than commonly assumed, challenging the prevailing narrative focused on manufacturing. Furthermore, we find significant trade-offs between skill mix, welfare outcomes, and sectoral production. Maximizing national GDP favors high-skilled immigration, but maximizing the welfare of the least benefited group suggests a low-skilled share closer to current levels. Crucially, the optimal skill mix varies significantly across sectors, and interregional reallocation of labor plays a key role in shaping the overall impacts.

This paper contributes to the broader literature on the economic impacts of immigration (e.g., Borjas, 2003; Card, 2001; Ottaviano and Peri, 2012; Dustmann and Glitz, 2015; Peri and Sparber, 2009) by providing a detailed, regionally disaggregated analysis within a framework that explicitly models occupational choice and sectoral heterogeneity. Our findings highlight the importance of considering these factors when evaluating the consequences of immigration policy.

We also contribute to the understanding of the Japanese labor market, which has faced unique challenges due to its aging population and historical reluctance to embrace large-scale immigration. 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 differed depending on region and sectors. Our results reveal the complex and often localized impacts of foreign employment in Japan, challenging simplistic narratives and providing valuable insights for policymakers.

Finally, the framework developed in this paper provides a valuable toolkit for policymakers, allowing for a comprehensive assessment of the welfare, output, and wage implications of various immigration policies, as well as a comparison with domestic policy alternatives. This toolkit is particularly relevant for advanced economies facing similar demographic challenges, such as the United States (where the proportion of older adults is projected to reach 23% in the next 40 years, a level comparable to that of Japan in 2010).

The rest of this paper is structured as follows: Section 2 introduces the motivating empirical evidence, Section 3 outlines the quantitative model, Section 4 calibrates the model using the Japanese data, Section 5 conducts policy counterfactuals, and Section 6 presents a conclusion.

2 Motivating Facts

This section presents descriptive evidence highlighting the importance of spatial and occupational dimensions for understanding the impacts of immigration policy in Japan. We begin by illustrating the spatial distribution of foreign workers across Japanese prefectures. We then examine the occupational sorting of these workers. Finally, we present a naive reduced-form analysis of the wage impacts of foreign workers, providing motivation for the quantitative model developed in the next section.

Our primary data source is the Basic Survey of Wage Structure (*Chingin Kōzō Kihon Tōkei Chōsa*, Wage Survey, henceforth), conducted annually by the Ministry of Health, Labour, and Welfare (MHLW). This establishment-level survey covers over one million workers in all sectors except primary industries. The survey provides information on worker attributes (e.g., gender, age, education level), work hours, and monthly wages. Since the 2019 survey, the foreign employment section was introduced, and sampled foreign workers are required to report their residence status (visa category). *Importantly*, this is the first and only comprehensive administrative dataset in Japan that provides detailed information on foreign workers' wages and other characteristics. While the 2022 survey identified 11,330 foreign nationals out of 1,077,380 sampled workers (1.1%), this fraction is lower than the actual proportion of foreign workers in the Japanese labor force. Therefore, using the more accurate 2.7% figure from the Foreign Employment Survey, we inflate the foreign worker sample size within the Wage Survey by a constant factor. This inflation preserves the regional, occupational, and demographic (age, gender, and skill) composition observed in the Wage Survey while aligning the overall foreign worker fraction with the benchmark 2.7% value. In the following analysis, foreign worker numbers reflect this adjustment.[4]

To highlight the heterogeneous spatial and occupational distribution of workers of different types, we classify workers by skill level (high- and low-skilled) and gender (male and female). For domestic workers, we further partition the sample by age group: Youth (less than 29), Middle-age (30-59), and Elderly (60 and above). Skill level is defined by educational attainment, with "low-skilled" designating those without a four-year college degree. Due to the limited sample size, we do not stratify foreign workers by age group. The first row of Table 1 summarizes the composition of our sample by skill level, gender, and age group. The number of workers in each category is normalized to sum to 100, allowing each value to be interpreted as a percentage. While there are some minor differences in skill and gender composition between domestic and foreign workers, they are not substantial. High-skilled workers comprise 65% of domestic workers and 68% of foreign workers. Male workers account for 61% of domestic workers and 57% of foreign workers.

We now present the spatial distribution of domestic and foreign workers. Our analysis focuses on prefectures as the geographic unit. The 47 prefectures of Japan and their locations are shown in Figure 1. Figure 2 compares the geographic distribution of low-educated males (aged 30-59 for domestic workers, all ages for foreign workers) in 2022. The numbers in the figure represent the

[4]We measure the mass of workers using work hours from the Wage Survey to account for differences in part-time and full-time employment. We confirmed a strong correlation (0.99) between this work-hour-based measure and a headcount-based measure.

Table 1: Nuber of Workers and Average Wages by Worker Groups

	Japanese												Foreign			
	Low-Skilled						High-Skilled						Low-Skilled		High-Skilled	
	Male			Female			Male			Female			M	F	M	F
	Y	M	E	Y	M	E	Y	M	E	Y	M	E				
Number	6.0	24.7	5.5	5.0	19.1	4.5	3.9	16.3	2.5	3.0	6.4	0.4	1.0	0.8	0.5	0.4
Wage	75.7	117.7	84.0	67.0	81.3	66.5	82.6	144.6	118.0	75.8	90.7	93.6	57.5	51.3	83.6	61.2

Source: MHLW Wage Survey 2022.
Note: Youth (Y) 15–29, Middle-age (M) 30–59, and Elderly (E) 60+. Number of workers are summed up to 100.
Average wages are notmalized such that the average wage of across all workers is 100.

fraction of workers of a given type residing in each prefecture. For domestic workers, Tokyo has the largest share (11.5%), followed by Aichi (8.0%) and Osaka (6.4%). These three major urban areas account for a quarter of all domestic workers. For foreign workers, Tokyo again ranks first (15.1%), followed by its neighboring prefectures, Saitama (9.2%) and Kanagawa (7.1%). These top three regions account for nearly one-third of all foreign workers, suggesting a greater geographic concentration of foreign workers in a few key regions.

To highlight the heterogeneous spatial distribution of domestic and foreign workers, we estimate the following regression and analyze the residualized spatial distribution:

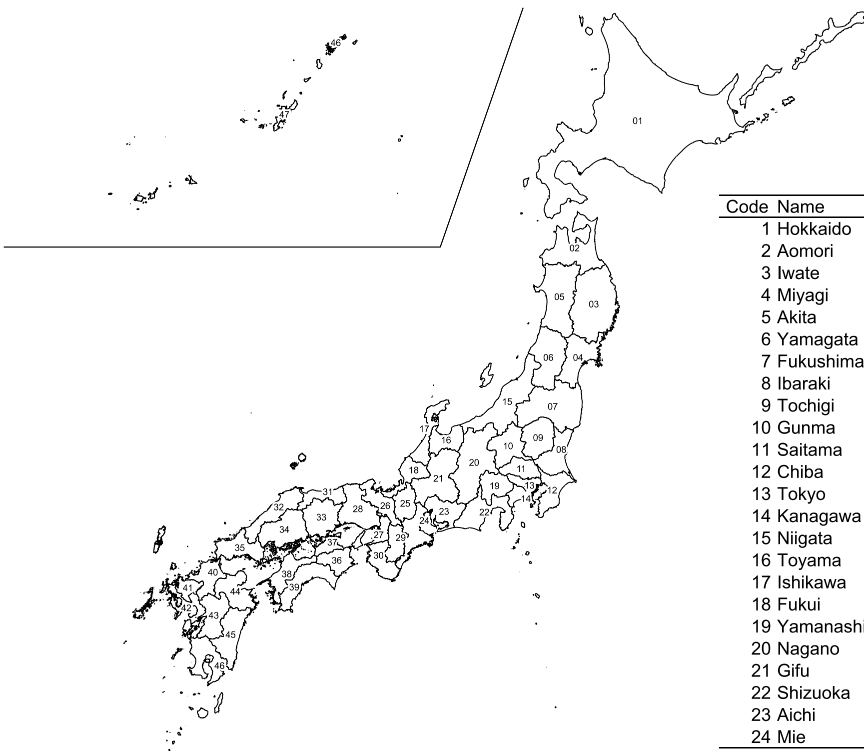
$$\psi_r(k) = \alpha + \alpha_W \overline{W}_r(k) + \sum_i \alpha_s^i s_r^i + \alpha_L L_r + \epsilon_r(k),$$

where $\psi_r(k)$ is the share of type k workers residing in region r, $\overline{W}_r(k)$ is the average wage adjusted by the consumer price index[5], s_r^i is the share of sector i employment, and L_r is the total population.[6] Figure 3 shows the residualized geographic distribution of low-educated males for domestic and foreign workers. Red (blue) regions indicate a higher (lower) concentration of workers than predicted by the model. Panel (b) reveals substantial variation in the geographic distribution of foreign workers unexplained by differences in real income, sectoral composition, and overall economic size (as captured by population). For example, Aichi and its neighbor Shizuoka (red) attract more foreign workers than predicted by these factors. Conversely, Tokyo (blue) has a lower concentration of foreign workers than expected, suggesting that its high share of foreign low-skilled workers is largely explained by its wages, sectoral composition, and population size. These findings suggest that amenities specific to different worker types *may play an important role* in understanding the spatial distribution of foreign workers.

We now turn our attention to the occupational distribution of workers. Using the mass of

[5] We use the prefectural consumer price index excluding housing prices.
[6] For the sectoral classification, see Section 4.

Figure 1: 47 Prefectures of Japan



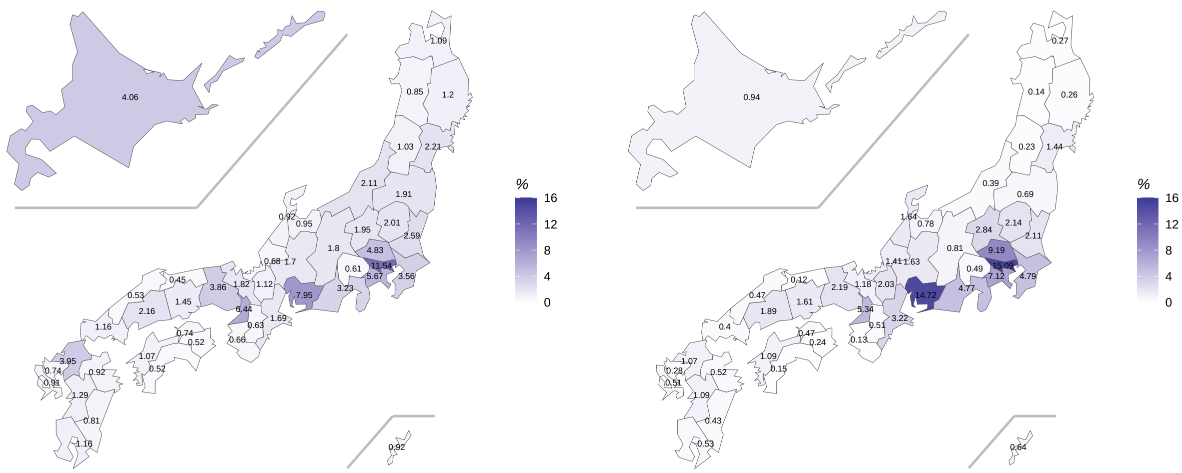
Code	Name	Code	Name
1	Hokkaido	25	Shiga
2	Aomori	26	Kyoto
3	Iwate	27	Osaka
4	Miyagi	28	Hyogo
5	Akita	29	Nara
6	Yamagata	30	Wakayama
7	Fukushima	31	Tottori
8	Ibaraki	32	Shimane
9	Tochigi	33	Okayama
10	Gunma	34	Hiroshima
11	Saitama	35	Yamaguchi
12	Chiba	36	Tokushima
13	Tokyo	37	Kagawa
14	Kanagawa	38	Ehime
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		

workers of a given type in each occupation, we calculate the fraction of workers in each of 25 occupations, classified according to the Japan Standard Occupational Classification (see Table 2). Figures 4 and 5 compare the occupational distributions of low- and high-education males, respectively, between domestic workers (aged 30-59) and foreign workers (all ages). In both figures, green bars represent domestic workers, and orange bars represent foreign workers. Occupations are sorted in descending order of the fraction of domestic workers in each occupation. The numbers in the figures indicate the fraction of workers employed in each occupation.

These figures reveal substantially different occupational sorting patterns between domestic and foreign workers, even after controlling for education level and gender. For low-education domestic males, the top occupations are Metal Product/Machinery Manufacturing (17%), Transport (13%), and Engineer (10%). In contrast, for foreign low-education males, the leading occupations are Metal Product/Machinery Manufacturing (33%), Construction (23%), and Food/Apparel/Wood Manufacturing (15%). Transport and Engineer occupations account for only 1% and 3% of foreign low-education male employment, respectively. Similar differences are evident for high-education males (Figure 5). The top three occupations for domestic high-education males are Clerical (18%), Engineer (18%), and Administrative (16%), while for foreign high-education males, they are Metal

Figure 2: Geographic Distribution of Low-Education Male (2022)

(a) Domestic (b) Foreign



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

Product/Machinery Manufacturing (25%), Food/Apparel/Wood Manufacturing (16%), and Construction (13%). These differences suggest that domestic and foreign workers may not compete directly in the labor market to the same degree, as the labor market is segmented by occupation.

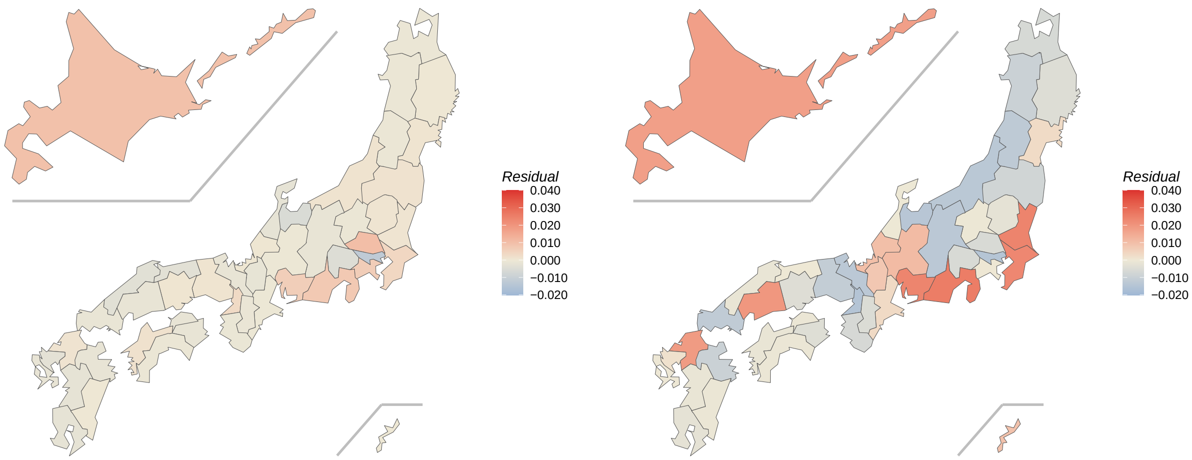
We also observe that the distribution of foreign low-education workers is highly concentrated in a few occupations. The top three occupations (Metal Product/Machinery Manufacturing, Construction, and Food/Apparel/Wood Manufacturing) account for nearly 70% of their employment. Given that these manufacturing occupations are concentrated in certain industries, this concentration of foreign workers may contribute to their geographic clustering, as observed earlier. In contrast, domestic high-education workers (compared with domestic low-education and foreign high-education workers) are concentrated in more generic occupations, such as Clerical, Engineer, and Administrative, which are utilized across many sectors. This difference in occupational specialization suggests that high- and low-education domestic workers may exhibit different mobility responses to regional immigration shocks.

Based on these findings, we now conduct a naive reduced-form analysis to explore potential empirical evidence of the wage impacts of foreign workers across different regions and occupations. Specifically, we estimate the following regression:

$$\log \Delta w_{rt}^{i}(s,o) = \beta_0 + \beta_1 m_{rt}(s) + \beta_2 m_t(s,o) + \beta_3 m_t^{i}(s) + \epsilon_{rt}^{i}(s,o),$$

Figure 3: Residualized Geographic Distribution of Low-Education Male (2022)

(a) Domestic (b) Foreign



Note: Figure shows the residualized spatial distribution of workers. See the text for the details.

where $\Delta w^i_{rt}(s, o)$ represents the logged change in average wages for worker group s in occupation o within industry i in region r between years $t-1$ and t. This change in wages is regressed on three measures of foreign worker inflows: (1) $m_{rt}(s)$, the inflow of foreign workers of type s into region r; (2) $m_t(s, o)$, the inflow of foreign workers of type s into occupation o; and (3) $m^i_t(s)$, the inflow of foreign workers of type s into industry i. The coefficients β_1, β_2, and β_3 capture the respective wage impacts of foreign worker inflows at the regional, occupational, and sectoral levels.

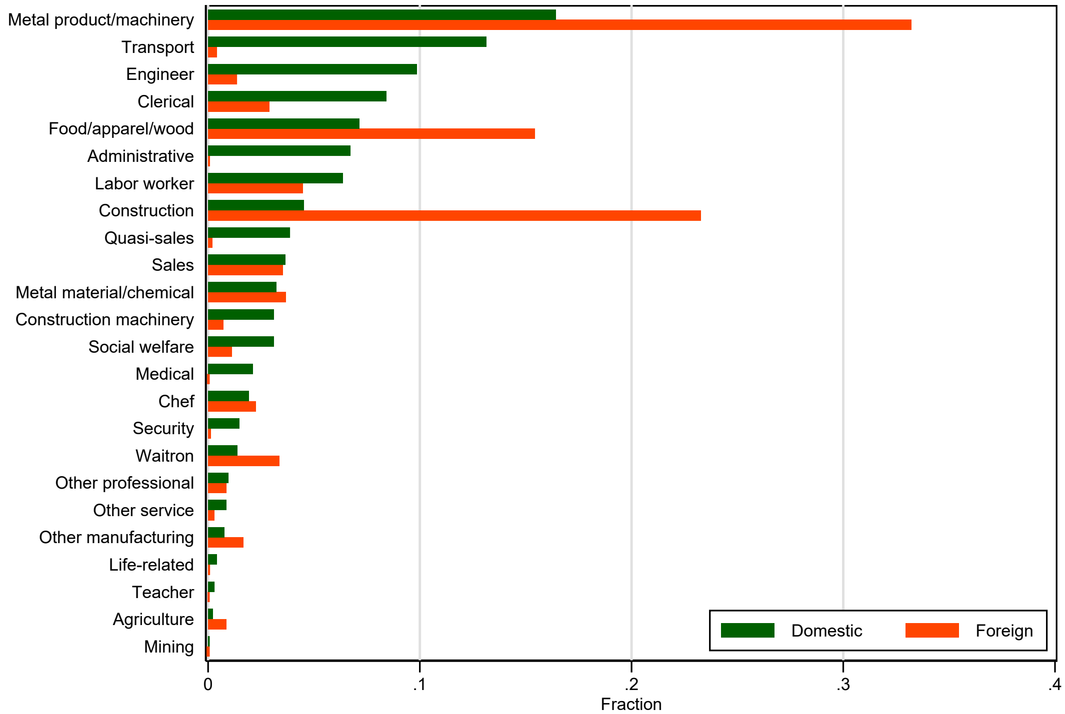
Estimating this regression requires data on wage changes and migration flows over time. We construct average wages across regions, occupations, and industries using the Wage Survey data from 1980, 1990, 2000, and 2010. Migration flows are constructed using the Census data for the corresponding years, conducted by the Ministry of Internal Affairs. A key limitation is that, until 2019, the Wage Survey did not separately identify wages for domestic and foreign workers. Therefore, our average wage calculations are based on all sampled workers, including any foreign workers potentially present in the sample. Furthermore, until 2019, the Wage Survey only recorded worker occupations if they appeared on a non-exhaustive list. Consequently, instead of using the disaggregated occupational classification described earlier, we aggregate occupations into four broader categories available in the data: administrative, clerical/engineering, production, and other. Finally, due to changes in sectoral classifications over time, we define six sectors: food manufacturing; metal manufacturing; machinery manufacturing; other manufacturing; construction; and services. Worker types are defined by gender and education level.

Table 2: List of Occupations

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

Table **??** summarizes the regression results. Our preferred specification, controlling for year, worker type, and region fixed effects, reveals that only the occupational immigration shock has a statistically significant negative impact on wages. This suggests that the inflow of foreign workers into a region does not imply negative wage effects. Rather, a negative impact is observed when foreign worker inflows are concentrated in occupations where domestic workers are also employed. In the next section, building on the motivating evidence presented here, we develop a spatial quantitative model that incorporates worker sorting into locations and occupations. Furthermore, the model also accounts for the rich regional heterogeneity in sectoral productivity and amenities that underlies the heterogeneous distribution of workers across space and occupations.

Figure 4: Occupational Distribution of Low-Education Male



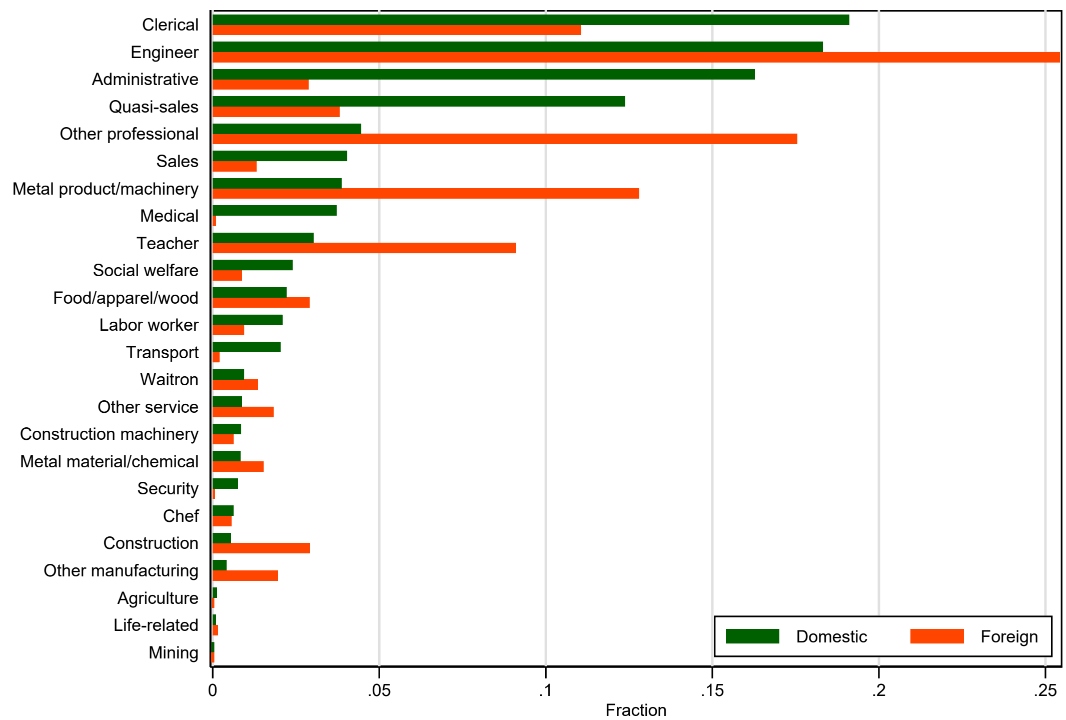
Note: workers of all ages are included for the foreign samples.
Source: MHLW Wage Survey (2022)

3 A Quantitative Framework

We develop a quantifiable spatial equilibrium model that features workers sorting into locations and occupations *à la* Roy (1951). The model features a finite number of domestic regions (prefectures) in Japan and the rest of the world (RoW). Regions are indexed by $r, m \in \{0, 1, 2, ..., R\}$, where region 0 refers to the RoW and R is the number of domestic regions. We denote the set of domestic regions as $\mathcal{R}$. Locations can differ from one another in terms of sectoral productivity, amenities, and geographic location relative to other regions. Labor is the only primary factor of production.

There is a continuum of workers indexed by z. Workers are partitioned into a finite number of groups. Each group is identified by the duplet (k, s), where $k \in \{D, F\}$ indicates Domestic or Foreign, and $s \in \mathcal{S}$ refers to other attributes of workers (education level, gender, and age group). The set of workers in group (k, s) in each country is given by $\mathcal{Z}(k, s)$ for Japan, which has the mass $L(k, s)$. We abstract from the workers' composition in the rest of the world. The set of workers in each country is exogenous in the model. A worker in Japan is mobile across domestic locations and determines the work location followed by the occupation choice. There is a finite number of

Figure 5: Occupational Distribution of High-Education Male



Note: workers of all ages are included for the foreign samples.
Source: MHLW Wage Survey (2022)

occupations indexed by $o \in \{1, 2, ..., O\} = \mathcal{O}$. At the predetermined work location, workers choose an occupation, inelastically supply one unit of labor, and consume a bundle of final goods.[7]

Lastly, there is a finite number of industries indexed by $i, j \in \{1, 2, ..., J\} = \mathcal{J}$. In each industry, there is a continuum of intermediate goods, which will be aggregated to form a final good. In the following subsections, we will consider workers and producers in Japan unless otherwise specified.

Consumer Preferences

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

$$u_r(z) = b_r(z)c_r(z).$$

[7]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.

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

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

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

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

where P_r^i is the price index of the final good i at region r, and 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 region $r \in \mathcal{R}$ across individuals. Following Redding (2016), we assume that the shocks are drawn independently across regions 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 region r for group (k, s) workers. Motivated by the empirical evidence presented in the previous section, 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 region r is given by:

$$v_r(z) = \frac{e_r(z)}{P_r} b_r(z), \tag{1}$$

where $e_r(z)$ is the nominal expenditure of worker z. As described below, workers choose work location before determining the occupation. Therefore, a worker forms expectations on the expenditure at each potential destination and choose the work location that maximizes the expected utility.

Occupation Production Units

Empirical evidence presented in the previous section highlighted substantial heterogeneity in occupational sorting between domestic and foreign workers. Furthermore, our naive reduced-form analysis suggested that the occupational inflow of immigrant workers is a key determinant of local labor market impacts. To model worker sorting into occupations, we follow Burstein et al. (2019, 2020) and introduce perfectly competitive occupation production units in each domestic region. Each unit hires labor, produces occupational services, and supplies them to intermediate good producers. This structure effectively segments the labor market by region and occupation.

The production function of each occupation production unit is linear in labor input, measured in efficiency units. Specifically, an occupation production unit o hiring l efficiency units of type (k, s) workers produces $S(k, s, o) \times l$ units of occupational service o. $S(k, s, o)$ represents the productivity of an efficiency unit of type (k, s) workers in occupation o, thus capturing the occupational comparative advantages of different worker types.

In addition to this *across-group* heterogeneity in efficiency, we also introduce *within-group* heterogeneity across individuals. We assume that a worker $z \in \mathcal{Z}_r(k, s)$ in region r supplies $\epsilon(z, o)$ efficiency units of labor if employed in occupation o. Each worker is endowed with a vector of $\epsilon(z, o)$ values for each o, allowing for variation in relative productivity across occupations. We assume that $\epsilon(z, o)$ is drawn independently across occupations from a Fréchet distribution with cumulative distribution function:

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

A worker chooses the occupation that offers the highest total compensation, given by $w_r(k, s, o) \times \epsilon(z, o)$, where $w_r(k, s, o)$ is the wage per efficiency unit of labor in occupation o in region r. This probabilistic formulation of within-worker heterogeneity in efficiency across occupations generates worker self-selection into occupations, consistent with Roy's (1951) assignment framework.[8]

Let $l_r(k, s, o)$ denote the total efficiency units of labor supplied by workers of group (k, s) in region r who choose occupation o. The occupational service produced by these workers is then given by:

$$\ell_r(k, s, o) = S_r(k, s, o) l_r(k, s, o).$$

[8]The Fréchet-Roy framework also introduces the curvature necessary to ensure that every region-occupation pair is populated with a positive mass of workers.

We assume that labor services produced by different worker types s within both native (D) and foreign (F) worker groups are perfectly substitutable. However, labor services produced by native and foreign workers are imperfect substitutes. Specifically, the aggregate output of occupation service o is given by a CES aggregate of labor services across different worker types:

$$\ell_r(o) = \left(\left(\sum_{s\in\mathcal{S}} \ell_r(D,s,o) \right)^{\frac{\xi-1}{\xi}} + \left(\sum_{s\in\mathcal{S}} \ell_r(F,s,o) \right)^{\frac{\xi-1}{\xi}} \right)^{\frac{\xi}{\xi-1}},$$

where $\xi > 0$ is the elasticity of substitution between domestic and foreign workers. The corresponding price index for occupation service o is:

$$p_r(o) = \left((p_r(D,o))^{1-\xi} + (p_r(F,o))^{1-\xi} \right)^{\frac{1}{1-\xi}},$$

where $p_r(k,o)$ represents the price of the occupation service produced by type k workers in region r. We abstract from occupation choices of workers in the rest of the world.

Intermediate Good Producers

The production side of the model is a Ricardian trade model, following Eaton and Kortum (2002), with sectoral roundabout production *à la* Caliendo and Parro (2015). In each sector i, there exists a unit continuum of intermediate goods indexed by $\kappa^i \in (0,1)$. The production of each κ^i requires two types of inputs: composites of occupational services and intermediate inputs from all sectors. Producers of intermediate goods differ in efficiency. Let $a_r^i(\kappa^i)$ denote the efficiency of producing intermediate good κ^i in sector i in region $r \in \{0,1,2,...,R\}$. Intermediate good κ^i is produced according to the following constant returns to scale production function:

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

where $y_r^i(\kappa^i)$ is the output of intermediate good κ^i, $\ell_r^i(\kappa^i)$ is the input of the composite occupation service, and $m_r^{j,i}(\kappa^i)$ is the intermediate input from sector j. The parameters $\beta^{\ell,i}$ and $\beta^{j,i}$ represent the cost shares of the composite occupation service and sector j input, respectively, such that $\beta^{\ell,i} + \sum_{j\in\mathcal{I}} \beta^{j,i} = 1$ for all i.

The composite occupation service is a Cobb-Douglas bundle of all occupation services:

$$\ell_r^i(\kappa^i) = \prod_{o \in \mathcal{O}} \left(\frac{\ell^i(o, \kappa^i)}{\gamma^i(o)} \right)^{\gamma^i(o)},$$

where $\ell^i(o, \kappa^i)$ is the input of occupation service o and $\gamma^i(o)$ is the cost share of occupation service o in the total cost of occupation services, such that $\sum_{o \in \mathcal{O}} \gamma^i(o) = 1$ for all i.

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

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

where the location parameter T_r^i governs the average productivity of sector i at region r and the shape parameter θ^j¿1 governs the dispersion of productivity. The location parameter captures the regional heterogeneity in sectoral composition, e.g., Aichi with its auto-sector orientation will have higher average productivity in that sector.

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

$$\tilde{c}_r^i = (\rho_r^{\ell,i})^{\beta^{\ell,i}} \prod_{j \in \mathcal{J}} (P_r^j)^{\beta^{j,i}}, \tag{2}$$

where $\rho_r^{\ell,i}$ is the corresponding Cobb-Douglas price index for the composite occupational services for section j,

$$\rho_r^{\ell,i} = \prod_{o \in \mathcal{O}} \left(p^i(o) \right)^{\gamma^i(o)}, \tag{3}$$

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

Final Good Producers

A perfectly competitive final good producer in each sector aggregates intermediate goods to form the sectoral final good. The final good producer in sector i at region $r \in \{0, 1, 2, ...R\}$ purchases intermediate good κ^i from the lowest-cost suppliers across locations and combines through the CES aggregator:

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

where $q_r^i(\kappa^i)$ is the demand for intermediate goods κ^i from the lowest-cost supplier and $\sigma^i > 0$ 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:

$$P_r^i = \left[\int_{\kappa^i \in [0,1]} p_r^i(\kappa^i)^{1-\sigma^i} d\kappa^i \right]^{\frac{1}{1-\sigma^i}}. \tag{4}$$

We assume that the final goods are non-tradable.

3.1 Equilibrium

Final Good Price Indices and Expenditure Shares

We assume that trade in intermediate goods is costly, and that there are standard iceberg trade costs. One unit of an intermediate good in sector i shipped from location m to location r requires producing $\tau_{mr}^i \geq 1$ units and $\tau_{mm}^i = 1$ for all $m \neq r \in \{0, 1, ..., R\}$. A final good producer in sector i sources each intermediate good κ^i from the lowest-cost supplier after taking into account the trade costs. Therefore, the price of intermediate good κ^i in sector i at the destination location r is

$$p_r^i(\kappa^i) = \min_{m \in \{0,1,...,R\}} \left\{ \frac{c_m^i \tau_{mr}^i}{a_m^i(\kappa^i)} \right\}.$$

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

$$P_r^i = \Gamma^i \left(\sum_{m \in \{0,1,...,R\}} T_m^i (c_m^i \tau_{mr}^i)^{-\theta^i} \right)^{-1/\theta^i}, \tag{5}$$

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:

$$\pi^i_{mr} = \frac{T^i_m (c^i_m \tau^i_{mr})^{-\theta^i}}{\sum_{m' \in \{0,1,\ldots,R\}} T^i_{m'} (c^i_{m'} \tau^i_{m'r})^{-\theta^i}}. \tag{6}$$

We label π^i_{mr} as the bilateral trade share. The bilateral trade share of goods sourced from region m is increasing in the average productivity T^i_m and decreasing in the cost of input bundle c^i_m and trade cost τ^i_{mr}.

Worker's Occupational Choice

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

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

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 offers the highest 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:

$$\varphi_r(k,s,o) = \frac{(S(k,s,o) p_r(k,o))^{\zeta}}{\sum_{o' \in \mathcal{O}} (S(k,s,o') p_r(k,o'))^{\zeta}}. \tag{7}$$

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

Let $\overline{w}_r(k,s,o)$ be the average wage of group (k,s) worker in occupation o at location r. The average wage, conditional on workers self-selecting into occupations, can be computed as:

$$\overline{w}_r(k,s,o) = \tilde{\Gamma} S(k,s,o) p_r(k,o) \left(\varphi_r(k,s,o)\right)^{-1/\zeta},$$

where $\tilde{\Gamma} = \Gamma(1 - 1/\zeta)$. By substituting $\varphi_r(k,s,o)$ with the expression obtained in equation (7), we have:

$$\overline{w}_r(k,s,o) = \overline{w}_r(k,s) = \tilde{\Gamma} \left(\sum_{o \in \mathcal{O}} (S(k,s,o) p_r(k,o))^{\zeta} \right)^{1/\zeta}. \tag{8}$$

This implies that the expected wage conditional on working in o is the same across all occupations. In our model, the more attractive occupation characteristics of o for group (k, s) workers, such as higher productivity $S(k, s, o)$ and higher price $p_r(k, o)$, 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 $z \in \mathcal{Z}(k, s)$ chooses the work location after observing the idiosyncratic preference shocks $b_r(z)$ but before drawing the idiosyncratic efficiency shocks $\varepsilon(z, o)$. Therefore, the individual's location choice depends on the expected income at each destination. Expected income (expenditure) is given by:

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

where the second equality follows from equation (8). Combined with the expression of the indirect utility in equation (1), the probability that a worker $z \in \mathcal{Z}(k, s)$ chooses to locate in the region $r \in \mathcal{R}$ is given by:

$$\psi_r(k, s) = \frac{B_r(k, s) \left(\overline{w}_r(k, s)/P_r\right)^{\eta}}{\sum_{m \in \mathcal{R}} B_m(k, s) \left(\overline{w}_m(k, s)/P_m\right)^{\eta}}, \tag{9}$$

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

$$L_r(k, s) = \psi_r(k, s) L(k, s). \tag{10}$$

Market Clearing

Let $I_r(o)$ be total labor income earned by workers in occupation o at location r:

$$I_r(o) = \sum_{k \in \mathcal{K}, s \in \mathcal{S}} \overline{w}_r(k, s) L_r(k, s, o) \tag{11}$$

where $L_r(k,s,o)$ is the mass of group (k,s) workers in occupation o at location r,

$$L_r(k,s,o) = \varphi_r(k,s,o)L_r(k,s) \tag{12}$$

Then, the total household expenditure at domestic location r is given by:

$$E_r = \begin{cases} (1+\omega)\sum_{o\in\mathcal{O}} I_r(o) & \text{for } r \in \mathcal{R} \\ \sum_{o\in\mathcal{O}} I_r(o) - \omega \sum_{m\in\mathcal{R}} \sum_{o\in\mathcal{O}} I_m(o) & \text{for } r = 0 \end{cases} \tag{13}$$

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

$$X_r^i = \sum_{j\in\mathcal{I}} \beta^{i,j} Y_r^j + \alpha^i E_r, \tag{14}$$

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 household expenditure. Y_r^i is the gross output (total revenue) of sector j, which can be expressed as the sum of sales.

$$Y_r^i = \sum_{m\in\{0,1,\ldots,R\}} \pi_{r,m}^i X_m^i. \tag{15}$$

Equation (14) and (15) implies that trade is balanced across domestic regions.

The occupation service market clearing condition is given by:

$$\sum_s \overline{w}_(k,s)L_r(k,s,o) = \left(\frac{p_r(k,o)}{p_r(o)}\right)^{1-\xi} \sum_{i\in\mathcal{I}} \beta^{\ell,i}\gamma^i(o)Y_r^i, \tag{16}$$

where the left-hand side is the supply of occupation service o produced by type k workers in value, and the right-hand side is the demand.

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 average wages $\{\overline{w}_r(k,s)\}_{k,s,r}$, prices of final goods $\{P_r^i\}_{r,i}$ and occupation services $\{p_r(k,o)\}_{k,r,o}$, 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 (2), (3), (4), (5), (6), (7), (8), (9), (10), (11), (12), (13), (14), (15),* *and* (16) *for all* k, s, r, o, i.

3.2 Equilibrium in Relative Changes

Using the model, we will conduct a counterfactual exercise to assess the impacts on equilibrium outcomes of immigration policies and other labor market policy alternatives. Specifically, we are interested in the aggregate implications of changes in the mass of workers of a given type. Let $\{L(k,s)\}_{k,s}$ be the factual mass of workers and $\{L'(k,s)\}_{k,s}$ be the counterfactual mass. Keeping everything else unchanged, we will compare the equilibrium under $\{L(k,s)\}_{k,s}$ with the equilibrium under $\{L'(k,s)\}_{k,s}$. Rather than solving the two equilibria in level, we solve the change in equilibrium from the one under $\{L(k,s)\}_{k,s}$ to the one under $\{L'(k,s)\}_{k,s}$. We define it as an *equilibrium in relative changes* and we will employ the exact hat algebra *à la* Dekle et al. (2008). This allows us match exactly the model to the data in a base year and identify the effects on equilibrium outcomes from the policy shocks without calibrating fundamentals that are difficult to estimate empirically.

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* $\{\overline{w}_r(k,s)\}_{k,s,r}$, $\{P_r^i\}_{r,i}$, $\{p_r(k,o)\}_{r,k,o}$, $\{L_r(k,s)\}_{r,k,s}$, *and* $\{L_r(k,s,o)\}_{r,k,s,o}$ *be an equilibrium under* $\{L(k,s)\}_{k,s}$ *and* Θ, *and let* $\{\overline{w}'_r(k,s)\}_{r,k,s}$, $\{P_r'^i\}_{r,i}$, $\{p'_r(k,o)\}_{r,k,o}$, $\{L'_r(k,s)\}_{r,k,s}$, *and* $\{L'_r(k,s,o)\}_{r,k,s,o}$ *be an equilibrium under* $\{L'(k,s)\}_{k,s}$ *and* Θ'. *Define* $\{\hat{\overline{w}}_r(k,s)\}_{r,k,s}$, $\{\hat{P}_r^i\}_{r,i}$, $\{\hat{p}_r(k,o)\}_{r,k,o}$, $\{\hat{L}_r(k,s)\}_{r,k,s}$, *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:

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

cost of input bundle:

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

price of composite occupation service:

$$\hat{\rho}_r^{\ell,i} = \prod_{o\in\mathcal{O}} \left(\hat{p}^i(o)\right)^{\gamma^i(o)},$$

price of each occupation service:

$$\hat{p}_r(o) = \left(\frac{(p_r(D,o))^{1-\xi}}{(\hat{p}_r(o))^{1-\xi}} (\hat{p}_r(D,o))^{1-\xi} + \frac{(p_r(F,o))^{1-\xi}}{(\hat{p}_r(o))^{1-\xi}} (\hat{p}_r(F,o))^{1-\xi} \right)^{\frac{1}{1-\xi}},$$

sectoral price index:

$$\hat{P}_r^i = \left(\sum_{m\in\{0,1,\ldots,R\}} \hat{T}_m^i \left(\hat{c}_m^i \hat{\tau}_{m,r}^i\right)^{-\theta^i} \pi_{m,r}^i \right)^{-1/\theta^i}.$$

bilateral trade share:

$$\hat{\pi}_{m,r}^i = \frac{\hat{T}_m^i \left(\hat{c}_m^i \hat{\tau}_{m,r}^i\right)^{-\theta^i}}{\sum_{m'\in\{0,1,\ldots,R\}} \hat{T}_{m'}^i \left(\hat{c}_{m'}^i \hat{\tau}_{m'r}^i\right)^{-\theta^i} \pi_{m',r}^i}.$$

occupation choice probability:

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

average wage:

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

location choice probability:

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

mass of workers in each region:

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

total labor income earned by individuals in each occupation:

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

occupation market clearing:

$$\hat{I}_r(o) = \sum_{i\in\mathcal{I}} \frac{\beta^{\ell,i}\gamma^i(o)Y_r^i}{\sum_{j\in\mathcal{I}}\beta^{\ell,i}\gamma^j(o)Y_r^j}\hat{Y}_r^i,$$

total household expenditure:

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

total spending:

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

gross output:

$$\hat{Y}_r^i = \sum_{m\in\{0,1,\ldots,R\}}\hat{\pi}_{r,m}^i\hat{X}_m^i\frac{\pi_{r,m}^iX_m^i}{\sum_{m'\in\{0,1,\ldots,R\}}\pi_{r,m'}^iX_{m'}^i}.$$

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

By inspecting the equilibrium conditions above, we can see that solving for an equilibrium in relative changes allows us to perform policy counterfactuals without calibrating fundamental parameters such as average regional amenities, worker type-specific productivity, and trade costs. Solving for an equilibrium in relative changes requires us to compute variables such as workers' regional and occupational allocation ($L_r(k,s)$ and $L_r(k,s,o)$), bilateral trade shares (π_{mr}^i), average wages ($\bar{w}_r(k,s)$), and so forth. We label these variables "base year equilibrium outcomes," which we condition on when solving for an equilibrium in relative changes. As described in the next section, all the base year equilibrium outcomes for domestic regions in Japan are observable in the data. However, for the rest of the world, some of these, such as the mass of workers and average wages by different groups, are not observable. Therefore, when conducting counterfactual analyses, we fix wages and prices of occupation services in the rest of the world. In addition to the base year equilibrium outcomes, we need to calibrate structural parameters such as the Cobb-Douglas

Table 3: List of Industries

1	Food	13	Utility
2	Textile	14	Construction
3	Paper	15	Commerve
4	Chemical	16	Transportation
5	Ceramic	17	Restaurants
6	Raw metal	18	Telecommunication
7	Metal product	19	Information
8	Machinery	20	Finance
9	Electronics	21	Real estate
10	Electric	22	Professional service
11	Vehicle	23	Education
12	Other manufacturing	24	Health
		25	Other serive

coefficients in the utility and production functions, the shape parameters in the Fréchet-distributed shocks, and the elasticity of substitution between domestic and foreign workers. We will outline our calibration strategy in the next section.

4 Calibration

We will calibrate the model using the Japanese data. We define our units of analysis in the quantification as follows: we consider 47 prefectures and the rest of the world (see Figure 1). Workers are classified by Japanese or foreign (k) and other attributes (s). Domestic workers are partitioned into 12 types by education level (edu, high-education and low-education), gender (sex, male and female), and age groups (age, Youth: 15–29, Middle-aged: 30–59, and Elderly: +60). High-education refers to a 4-year college degree or more (excluding 2-year junior college). Due to the limited number of sampled foreign workers in the data, we omit the age groups from the worker's attribute and partition them into 4 types based on education level and genders. In our notation, s is a vector of $\{edu, sex, age\}$ for domestic worker ($k = D$) and $\{edu, sex\}$ for foreign worker ($k = F$). We consider 24 occupations based on the Japan Standard Occupation Classification, listed in Table 2. Lastly, we consider 25 industries covering manufacturing and service sectors, summarized in Table 3. Sectoral classification is based on the Inter-Prefectural Input-Output Table 2011 compiled by Research Institute of Economy, Trade, and Industry (RIETI). We rule out the primary sectors (agriculture, forestry, and fishery) and mining due to the data availability.

The primary data source for the calibration is the Wage Survey. See Section 2 for the details. We complement the MHLW Wage Survey with the Basic Survey of Employment Structure (*Shūgyō*

Kōzō Kihon Chōsa) conducted by the Ministry of Internal Affairs and Communications (MIC). The MIC Employment Survey is a household-level survey conducted every five years. Individuals aged 15 and older report their employment status. We also use several other sources of data: price deflators (consumer price indices) are taken from the Retail Price Survey (Ministry of Internal Affairs and Communications, 2015) and Consumer Price Index (Ministry of Internal Affairs and Communications, 2020) conducted and compiled by the Ministry of Internal Affairs and Communications. The bilateral distance across prefectures is sourced from Geospatial Information Authority of Japan (n.d.). We also use the Inter-Prefectural Input-Output (IO) Table compiled by Research Institute of Economy, Trade, and Industry (RIETI) and OECD Inter-Country IO Table (OECD, 2019) to construct the inter-prefectural bilateral trade flow matrix. We will discuss the use of the IO table in detail below.

4.1 Calibration of Structural Parameters

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 OECD Inter-Regional IO Table. We use data for 2019, the latest year available before the pandemic. We assume that parameter values differ between Japan and the rest of the world, but are the same across domestic regions. We drop primary sectors (i.e., agriculture, forestry, and fishery) when calibrating the parameter values. Expenditure share on occupation services within a sector, $\gamma^i(o)$, is computed using data from the MHLW Wage Survey 2022. Specifically, we compute the total wage bill by occupation and sector to compute the occupational expenditure share accordingly.

The remaining structural parameters to be calibrated are the shape parameter of the amenity shock, η, the efficiency shocks ζ, the productivity shock θ^j, and the elasticity of substitution between native and foreign workers ξ^i. We outline how to construct the moment conditions to estimate those parameters. Then we show the estimation results. From here on, we index variables by time subscript t. For a generic variable x, let $\hat{x}_t$ be the relative change in variable x between any two consecutive periods t and $t' > t$, i.e, $\hat{x}_t = x_{t'}/x_t$.

From the equilibrium condition (9), we have:

$$\psi_{rt}(k,s) = \frac{B_r(k,s)\left(\overline{w}_{rt}(k,s)/P_{rt}\right)^{\eta}}{\Upsilon_t(s)}$$

where $\Upsilon_t(k,s) = \sum_{r\in\mathcal{R}} B_{r'}(k,s)\left(\overline{w}_{rt}(s)/P_{rt}\right)^{\eta}$ is the multilateral resistance term. Taking logs, we have the following moment condition:

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

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.

Unobserved shocks to location choice probabilities may affect average wages. For example, a positive shock to a region that attracts more workers could lower average wages due to increased labor supply, potentially leading to biased OLS estimates. To address this potential endogeneity, we construct an instrument. Following Tombe and Zhu (2019), we construct a Bartik-style expected income as follows:

$$\mathbb{E}\left[\overline{w}\right]_{r,t}(k,s) = \sum_i \lambda_{rt}(k,s)^i \overline{w}^i_t(k,s)$$

where $\lambda_{rt}(k,s)^i$ is the fraction of type (k,s) workers in sector i in region r at time t, and $\overline{w}^i_t(k,s)$ is the average wage of type (k,s) workers in sector i nationwide at time t.

Location choice probabilities and average wages by region, worker type, and industry are constructed using the MIC Employment Survey from 1997 to 2017. This survey does not identify an individual's nationality; therefore, we define worker types based on gender, education level, and age, i.e., dropping native-foreign identifier from the equation k. Furthermore, recognizing that workers are less likely to relocate after the age of 60, we exclude individuals in this age group from our estimation. The Employment Survey reports annual workdays, weekly work hours, and annual income using bins rather than exact values. For instance, the 2017 survey uses 12 bins for weekly work hours: less than 15 hours, 15-19 hours, ..., and more than 74 hours per week. We assign the midpoint of each bin's range as the representative value, except for the first and last bins. For example, we use 17 hours for the 15-19 hours/week bin. For the first and last bins, we use the upper and lower bounds, respectively (e.g., 14 and 75 hours/week for the first and last bins). [9]

To measure location choice probabilities, we calculate the mass of workers by region and worker type based on total work hours.[10] We then derive hourly wages using reported annual income,

[9] Because the bin ranges may vary across survey years (later surveys have more granular bins), we redefine the bins to ensure consistency over time.

[10] We use the sample weights associated with each observation to calculate aggregate work hours for each worker

Table 4: 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

annual workdays, and weekly work hours. Average wages are then computed for each worker group within each region. These average wages are deflated using the consumer price index (CPI).[11]

Table 4 summarizes the estimation results. As anticipated from the preceding discussion, the point estimate of η under OLS is lower than the IV estimate. The IV estimate yields a point estimate of 0.64, a value we will employ for the quantitative exercise. This estimate aligns closely with Yuta (2199)'s finding of 0.49 for Japan. For broader context, Balboni (2025) report an elasticity of 0.33 for Vietnam, while Tombe and Zhu (2019) and Fajgelbaum et al. (2019) find notably higher figures of 1.8 for Chinese provinces and 1.5 for U.S. states, respectively.

We estimate the shape parameter of the Fréchet efficiency shock ζ by leveraging the moments of the wage distribution. The identification strategy follows Bryan and Morten (2019), Fan (2019) and Hsieh et al. (2019). The second moment of the wage distribution conditional on individual self-selecting into occupations are given by,

$$\overline{w^2}_r(k,s) = \Gamma\left(\frac{\zeta-2}{\zeta}\right)\left(\sum_o w_r(s,o)^{\zeta}\right)^{\frac{2}{\zeta}}$$

where $\Gamma(\cdot)$ is the gamma function. Therefore, the variance of the wage distribution is given by,

$$\begin{aligned}\mathrm{Var}\left(w_r(k,s)\right) &= \overline{w^2}_r(k,s) - \left(\overline{w}_r(k,s)\right)^2 \\ &= \left(\sum_o w_r(s,o)^{\zeta}\right)^{\frac{2}{\zeta}}\left(\Gamma\left(\frac{\zeta-2}{\zeta}\right) - \Gamma\left(\frac{\zeta-1}{\zeta}\right)^2\right)\end{aligned}$$

group and region.

[11] We construct a panel CPI comparable across prefectures and over time by combining the cross-sectional CPI at the prefecture level in 2015 (national average = 100) with the time-series CPI for each prefecture from 1992 to 2017 (CPI in 2020 normalized to 100).

This suggest that the variance to the squared mean ratio is a function ζ, specifically,

$$\frac{\mathrm{Var}\left(w_r(k,s)\right)}{\left(\overline{w}_r(k,s)\right)^2} = \frac{\Gamma\left(\frac{\zeta-2}{\zeta}\right) - \Gamma\left(\frac{\zeta-1}{\zeta}\right)^2}{\Gamma\left(\frac{\zeta-1}{\zeta}\right)^2}$$

Guided by this relationship, we first regress individual wages on the fixed effects of region (r) and worker type (k,s) to compute the variance and mean of the residualized wage. We then can calibrate ζ such that the ratio of variance to squared mean matches the above expression. Our estimates ranges from 2.95 to 3.14, which is in line the estimates in the previous work; 1.8 of Burstein et al. (2019), 2.69 for Bryan and Morten (2019) and 2.5-2.7 for Fan (2019). We use 2.95 as the value of ζ in the quantitative exercise.

The elasticity of substitution between domestic and foreign workers are calibrated in the the spirit of Ottaviano and Peri (2012). They consider the constant-returns-to-scale production function with the nested CES structure in aggregating different types of workers including native and foreign as well as skills and gender. Our production function speficiation has the same nested structure with more simple assumption where the 1st teer is Cobb-Douglas, second tier is the CES with elasticity of substitution ξ, and the third tier is the perfect substitution. Following their identification strategy, we estimate the following equation:

$$\ln\left(\frac{w^i_{r,t}(F,s,o)}{w^i_{r,t}(D,s,o)}\right) = -\frac{1}{\xi}\ln\left(\frac{l^i_{r,t}(F,s,o)}{l^i_{r,t}(F,s,o)}\right) + \delta_t + \delta^i(o,s) + \epsilon^i_{r,t}(s,o)$$

where the left-hand-side variable is the relative average wage of foreign to domestic workers of group s in occupation o in sector i in region r at time t. The right-hand-side variable is the relative employment share. We constructed the data from the Wage Survey for the period from 2020 to 2022. The estimated coefficent $(-1/\xi)$ is displayed in Table 5. The point estimate of -0.0815 implies that the elasticity of substitution between domestic and foreign workers is 12.3, which is in the range of the estimates 11–33 by Ottaviano and Peri (2012) .

Lastly, the Fréchet shape parameters for sectoral productivity θ^i are externally calibrated from Caliendo and Parro (2015) for manuacturing sectors. As our sectoral classification is more aggregated, we use the simple average of the point estimates across sub-sectors within each sector. For the service sectors, we apply 3/4 of the manufacturing trade elasticity (4.55) following Gervais and Jensen (2019).

Table 5: Native-Foreign Elasticity of Substitution

	Relative Wage
ln(relative employment)	-.0815
	(.001872)
Year FE	YES
Type-occupation-industry FE	YES
Observations	34,623

Standard errors in parentheses

4.2 Base Year Equilibrium Outcomes

In the policy counterfactuals, we solve equilibriua in relative changes, conditioning on the equilibrium outcomes in 2022. We construct the average wages at the worker type and region levels, the mass of workers at the worker type, region, and occupation levels, and occupational expenditure shares for each sector using the MHLW Wage Survey 2020. In the Wage Survey, temporary workers are not required to report their education attainment. Sampled workers with missing education information account for approximately 11% of the observations. More importantly, among sampled foreign workers, education is missing for 34% of the samples. To impute the missing education, we first assume that workers below 22 are low-education, since 22 is the age at which students graduate from the 4-year colleges. Given the nature of each visa classification, we assume that foreign workers who are admitted under the visa categories of Professor, Highly Skilled Professionals, Education, Engineer, and Specialist in Humanities and International Services are high-education. Those admitted under the Technical Intern Trainee Program are assumed to be low-education. This leaves 62% of sampled foreign workers with missing education. We drop the rest of the observations from the sample[12].

We computed the mass of workers based on the work hours as described in Sectoin 2.Average wages by region and worker type, $\overline{w}_r(k, s)$, are also computed based on the hourly wages. Individual hourly wage is computed by summing up the scheduled wage and the bonus.[13] Having the mass of workers and the average wages in hand, we then compute the value added by region according to equations (11), which we will use later.

The inter-prefectural IO table compiled by Research Institute of Economy, Trade, and Industry

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

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

(RIETI) provides data for bilateral trade flows across 47 Japanese prefectures. However, directly calculating bilateral trade shares for our model from this dataset is not feasible due to two key limitations: first, the absence of sectoral external import and export data at the regional level, and second, the requirement to drop primary and mining sectors to ensure IO table consistency with our model. Consequently, we proceed with the following steps, in the spirit of Eckert (2019), that leverages the Inter-Prefectural IO Table, national IO table, and the model.

First, using the Inter-Prefectural IO Table from Research Institute of Economy, Trade, and Industry (RIETI), we construct bilateral iceberg trade costs for each sector across prefectures, assuming symmetric costs and following (Head and Ries, 2001). This allows us to compute the Head-Ries Index (HRI) using the observed bilateral trade flows X_{rm} as follows:

$$HRI^{i}_{rm} = \sqrt{\frac{X^{j}_{rm}}{X^{j}_{mm}}\frac{X^{j}_{mr}}{X^{j}_{rr}}} = \tau^{-\theta}_{rm} (= \tau^{-\theta^{j}}_{mr})$$

We assume that the trade costs between the RoW and Japanese regions are twice as high as the trade costs between the most distant pair of domestic regions.

Second, we compile a national IO table without primary sectors using OECD (2019) data. Dropping these sectors breaks the IO table identity so we need to adjust the table to restore this identity while preserving the selected sectors. This process generates gross and net exports to the rest of the world for each sector. Details are provided in Appendix B.

Third, we impute inter-prefectural bilateral trade shares, in the spirit of Eckert (2019), using the HRIs, the adjusted national IO table with external trade, and sectoral value-added by sector and prefecture computed above. This recovers bilateral trade shares that are consistent with observed external trade and our model. This imputation ensures balanced bilateral trade across domestic regions. The imputation method is detailed in Appendix B.

With imputed inter-prefectural trade shares, we then recover model-consistent base year total expenditure (X^{i}_{r}) and gross output (Y^{i}_{r}) by region and sector. This is achieved by solving equations (14) and (15), given total household expenditure (E_r) and the bilateral trade share (π^{i}_{mr}). Further details are available in Appendix C.

5 Policy Counterfactuals

This section uses counterfactual analyses to explore the gains from foreign employment in the Japanese economy, both retrospectively and prospectively. Using 2022 as our base year, we examine two distinct policy scenarios. First, to quantify the current contribution of foreign workers to aggregate welfare and output, we simulate a labor market autarky by eliminating all foreign workers, approximating pre-1990s immigration restrictions. Second, we investigate the potential of expanded foreign employment as a future policy option to address Japan's declining birth rate and shrinking working-age population. This future-oriented analysis compares the effectiveness of increased levels of foreign employment with domestic labor market alternatives, specifically policies encouraging female and elderly labor force participation. We then further refine this analysis by exploring the implications of different skill compositions among foreign workers.

In the following counterfactuals, we will examine the welfare implications implied by the model. In our framework, the aggregate welfare of each type of worker can be assessed as an ex-ante expected utility. Formally, it can be expressed as:

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

5.1 Move to Labor Market Autarky

Table 6 summarizes the welfare implications of a move to labor market autarky, showing percentage changes relative to the 2022 base year. We consider the elimination of all foreign workers (first column), only low-skilled foreign workers (second column), and only high-skilled foreign workers (third column).

The first column shows that every group of domestic workers, regardless of skill, gender, or age, is worse off in a move to labor market autarky, implying an aggregate welfare gain from foreign employment. The welfare loss for low-skilled workers ranges from 0.10% to 0.14%, while the loss for high-skilled workers ranges from 0.07% to 0.13%. Importantly, the magnitude of the welfare loss is generally larger for low-skilled workers, indicating that they benefit more from the presence of foreign workers.

The second and third columns show the welfare implications of eliminating only low-skilled or high-skilled foreign workers, respectively. Eliminating only low-skilled foreign workers results in a small welfare *gain* (0.02%) for low-skilled male workers aged 15–29, while all other groups are

Table 6: Change in Welfare (Moving to Labor Market Autarky)

			Elimination of ...		
			All workers	Low-skilled	High-skilled
Low-skilled	Male	15-29	-0.10	0.02	-0.11
		30-59	-0.10	0.00	-0.10
		60+	-0.11	-0.01	-0.10
	Female	15-29	-0.13	-0.05	-0.09
		30-59	-0.14	-0.06	-0.08
		60+	-0.14	-0.03	-0.11
High-skilled	Male	15-29	-0.07	-0.08	0.01
		30-59	-0.07	-0.08	0.01
		60+	-0.09	-0.07	-0.02
	Female	15-29	-0.09	-0.09	0.00
		30-59	-0.09	-0.09	0.00
		60+	-0.13	-0.09	-0.04

Note: numbers are in percentage.

worse off. Female low-skilled workers experience a welfare loss, but of smaller magnitude than under complete autarky. Eliminating only high-skilled foreign workers makes all domestic low-skilled workers worse off (approximately by 0.10%), while high-skilled workers aged below 60 *gain* by 0.01%. These results are consistent with the occupational sorting patterns presented in Table 6, which shows the correlation between the occupations of domestic and foreign workers. Within the framework of our model, where workers self-select into occupations based on comparative advantage, the higher correlation in occupational choices observed within each skill group suggests a greater similarity in occupational comparative advantages between domestic and foreign workers of the same skill level. This pattern of occupational sorting implies greater direct competition in the labor market between domestic and foreign workers within the same skill group, as workers with similar comparative advantages are more likely to compete for the same jobs. This direct competition explains why domestic low-skilled young men benefit from the removal of low-skilled foreign workers and domestic high-skilled benegit from the removal of high-skilled foreign workers.

Table 7 summarizes the changes in regional real wages for different types of domestic workers, showing the prefectures with the maximum and minimum changes for each group. The key takeaway is that, despite the overall welfare gains from foreign employment for all groups (as shown in Table 6), there is substantial heterogeneity in real wage impacts across regions.

For instance, under a move to labor market autarky (complete elimination of foreign workers), the real wage for low-skilled male workers aged 30–59 *decreases* by 0.18% in Yamanashi, contrasting with a 0.03% increase in Tokyo. This demonstrates that the real wage impacts can vary significantly

Figure 6: Correlations of Occupational Sorting

across regions, even within the same worker group.

Looking at the second scenario, with a complete elimination of *only* low-skilled foreign workers, we find further evidence of regional heterogeneity. For example, the real wages of low-skilled *male* workers increase by 0.14% in Mie and 0.08% in Aichi, part of the Tokai region – a manufacturing cluster with a high concentration of low-skilled foreign workers. Conversely, in Kochi, a prefecture with low concentrations of foreign workers, *the real wage declines by* 0.09%.

These results demonstrate that the impact of foreign worker presence on domestic wages is highly localized. *Areas* with higher concentrations of foreign workers tend to experience more varied wage effects (including some positive effects), while *those with* lower concentrations tend to experience negative wage effects when foreign workers are removed. This finding contrasts with Monras (2019), who argues that immigration shocks are dissipated across regions due to the internal migration of native workers. Our results suggest that, in the Japanese context, the impact of immigration remains highly localized, possibly reflecting lower internal labor mobility.

Finally, we examine the sectoral production implications. Table 8 summarizes the changes in national GDP, as well as sectoral GDP, showing the maximum and minimum changes across prefectures under the different scenarios. Under the complete elimination of foreign workers, national GDP declines by approximately -1%. The service sector GDP experiences a larger decline

Table 7: Change in Real Wages (Moving to Labor Market Autarky)

			All workers				Low-Skilled				High-Skilled			
			Min		Max		Min		Max		Min		Max	
Low	Male	15–29	Yamanashi	-0.19	Tokyo	0.08	Kochi	-0.09	Mie	0.14	Mie	-0.26	Tokyo	-0.03
		30–59	Yamanashi	-0.18	Tokyo	0.03	Kochi	-0.08	Mie	0.14	Mie	-0.26	Tokyo	0.00
		60+	Saitama	-0.20	Tokyo	0.04	Shimane	-0.10	Mie	0.13	Mie	-0.24	Okinawa	-0.03
	Female	15–29	Gunma	-0.30	Tokyo	0.05	Fukui	-0.19	Tokyo	0.10	Yamanashi	-0.14	Miyazaki	-0.02
		30–59	Fukui	-0.29	Tokyo	0.03	Fukui	-0.21	Tokyo	0.02	Gunma	-0.13	Tokyo	-0.01
		60+	Fukui	-0.33	Tokyo	0.04	Fukui	-0.24	Tokyo	0.18	Mie	-0.17	Miyazaki	-0.04
High	Male	15–29	Yamanashi	-0.21	Tokyo	0.04	Saitama	-0.10	Hyogo	-0.02	Gunma	-0.12	Tokyo	0.15
		30–59	Fukui	-0.19	Tokyo	0.04	Fukui	-0.13	Hyogo	-0.02	Yamanashi	-0.11	Tokyo	0.15
		60+	Fukui	-0.23	Tokyo	0.05	Fukui	-0.16	Mie	0.00	Gunma	-0.12	Tokyo	0.11
	Female	15–29	Fukui	-0.31	Tokyo	0.04	Fukui	-0.24	Hyogo	-0.05	Yamanashi	-0.13	Tokyo	0.11
		30–59	Fukui	-0.31	Tokyo	0.04	Fukui	-0.24	Hyogo	-0.05	Nagano	-0.12	Tokyo	0.10
		60+	Gunma	-0.39	Tokyo	0.06	Fukui	-0.27	Tokyo	-0.02	Yamanashi	-0.15	Tokyo	0.08

Note: numbers are in percentage.

(-1.01%) than the manufacturing sector GDP (-0.70%), highlighting the service sector's increasing reliance on foreign labor. This finding challenges the prevailing narrative, which often focuses on the manufacturing sector's dependence on foreign workers.

When only low-skilled foreign workers are removed, the national GDP decline is -0.50%. Notably, the impact on the manufacturing sector is relatively small (-0.08%), while the service sector again experiences a more substantial decline (-0.61%). On the other hand, with the elimination of only high-skilled foreign workers, the national GDP drops by -0.40%. In this scenario, the service sector shows a smaller decline (-0.38%) compared to the manufacturing sector (-0.60%).

Beyond these sectoral differences, significant regional heterogeneity also exists. For example, under the complete autarky scenario, GDP in Fukui prefecture declines by -3.50%. This result is surprising, given that Fukui has a relatively low concentration of foreign workers (as reflected in the real wage changes shown in Table 7). Examining the reallocation of workers across prefectures, we find a general trend of workers moving from prefectures with lower concentrations of foreign workers (such as Fukui) to those with higher concentrations (such as Tokyo). This may be driven by increased wages in the regions with initially higher foreign worker concentrations, due to the removal of foreign labor, making regions with initially lower foreign worker concentrations less attractive to domestic workers. Consequently, the GDP decline in these less-populated regions can be larger than in regions with initially higher concentrations of foreign workers. This highlights the importance of interregional worker reallocation in shaping the overall production impacts of immigration.

5.2 Expanding Foreign Employment and Domestic Labor Policy Alternatives

We next examine the potential of expanded foreign employment as a future policy option to address Japan's shrinking native population. We consider the impact of an increase in foreign employment equivalent to 10% of the current number of domestic workers. This 10% increase would roughly restore the working-age population to its 1995 peak level. We analyze three scenarios: an increase in low-skilled foreign workers, an increase in high-skilled foreign workers, and an increase that maintains the current skill composition of the foreign workforce. In addition to these scenarios, we also evaluate the potential impacts of domestic policy alternatives, specifically policies designed to encourage greater labor force participation among women and older workers.

Figure 7 summarizes the welfare changes under these different policy scenarios. The vertical axis measures the percentage change in welfare. For each domestic worker type, labeled on the

Figure 7: Change in Welfare (Expanding Labor Supply)

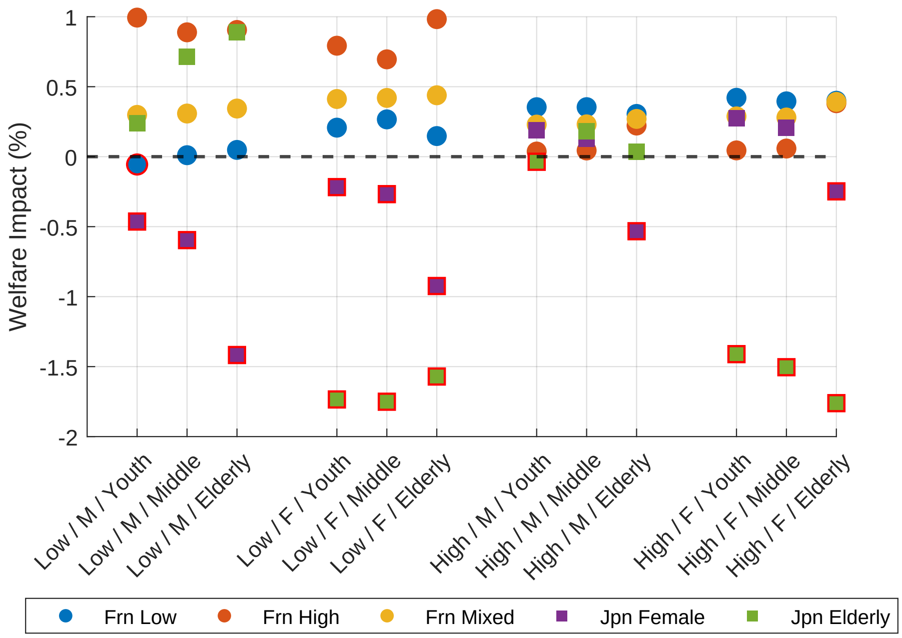


Table 8: Change in Output (Moving to Labor Market Autarky)

	All workers					Low-Skilled					High-Skilled				
	National	Min		Max		National	Min		Max		National	Min		Max	
GDP	-0.93	Fukui	-3.50	Iwate	-0.52	-0.50	Fukui	-3.11	Iwate	-0.54	-0.40	Tokyo	-1.50	Iwate	0.03
Manufacturing	-0.71	Tokyo	-4.46	Iwate	0.81	-0.08	Tokyo	-4.46	Iwate	0.81	-0.60	Tokyo	-4.46	Iwate	0.81
Food	-1.04	Tokyo	-1.73	Akita	-0.65	-0.73	Fukui	-1.25	Akita	-0.54	-0.29	Tokyo	-0.67	Akita	-0.10
Textile	-0.82	Tokyo	-2.45	Kochi	-0.20	-0.41	Mie	-1.24	Nagano	-0.04	-0.38	Tokyo	-1.31	Kochi	-0.05
Paper	-0.91	Tokyo	-3.02	Ishikawa	0.56	-0.38	Tokyo	-1.28	Ishikawa	0.40	-0.50	Tokyo	-1.66	Wakayama	0.23
Chemical	-0.49	Tokyo	-9.98	Kochi	3.86	0.94	Mie	-2.11	Kagoshima	4.93	-1.38	Tokyo	-7.53	Shiga	0.44
Ceramic	-0.83	Tokyo	-1.73	Shimane	-0.19	-0.46	Mie	-0.73	Kagoshima	-0.18	-0.35	Tokyo	-1.03	Shimane	0.01
Raw metal	-0.59	Tokyo	-2.53	Kochi	0.04	-0.18	Mie	-0.92	Kagoshima	0.25	-0.39	Tokyo	-1.80	Kochi	-0.04
Metal product	-0.88	Tokyo	-2.60	Kochi	-0.16	-0.49	Mie	-1.13	Kochi	-0.13	-0.36	Tokyo	-1.48	Shimane	0.00
Machinery	-0.69	Tokyo	-1.43	Kochi	-0.19	-0.45	Tokyo	-0.65	Kochi	-0.17	-0.22	Tokyo	-0.73	Kochi	-0.02
Electronics	-0.59	Tokyo	-4.45	Fukui	0.96	0.19	Mie	-0.76	Fukui	0.77	-0.75	Tokyo	-3.82	Fukui	0.18
Electric	-0.63	Tokyo	-3.94	Fukui	0.87	0.00	Mie	-0.84	Fukui	0.80	-0.60	Tokyo	-3.02	Shiga	0.15
Vehicle	-0.58	Tokyo	-1.29	Wakayama	-0.17	-0.39	Tokyo	-0.64	Wakayama	-0.15	-0.18	Tokyo	-0.61	Kochi	0.00
Other	-0.92	Tokyo	-2.65	Kochi	-0.17	-0.49	Tokyo	-1.15	Aomori	-0.02	-0.41	Tokyo	-1.43	Kochi	-0.09
Service	-1.01	Tokyo	-1.81	Hokkaido	-0.13	-0.61	Tokyo	-1.81	Hokkaido	-0.13	-0.38	Tokyo	-1.81	Hokkaido	-0.13
Utility	-0.97	Tokyo	-2.39	Fukuoka	-0.29	-0.60	Mie	-1.16	Fukuoka	-0.27	-0.35	Tokyo	-1.48	Shiga	0.08
Consurtcution	-1.07	Mie	-1.94	Iwate	-0.39	-0.79	Saitama	-1.49	Fukuoka	-0.45	-0.26	Tokyo	-0.64	Shimane	0.12
Commerce	-0.87	Tokyo	-2.06	Shimane	0.10	-0.41	Mie	-0.95	Shiga	-0.01	-0.44	Tokyo	-1.24	Iwate	0.21
Transportation	-0.90	Tokyo	-2.27	Tokushima	-0.06	-0.48	Mie	-1.31	Tokushima	-0.11	-0.39	Tokyo	-1.32	Kochi	0.07
Hospitality	-1.03	Mie	-1.92	Fukuoka	-0.39	-0.71	Mie	-1.27	Fukuoka	-0.36	-0.30	Tokyo	-0.64	Kochi	0.07
Telecom	-1.03	Tokyo	-1.67	Fukushima	0.34	-0.65	Mie	-1.14	Iwate	-0.18	-0.35	Tokyo	-0.92	Fukushima	0.72
Information	-1.12	Tokyo	-1.80	Wakayama	0.35	-0.47	Mie	-0.80	Akita	0.12	-0.63	Tokyo	-1.22	Shizuoka	0.68
Finance	-1.00	Mie	-1.87	Oita	-0.02	-0.63	Mie	-1.13	Iwate	-0.20	-0.35	Tokyo	-0.97	Ehime	0.41
Real estate	-1.07	Tokyo	-1.65	Niigata	0.74	-0.80	Mie	-1.37	Iwate	-0.35	-0.25	Tokyo	-0.77	Niigata	1.08
Professional service	-0.97	Tokyo	-1.94	Ishikawa	0.48	-0.46	Mie	-0.92	Akita	0.02	-0.49	Tokyo	-1.31	Ishikawa	0.66
Education	-1.07	Mie	-2.16	Iwate	-0.31	-0.79	Fukui	-1.65	Iwate	-0.40	-0.25	Mie	-0.85	Iwate	0.10
Health	-1.07	Tokyo	-2.07	Iwate	-0.34	-0.80	Mie	-1.44	Iwate	-0.46	-0.25	Tokyo	-1.06	Kochi	0.18
Other	-1.05	Mie	-1.83	Iwate	-0.31	-0.75	Fukui	-1.41	Iwate	-0.39	-0.28	Tokyo	-0.68	Kochi	0.17

Note: numbers are in percentage.

Table 9: Change in GDP (Expanding Labor Supply)

	Foreign Employment Policy			Domestic Policy	
	Low-skilled	High-skilled	Mix	Female	Elderly
GDP	2.31	3.78	2.87	7.30	6.48
Manufacturing	0.45	5.41	2.14	7.35	6.41
Service	2.85	3.30	3.08	7.28	6.50

horizontal axis, five symbols represent the welfare change for each policy scenario; a red border indicates a welfare loss. As expected, increasing female labor supply (purple) and senior labor supply (green) results in substantial welfare losses for female and elderly workers, respectively. Increasing the number of low-skilled foreign workers (blue) results in a welfare loss for low-skilled *male* workers aged 15–29, but welfare gains for all other groups. Increasing the number of foreign workers within a specific skill group (high-skilled in orange, low-skilled in blue) generally leads to larger welfare gains for domestic workers *of the same skill group* (with the exception of low-skilled young men in the low-skilled worker scenario) compared to increasing a mix of low- and high-skilled foreign workers (yellow).

In terms of production, Table 9 summarizes the changes in national GDP, as well as manufacturing and service output. The table shows that encouraging the participation of domestic female workers leads to the largest increase in GDP, followed by policies encouraging senior labor market participation. This reflects the higher average productivity of these groups (as indicated by their higher average wages, summarized in Table 1). Among the foreign employment policies, increasing the number of high-skilled foreign workers results in the largest GDP and sectoral output growth. However, foreign employment policies also exhibit more heterogeneous sectoral impacts compared to domestic policies. For instance, increasing the number of high-skilled foreign workers leads to a 5.4% increase in manufacturing output and a 3.3% increase in service output, while increasing female and elderly worker participation leads to increases of 7.3% and 6.4%, respectively, across both sectors. This suggests that targeted foreign employment policies could be a more effective tool for addressing specific sectoral needs or revitalizing particular industries. We further examine the sectoral implications of varying the skill composition of foreign workers below.

We now turn to a more detailed examination of the welfare and sectoral production implications of expanding foreign employment, focusing on the optimal skill mix. We maintain the overall expansion size at 10% of the current domestic workforce, but vary the proportion of low- and high-skilled foreign workers. To evaluate the welfare implications of different skill mixes, we use a welfare criterion in the spirit of a Rawlsian social welfare function. Specifically, we focus on:

$$U_{D,Min} = \min_{s} \hat{U}(D, s)$$

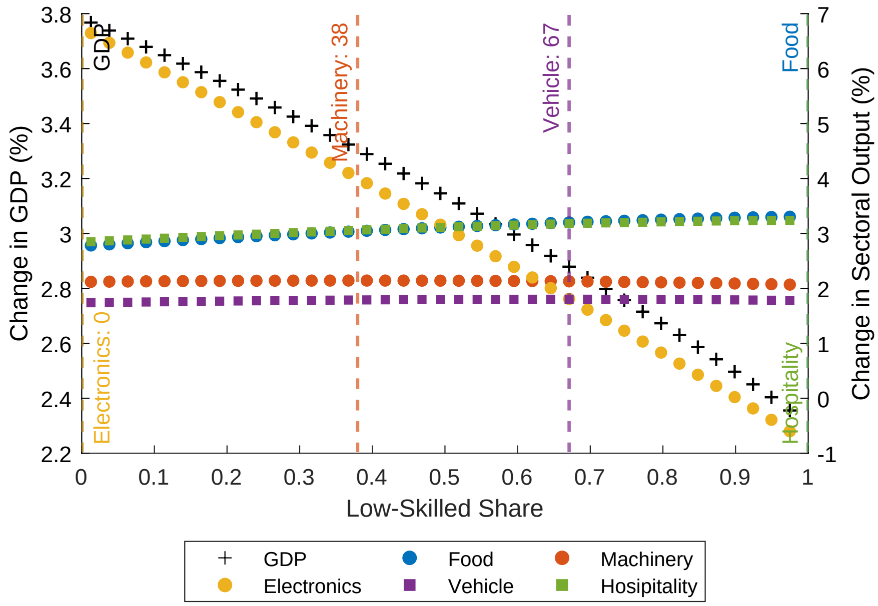
which gauges the welfare implications for the domestic worker group experiencing the minimum welfare change. This criterion allows us to identify the group that benefits the least from each policy and to evaluate which policy provides the greatest benefit to this group.

Figure **??** shows the minimum welfare change (welfare change of the least benefited group) across different skill mixes. The vertical axis measures the minimum welfare change (in percentage change). The horizontal axis represents the fraction of low-skilled foreign workers in the expanded workforce. A low-skilled share of 1 corresponds to the scenario with only low-skilled foreign workers (as in the first scenario of Figure 7), while a share of 0 corresponds to the scenario with only high-skilled foreign workers (as in the second scenario). The red *vertical* line marks the base-year low-skilled share (0.68), corresponding to the third scenario in Figure 7.

The figure shows that the *least benefited* group is high-skilled males aged 15–29 until the low-skilled share reaches approximately 0.72; beyond that point, the *least benefited* group becomes low-skilled males aged 15–29. This is consistent with our earlier findings. To maximize the welfare of the *least benefited* group, the optimal low-skilled share in the newly admitted foreign workforce is approximately 0.72. This suggests that the current skill composition of foreign workers is relatively close to the welfare-maximizing mix.

We then compare the production implications of different skill mixes. Figure 8 shows the changes in national GDP (percentage change, left vertical axis) and sectoral output for selected sectors (percentage change, right vertical axis). Again, the horizontal axis represents the low-skilled share of the expanded foreign workforce. The sectors shown are food, machinery, electronics, vehicles, and hospitality services (lodging and restaurants). The figure shows that *maximizing* national GDP requires minimizing the low-skilled share (i.e., admitting only high-skilled workers). Although maximizing GDP requires minimizing the low-skilled share, the optimal skill mix for specific sectors varies significantly. For instance, maximizing output in the electronics sector also requires minimizing the low-skilled share. However, the optimal low-skilled share is approximately 0.38 for maximizing output in the machinery sector, and 0.67 for the vehicle sector, a key industry in Japan. Conversely, maximizing output in the food manufacturing and hospitality sectors requires maximizing the low-skilled share (i.e., admitting only low-skilled workers). This result highlights that the optimal skill mix of newly admitted foreign workers depends critically on the specific

Figure 8: Change in Aggregate Welfare



sectoral objectives of the policy.

In conclusion, our analysis reveals a complex interplay between skill mix, welfare outcomes, and sectoral production. Maximizing national GDP favors a high-skilled immigration policy, but maximizing the welfare of the least benefited group suggests a low-skilled share closer to the current level. Furthermore, the optimal skill composition varies significantly across sectors. These findings highlight the need for a nuanced approach to foreign employment policy in Japan, one that carefully considers the trade-offs between different objectives and tailors policies to specific sectoral needs.

6 Conclusion

This paper developed a quantitative spatial general equilibrium model to evaluate the labor market and production impacts of foreign employment in Japan, incorporating regional, occupational, and sectoral heterogeneity. Using newly available micro-data, we calibrated the model to the Japanese economy and conducted counterfactual analyses to assess both past and potential future immigration policies. By simulating a labor market autarky, we find an overall welfare gain from foreign employment; while this gain is quantitatively modest, ranging from 0.07% to 0.14%. Across our counterfactual scenarios, we also find substantial regional heterogeneity in the wage impacts of immigration, with low-skilled foreign workers having negative effects on low-skilled native wages in regions with high concentrations of these workers, contrasting with more dispersed impacts predicted by models assuming higher internal labor mobility. The service sector shows a greater reliance on foreign labor than commonly assumed, challenging the prevailing narrative focused on manufacturing. Furthermore, we find a complex interaction between skill mix, welfare outcomes, and sectoral production. Maximizing national GDP favors high-skilled immigration, but maximizing the welfare of the least benefited group suggests a low-skilled share closer to current levels. Crucially, the optimal skill mix varies significantly across sectors, and interregional reallocation of labor plays a key role in shaping the overall impacts. The framework developed in this paper provides a valuable toolkit for analyzing the multifaceted impacts of immigration – on welfare, output, and wages – in diverse economic contexts, accounting for regional, occupational, and sectoral heterogeneity.

Appendices

A Sequence of Worker's Decisions

A.1 Suggestive Evidence

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

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

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.

B Imputation of Interregional Trade Flow

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

B.1 Constructing the IO Table without Primary Sectors

Table B1 shows the illustrative example of national IO table that consists of Japan. J and F refer to the country, Japan (J) and foreign (F). The Table consists of three sectors, agriculture (Agri), manufacturing (Manf), and Service (Serv). $M^{i,j}_{r,m}$ is the intermediate input from country r to m from sector i to$j$, VA^i is the value added in sector i, $FD^i_{r,m}$ is final demand of sector i in region m sourced from region r, and $GO^i_{sales} = GO^i_{inpur}$ is the gross output of sector i at sales side and input side.

Table B1: Illustrative Example of IO Table

	Source	Agri	Manf	Serv	FD	EXP	GO
Agri	J	$M^{A,A}_{J,J}$	$M^{A,M}_{J,J}$	$M^{A,S}_{J,J}$	$FD^A_{J,J}$	$FD^A_{J,F}$	GO^A_{sales}
Manf	J	$M^{M,A}_{J,J}$	$M^{M,M}_{J,J}$	$M^{M,S}_{J,J}$	$FD^M_{J,J}$	$FD^M_{J,F}$	GO^M_{sales}
Serv	J	$M^{S,A}_{J,J}$	$M^{S,M}_{J,J}$	$M^{S,S}_{J,J}$	$FD^S_{J,J}$	$FD^S_{J,F}$	GO^S_{sales}
Agri	F	$M^{A,A}_{F,J}$	$M^{A,M}_{F,J}$	$M^{A,S}_{F,J}$	$FD^A_{F,J}$		
Manf	F	$M^{M,A}_{F,J}$	$M^{M,M}_{F,J}$	$M^{M,S}_{F,J}$	$FD^M_{F,J}$		
Serv	F	$M^{S,A}_{F,J}$	$M^{S,M}_{F,J}$	$M^{S,S}_{F,J}$	$FD^S_{F,J}$		
VA		VA^A_J	VA^M_J	VA^S_J			
GO		GO^A_{input}	GO^M_{input}	GO^S_{input}			

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

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

We then repeat the following steps:

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

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

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

2. Compute value added share of sector i

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

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

3. Compute the intermediate input share,

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

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

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

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

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

6. Analogously compute the intermediate inputs

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

7. Compute the final demand sourced domestically

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

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

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

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

B.2 Impute the Bilateral Trade Shares across Prefectures

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

$$\frac{VA^i_r}{\sum_{r'} VA^i_{r'}}$$

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

$$\tilde{VA}^i_r = \tilde{VA}^i$$

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

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

Now, $\{Y^i_r\}^r_k$ and $\{X^i_r\}^i_r$ are data. For each sector, we have:

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

From the market clearing condition, we have

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

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

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

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

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

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

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

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

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

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

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

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

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

4. Using the results in the previous steps, compute

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

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

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

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

C Constructing Gross Output and Total Expenditure

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

$$VA_r^{Data} = \sum_{k,s} \overline{w}_r^{Data}(k,s) L_r^{Data}(k,s)$$

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

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

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

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

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

We can recover the model implied value added as:

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

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

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

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