Immigration and Sectoral Reallocation: Evidence from Japan*

Takahiro Hasebe†

Abstract

This study examines the impact of immigration on the local labor market outcomes in Japan between 2010 and 2020. Exploiting regional variation in immigrant inflows, I find that immigration increases native employment while having modest effects on aggregate wages. Industry-level estimates reveal substantial heterogeneity across sectors: native employment expands in sectors that have recently absorbed immigrants and contracts modestly in manufacturing. Evidence from job-transition patterns suggests that sectoral reallocation of native workers is a key adjustment mechanism in Japan. These results are consistent with the implications of a multi-sector specific factors model.

Keywords: Immigration; local labor markets; sectoral reallocation; native employment; Japan

*I am grateful to my advisor, Daiji Kawaguchi, for his invaluable guidance and continued support. All remaining errors are my own.

†Graduate School of Economics, The University of Tokyo, 7-3-1 Hongo, Bunkyoku, Tokyo 113-0033, Japan; Email: takahiro0514@g.ecc.u-tokyo.ac.jp

1 Introduction

Over the past several decades, Japan has experienced a persistent decline in its working-age population. This trend represents one of the most rapid demographic transitions in the world. As the domestic labor supply contracts, foreign workers have increasingly played an important role in the labor market. Between 2010 and 2020, the number of immigrants increased sharply in Japan. According to the Population Census, the share of foreign nationals in the working-age population nearly doubled from 1.6% in 2010 to 3.1% in 2020.[1] While the level of the immigrant share remains low relative to other developed countries, the rate of increase suggests potential impacts on the labor market. Despite growing public and policy concerns, empirical evidence on the labor market effects of immigration in Japan remains limited.

This paper examines the impact of immigration on the local labor market outcomes in Japan over the period 2010–2020. I focus on the effects on native employment and aggregate wages, exploiting variation in immigrant shares across prefectures. To address potential endogeneity concerns highlighted in the existing literature, I use a shift-share (Bartik) instrument based on historical settlement patterns of immigrants.

The empirical analysis yields two main findings. At the aggregate level, immigrant inflows are associated with increases in native employment but have modest effects on wages. To explore underlying mechanisms, I extend the analysis to the industry level, motivated by the fact that immigrants in Japan are unevenly distributed across industries. At the industry level, the estimates reveal substantial heterogeneity across sectors: employment gains are concentrated in industries that have recently received immigrant inflows, while manufacturing, traditionally an immigrant-intensive sector, exhibits a modest decline in native employment.

A central finding of this study is that these heterogeneous patterns are shaped by sectoral adjustment through the reallocation of native workers. By analyzing worker transition patterns, I demonstrate that the decline in manufacturing employment represents reallocation rather than displacement. Especially, workers who leave the manufacturing sector appear to be transitioning into expanding sectors. These results suggest that immigration in Japan acts as a catalyst for shifting the native workforce toward industries with growing labor demand.

This finding contributes to the literature on immigration and industry-level adjustment by providing novel evidence that immigration induces between-industry adjustment through the reallocation of native workers. Much of the existing literature is motivated by the Heckscher–Ohlin (HO) framework, which predicts that immigration shocks are accommodated through changes in industry structure. In the standard HO model, industries differ in their factor intensities, and immigrants are generally assumed to be low-skilled workers. As a result, an increase in immigrant workers induces the expansion of low-skill–intensive industries without affecting relative wages.

However, empirical studies have found limited support for this prediction. In the U.S., Lewis (2003) and Card and Lewis (2007) show that immigration-induced supply shocks are

[1] Most studies define immigration by country of birth. In Japan, however, official statistics record nationality rather than place of birth. Accordingly, this paper defines immigrants based on nationality and uses foreign nationals or foreign workers interchangeably to refer to the immigrant population.

absorbed primarily through within-industry changes in factor intensity as opposed to shifts in industry composition. Similar patterns are documented by González and Ortega (2011) in the context of Spain's large immigration wave, where employment expansion occurred largely within industries. Furthermore, using firm-level data for Germany, Dustmann and Glitz (2015) show that firm heterogeneity can mask between-industry responses and find that the majority of adjustment occurs within firms through changes in factor intensity.

Unlike much of the existing literature, my empirical analysis suggests that between-industry adjustment is a primary mechanism in the Japanese context. I interpret these findings through a specific factors model, in which native workers are mobile across industries while immigrant workers face limited mobility across industries in the short run. In this framework, immigration shocks induce reallocation of native employment across sectors. The direction and magnitude of this reallocation depend on the degree of substitutability or complementarity between native and immigrant workers.

The study most closely related to this paper is Braun and Kvasnicka (2014), which shows that the large influx of expellees into postwar West Germany accelerated structural change from agriculture to manufacturing. Using a simple two-sector specific factors model, they demonstrate that immigrants were disproportionately absorbed into the manufacturing sector, thereby fostering structural transformation. In contrast, this paper documents a distinct channel of immigration-induced structural change: between-industry adjustment operates primarily through the reallocation of native workers, alongside the sectoral absorption of immigrants.

This paper also contributes to the broader literature on the labor market effects of immigration. A seminal paper by Altonji and Card (1991) adopts a spatial approach that exploits regional variation in immigrant shares and finds modest effects on native wages and employment. This geographic approach has been widely adopted in the literature.

However, Borjas (2003) raises a critique of this strategy by exploiting national-level variation across education–experience groups. He finds larger negative wage effects and argues that estimates based on regional variation may be attenuated because local labor markets are not closed systems. In this view, native workers may respond to local immigration shocks by migrating to other regions, which obscures the true effects of immigration shocks.

This paper adopts a spatial approach in the spirit of Altonji and Card but explicitly addresses the concerns raised by Borjas. Using prefecture-level variation in Japan while examining population movements across regions, I provide direct evidence on whether immigration effects are mitigated through spatial adjustment.

Following this approach, a substantial literature has examined the labor market effects of immigration in various countries (e.g., Dustmann et al., 2013; Foged and Peri, 2016; Dustmann et al., 2017). Empirical evidence on Japan, however, remains relatively scarce. One notable exception is Nakamura et al. (2009), which provides a comprehensive analysis of the labor market effects of immigration in Japan during the 1990s and early 2000s.[2] Using municipality-level data from 1990 to 2000, they find no evidence of adverse effects on wages. However, they document labor-supply adjustments, in particular through the out-migration of native men and the exit of native women from the labor force. More recently, Sasahara et al. (2023) examine long-run wage effects interacted with the China shock, showing that

[2]A summary of their main findings is provided in Nakamura (2010).

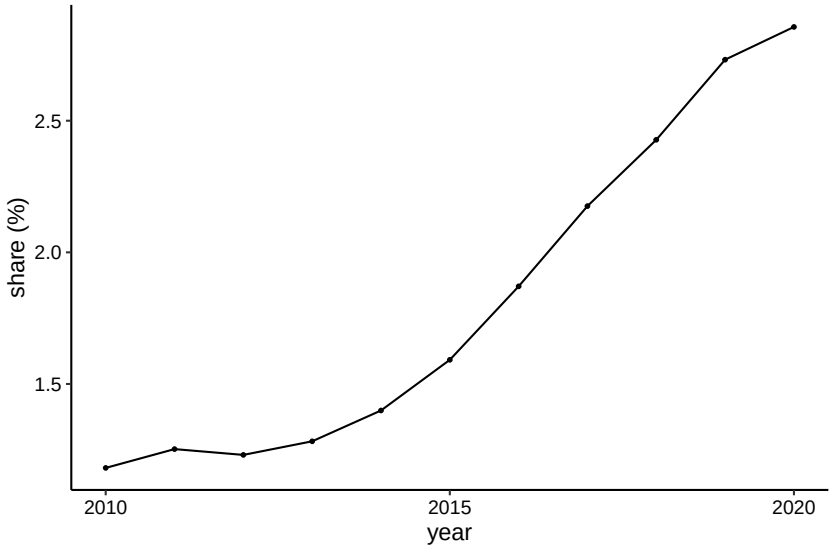
negative effects are confined to the 1990s. Taken together, little is known about how the recent and rapid increase in immigration has affected local labor-market outcomes in Japan, particularly the effects on native employment and industrial structure.

The remainder of the paper is organized as follows. Section 2 provides an overview of immigration trends in Japan over 2010–2020. Section 3 outlines the empirical model and identification strategy. Section 4 describes the data sources and the construction of key variables. Section 5 presents the main results. Section 6 introduces a theoretical framework to interpret the empirical findings, and Section 7 concludes.

2 Overview of Immigration Trends in Japan

In this section, I provide an overview of recent immigration trends in Japan and describe their distributional patterns. Figure 1 shows the evolution of foreign workers in Japan between 2010 and 2020.[3] In 2010, there were approximately 650,000 foreign workers, accounting for 1.18% of the total employees. By 2020, the number has increased to roughly 1.72 million, which is equivalent to 2.86 % of the total employees. Over the decade, the share of foreign workers rose by 1.68 percentage points.

Figure 1: Trends in Foreign Worker Shares in Japan, 2010–2020



Note: The figure plots the share of foreign employees in total employees between 2010 and 2020. The number of foreign employees is obtained from the Notification of the Employment Status of Foreign Nationals, and total employees is taken from the Labor Force Survey.

The sharp increase was driven by several policy reforms introduced during this period.

[3]The Notification of the Employment Status of Foreign Nationals is a mandatory administrative reporting system under which employers are required to report all foreign workers employed at their establishments, as of October each year. The Labor Force Survey is a monthly household survey that asks about 40,000 households their labor force status in the last week of every month. Both surveys are conducted by the Ministry of Health, Labor and Welfare.

Since 2012, Japan has progressively liberalized the entry of foreign workers in response to severe labor shortages. Under Abenomics—the policy regime implemented by former Prime Minister Shinzo Abe from 2012 to 2020—the government expanded the acceptance of foreign workers through multiple channels. The reforms relaxed eligibility requirements for highly-skilled foreign professionals under the points-based system, easing the path to long-term residency. The government also expanded international student admissions, with the aim of increasing enrollment to 300,000 as a potential source of future workers. In addition, Japan established bilateral agreements with several Asian countries to facilitate the admission of foreign workers, particularly in sectors facing severe labor shortages. These policy changes contributed to the sustained growth of foreign workers over the past decade.

Table 1: Distributions of Native and Foreign Employment by Industries

	Among Natives			Among Foreigners		
Industry	2010	2020	2010–2020	2010	2020	2010–2020
Agriculture, Forestry, and Fisheries	4.26	3.51	-0.75	3.00	3.61	0.62
Mining	0.04	0.03	-0.01	0.02	0.02	-0.01
Construction	8.00	7.50	-0.51	5.06	6.85	1.78
Manufacturing	16.88	15.78	-1.10	39.36	38.57	-0.79
Public Utilities	0.51	0.50	-0.01	0.03	0.07	0.04
Information and Communications	2.89	3.47	0.58	3.32	4.86	1.54
Transport and Postal Activities	5.77	5.62	-0.15	2.96	3.33	0.37
Wholesale and Retail Trade	17.53	15.83	-1.70	11.41	11.41	0.00
Finance and Insurance	2.71	2.45	-0.26	1.15	0.83	-0.33
Real Estate and Lease	1.99	2.26	0.27	1.35	1.19	-0.16
Research and Technical Services	3.40	3.77	0.38	2.52	3.08	0.56
Hotel and Restaurant	6.03	5.47	-0.56	11.85	9.01	-2.84
Life-Service and Leisure	3.92	3.57	-0.36	3.37	2.20	-1.18
Education	4.68	5.07	0.39	5.90	4.82	-1.07
Medical, Health Care, and Welfare	11.00	13.82	2.83	3.67	4.71	1.04
Miscellaneous Services	6.76	7.63	0.87	4.63	5.19	0.56
Government	3.63	3.70	0.07	0.41	0.27	-0.14

Note: The table reports the distribution of native and foreign employment across industries for each group and year. Within each group and year, entries sum to 100. Values for 2010 and 2020 are expressed in percent, while the 2010–2020 column reports percentage-point changes. The sample includes individuals aged 15 and older. The data are drawn from the 2010 and 2020 Population Censuses.

To understand how these inflows were absorbed, I next examine the industry distribution of native and foreign workers.[4] Table 1 summarizes the distribution of native and foreign employment across industries. During this period, native workers gradually shifted toward the medical, health care, and welfare sector. According to Kawaguchi et al. (2021), this compositional change was caused by the demand-side channel from population aging as well as supply-side effects by an increase in female labor force participation.

[4]Some studies emphasize the importance of occupation-level or task-based analysis (Card, 2001, Peri and Sparber, 2009). In Appendix B, I describe the occupational distribution of native and foreign workers.

By contrast, foreign workers are disproportionately concentrated in the manufacturing sector. This pattern reflects the historical and institutional background. Since the 1990s, Japan has relied on foreign workers to mitigate labor shortages especially in blue-collar jobs. As a result, most of the early immigrants were employed in this sector and contributed to the high concentration. More recent arrivals, however, have increasingly entered sectors facing acute labor shortages, including primary industries, construction, and health care. In addition, the expansion of high-skilled foreign worker policies also contributed to employment growth in information and communication services as well as professional and technical activities.

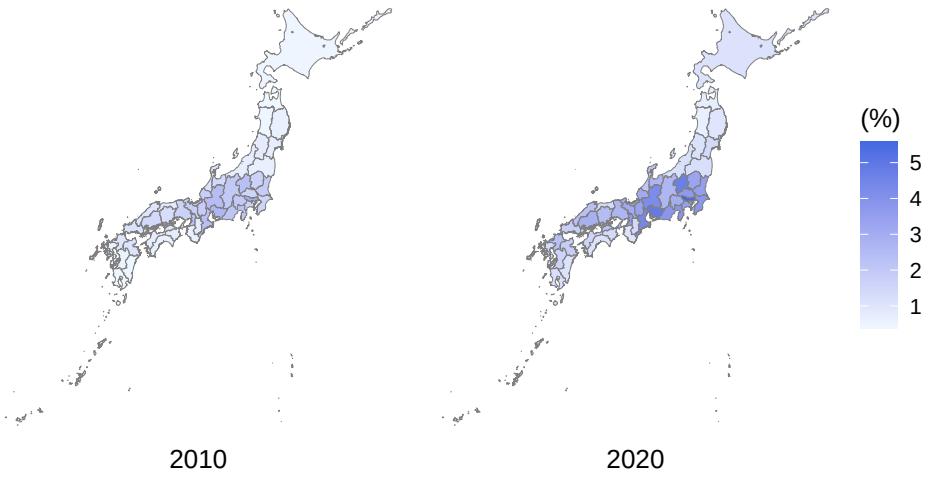
Table 2: Relative Share of Native and Foreign Employment by Industries

	Foreign-to-Native ratio		
Industry	2010	2020	2010–2020
Manufacturing	2.72	4.60	1.88
Information and Communications	1.34	2.63	1.29
Agriculture, Forestry, and Fisheries	0.82	1.94	1.12
Construction	0.74	1.72	0.98
Hotel and Restaurant	2.30	3.10	0.80
Research and Technical Services	0.87	1.53	0.67
Wholesale and Retail Trade	0.76	1.36	0.60
Transport and Postal Activities	0.60	1.11	0.51
Miscellaneous Services	0.80	1.28	0.48
Education	1.47	1.79	0.32
Medical, Health Care, and Welfare	0.39	0.64	0.25
Real Estate and Lease	0.79	0.99	0.19
Public Utilities	0.07	0.26	0.19
Life-Service and Leisure	1.00	1.16	0.16
Finance and Insurance	0.50	0.63	0.14
Mining	0.71	0.84	0.12
Government	0.13	0.13	0.00

Note: The table reports the relative share of foreign-to-native employment by industry. Values for 2010 and 2020 are expressed in percent, while the 2010–2020 column reports percentage-point changes between 2010 and 2020. The sample includes individuals aged 15 and older. The data are drawn from the 2010 and 2020 Population Censuses.

Table 2 provides descriptive evidence on the degree of competition between native and immigrant workers across industries. As expected, the manufacturing sector exhibits the highest foreign-to-native employment ratio and also experienced the largest increase over the decade. Likewise, other sectors that have attracted recent immigrant inflows display relatively higher foreign-to-native ratios and growth rates, although the ratio in the medical, health care, and welfare sector remains modest since native employment in this sector also expanded substantially over the same period.

Figure 2: Regional Distribution of Immigrants in Japan



Note: The figure shows the foreign-to-native ratio in the working-age population at the prefecture level. The ratio is calculated based on the 2010 and 2020 Population Censuses

Table 3: Immigrant Share Growth: Top vs Bottom Prefectures

	Foreign-to-Native ratio		
Prefecture	2010	2020	2010–2020
Highest			
Tokyo	3.01	5.58	2.57
Gunma	2.35	4.69	2.35
Aichi	2.65	4.86	2.22
Chiba	1.62	3.83	2.21
Saitama	1.58	3.68	2.10
Lowest			
Iwate	0.60	1.03	0.43
Wakayama	0.63	1.05	0.42
Aomori	0.37	0.76	0.38
Yamagata	0.82	1.17	0.35
Akita	0.48	0.68	0.21

Note: The table lists the top five and bottom five prefectures measured by the increase in immigrant shares among Japan's 47 prefectures. Values for 2010 and 2020 are expressed in percent, while the 2010–2020 column reports percentage-point changes.

Table 4: Top Shares among Foreign Nationals in 2010

	Percent of Total		
Country	2010	2020	2010–2020
China	40.05	30.10	-9.94
Brazil	13.55	8.07	-5.48
Philippines	11.86	10.83	-1.03
Korea	9.81	5.94	-3.87
Peru	3.10	1.87	-1.24
United States	2.92	2.13	-0.79
Vietnam	2.45	17.35	14.90
Thailand	2.27	2.07	-0.20
Indonesia	1.44	2.59	1.14
India	1.29	1.49	0.21

Note: The table reports the ten largest country groups ordered by their share among all foreign residents in 2010. Shares are calculated based on total foreign residents in each year. The 2010–2020 column reports percentage-point changes. Country classifications follow the 34 nationality categories used in the 2010 Census. Data are drawn from the Statistics on Foreign Residents. The sample excludes Special Permanent Residents and short-term stayers.

These industry patterns suggest that the absorption of immigrants has not been uniform across sectors. While the traditionally immigrant-intensive manufacturing sector absorbed some of the inflows, more recent arrivals have been allocated to labor-intensive and high-skilled industries that benefited from the policy reforms. The heterogeneity in sectoral exposure suggests that the potential labor market effects of immigration are likely to vary across industries.

Next, I show regional patterns of foreign nationals. Figure 2 illustrates the geographic distribution of the foreign-to-native ratio in the working-age population at the prefecture level. While the share of foreign nationals increased across prefectures, the magnitude of the increase is pronounced in a subset of prefectures. Table 3 presents the top five and bottom five prefectures by growth rates in immigrant shares among Japan's 47 prefectures. As the table shows, the most exposed prefectures experienced increases in immigrant shares of more than 2 percentage points, whereas those in the least-exposed group saw changes of less than 0.5 percentage points. These regional differences in exposure provide a key source of variation for my empirical analysis.

Finally, I examine trends in immigration by nationality. Although nationality itself is not directly related to the labor market outcomes, it plays a central role in my identification strategy. Table 4 summarizes the ten largest country groups by share among foreign nationals in 2010. The composition in 2010 largely reflects nationality of earlier inflows. The sizable share of Chinese and Korean residents is attributed to historical connections and geographic proximity. The presence of Brazilian and Peruvian population is rooted in the 1990 policy reform that granted eligibility for residency to descendants of Japanese emigrants. While these groups continue to represent a large share of the foreign population, their relative

Table 5: Top Growth Rates among Foreign Nationals over 2010–2020

	Percent of Total		
Country	2010	2020	2010–2020
Vietnam	2.45	17.35	14.90
Other Asia	0.60	3.40	2.79
Nepal	1.02	3.72	2.70
Indonesia	1.44	2.59	1.14
Myanmar	0.45	1.36	0.91
Sri Lanka	0.46	1.13	0.68
Mongolia	0.28	0.52	0.24
Pakistan	0.53	0.74	0.21
India	1.29	1.49	0.21
Bangladesh	0.54	0.68	0.14

Note: The table reports the ten largest country groups ordered by their size of change over 2010–2020. Shares are calculated based on total foreign residents in each year. The 2010–2020 column reports percentage-point changes. Country classifications follow the 34 nationality categories used in the 2010 Census. Data are drawn from the Statistics on Foreign Residents. The sample excludes Special Permanent Residents and short-term stayers.

shares have declined over the past decade.

For additional detail, Table 5 reports the ten country groups that experienced the largest increase over the period. The most pronounced growth is observed among Vietnamese. This abrupt surge reflects a combination of push factors in Vietnam and pull factors in Japan. Since the mid-2000s, Vietnam has implemented labor export policies. Combined with persistent labor market instability and low domestic wages, these policies have generated strong incentives for overseas employment. At the same time, the policy reforms in Japan, as described above, increased labor demand for these workers. In addition, substantial increases are observed among several Southeast and South Asian groups. These patterns suggest that the origins of immigration have changed over the past decade.

3 Empirical Strategy

This section introduces empirical models used to estimate the effects of immigration on the local labor market outcomes. I also discuss potential threats to identification and clarify the assumptions required for a causal interpretation.

3.1 Empirical Model

Following the spatial approach of Dustmann et al. (2016), I relate regional labor market outcomes to immigrant inflow rates:

$$\Delta L_{rt}^{N} = \beta^{l} \Delta m_{rt} + X'_{rt_0} \gamma^{l} + \delta_t^{l} + \varepsilon_{rt}^{l}$$
$$\Delta \log w_{rt} = \beta^{w} \Delta m_{rt} + X'_{rt_0} \gamma^{w} + \delta_t^{w} + \varepsilon_{rt}^{w}$$

where r represents prefectures and t denotes years.

The dependent variable ΔL_{rt}^{N} is the five-year change in native employment-to-population ratio in prefecture r defined as the change in native employment $L_{rt}^{N} - L_{rt-5}^{N}$ divided by the baseline native population N_{rt-5}. Similarly, $\Delta \log w_{rt}$ denotes the five-year difference in log of the aggregate average hourly wages.

The key explanatory variable Δm_{rt} measures immigrant inflow rates and is defined as the five-year change in the number of immigrants $M_{rt} - M_{rt-5}$ divided by the baseline native population N_{rt-5}. Several measures of immigration shocks are used in the existing literature. This paper uses the immigrant-to-native population ratio, as it captures potential labor supply shocks over five years.

The vector X_{rt_0} includes several controls measured in 2010, such as the initial immigrant share, demographic characteristics, and the log of regional capital stock. δ_t captures period fixed effects common to all prefectures, and ε_{rt} is an unobserved error term.

When estimating these models over the period 2010-2020, I stack the models for each five year interval. Since the specification corresponds to the first-difference estimation, region fixed effects are not included. In this estimation, β measures the impact of immigrant inflows on native employment and aggregate wages respectively.

After examining the overall effects, I estimate heterogeneous effects across industries using the same empirical model and discuss the underlying mechanisms.

3.2 Identification Strategy

Although the spatial approach is widely used in empirical analysis, it raises both conceptual issues and endogeneity concerns. First, prefectures may not be the appropriate geographic unit of analysis. As noted by Borjas (1999), if natives move away from prefectures or cities that receive large immigrant inflows, the estimated coefficient is likely to understate the true effects. In Section 5, I examine whether such crowding-out or mobility responses are observed in the data.

The second concern is the endogeneity problem. As emphasized in the existing literature, if immigrants choose locations based on local economic conditions, the OLS estimator of β will be upwardly biased due to the correlation between immigrant inflows Δm_{rt} and unobserved local demand shocks ε_{rt}. To address this issue, I use a shift-share instrument following Card (2009), defined as

$$\begin{aligned} \Delta m_{rt}^{ssiv} &= \sum_{c \in C} \frac{M_{rct_0}}{N_{rt_0}} \cdot \frac{\Delta M_{ct}}{M_{ct_0}} \\ &= \sum_{c \in C} z_{rc} \cdot g_{ct} \end{aligned}$$

where C denotes a set of country groups. In the first term, M_{rct_0} denotes the population of immigrants from country group c in region r in 2010, and N_{rt_0} is the native population in region r in 2010. In the second term, ΔM_{ct} captures the national-level inflow of immigrants from country group c over five-year period, normalized by the initial national stock M_{rt_0}.

The intuition behind this instrument is to predict local immigrant inflows by using historical settlement patterns z_{rc} interacted with national-level inflows g_{ct}. The instrument exploits immigration networks to generate plausibly exogenous variation in local inflows that is unlikely to be correlated with local labor demand shocks.

A recent paper by Goldsmith-Pinkham et al. (2020) formalizes the identification condition under the share exogeneity assumption[5]. According to Goldsmith-Pinkham et al. (2020), the parameter β is identified if the relevance condition and the following exogeneity condition are satisfied:

$$E[z_{rc}\varepsilon_{rt}|X_{rt_0}] = 0, \quad \text{for all } c \text{ and } t.$$

The exogeneity condition requires that the initial share of each region r for country c be orthogonal to unobserved determinants of subsequent outcome growth in region r, conditional on start-period controls X_{rt_0}. While most studies adopt lagged shares to justify these assumptions, I use shares measured in 2010 for three reasons.

First, using lagged shares tends to weaken the relevance condition. As shown in Section 2, the composition of recent immigrant flows has changed substantially [6]. Using older settlement patterns therefore reduces predictive power in the first-stage estimation.

Second, my empirical specifications are estimated in first differences. In this setting, the exogeneity condition is satisfied if the shares are not correlated with changes in the error terms rather than with the level of the error term. As a result, start-period shares can still satisfy the orthogonality condition.

Third, I include a rich set of regional controls measured in 2010. In the main specification, I control for regional demographic characteristics, including the share of college graduates, the share of manufacturing employment, the female employment share, the share of population aged 65 and older as well as log of regional capital stock. I also include the sum of the initial share $\sum_c z_{rc}$. This ensures that identification is driven by variation in the composition of immigrants across locations rather than by regional differences in overall immigration intensities (Borusyak et al., 2025). Conditional on these controls, the share exogeneity assumption is plausibly satisfied.

4 Data

In this section, I describe the data sources and the construction of key variables. In my analysis, most of the variables are drawn from tabulations of the Population Census of

[5]By contrast, Borusyak et al. (2022) clarifies identification condition based on shock exogeneity. Borusyak et al. (2025) demonstrates that the shock-based identification is generally not applicable in standard immigration settings. Hence, I focus on the share-based approach.

[6]This fact also mitigates concerns about serial correlation between past and current shifts as pointed out in Jaeger et al. (2019).

Japan conducted in 2010, 2015, and 2020. The Census provides detailed information on nationality, employment status, and demographic characteristics. The sample consists of all residents who have lived in or are expected to live in Japan for at least three months. The employment status is measured during the census week. Using the Census, I construct prefecture-level measure of native employment outcomes, the foreign-to-native population ratio which is the indicator of immigrant inflow rate, and demographic control variables. I restrict the sample to the working-age population aged 15–64.

Because the Population Census does not report information on wages, I complement the Census data with the Basic Survey on Wage Structure (BSWS) for the years 2010, 2015, and 2020. The BSWS is an annual establishment-based survey conducted by the Ministry of Health, Labor and Welfare. It samples private establishments with five or more employees and public establishments with ten or more employees. The survey records employees' wage conditions as of June each year and excludes establishments in agriculture, forestry, and fisheries. The samples are drawn using a two-stage sampling method: establishments are first selected based on industry, size, and region, and then wages of sampled employees within these establishments are collected[7]. For the empirical analysis, I use the tabulated data for full-time employees aged 15–64 in private firms with more than ten employees. I use prefecture-level average hourly wages. Average hourly wages are constructed as the sum of contractual earnings and bonuses divided by total hours worked.[8] Wages are deflated by prefectural CPIs.

One limitation of the BSWS is that it cannot distinguish wages by worker's nationality.[9] Given this limitation, my estimation results should be interpreted as the impact on the aggregate wage rather than native wage.

In constructing the shift–share instrument, defined as the sum of the products of initial nationality shares in each region and national-level shifts, I use 34 source-country groups available in the 2010 Census. Of these, 28 country groups correspond to individual countries and together account for more than 90% of the foreign working-age population in 2010. Because the vast majority of source-country groups consist of a single country, aggregation across countries is minimal and unlikely to affect the construction of the instrument. Initial nationality shares are measured using the 2010 Census. I keep these shares fixed throughout the analysis because shares measured after 2010 may respond endogenously to immigration shocks and local economic conditions, thereby violating the exogeneity assumption.

For the shifts part, because the 2015 and 2020 Censuses do not report detailed information on nationality, I obtain national-level flow data from the Statistics on Foreign Residents (SFR) for 2010, 2015, and 2020. The SFR is conducted twice a year, in June and December[10]. The number of foreign nationals is counted based on their nationality and visa status. I restrict the sample to residents expected to live in Japan for at least three months.[11] I

[7]For further details, see Kawaguchi and Toriyabe (2024).

[8]The BSWS reports annual bonus payments paid in the previous year. Therefore, bonus payments are converted to monthly values by dividing by 12.

[9]The BSWS began asking worker's visa statuses from the 2019 survey, but this almost falls outside the analysis period. I therefore use aggregate wages.

[10]Before 2013, the survey was conducted only in December. Accordingly, I use December data for consistency

[11]The SFR does not jointly tabulate nationality, visa status, and age. Here, I use the tabulations by

Table 6: Descriptive Statistics of Main Variables

	2010–2015	2015–2020	Full Sample
Employment change relative to population (pp)	-3.15	-4.69	-3.92
	(1.02)	(1.58)	(1.54)
Change in log hourly wage (%)	1.31	3.58	2.45
	(2.97)	(2.69)	(2.98)
Immigrant inflow rate (pp)	0.17	0.75	0.46
	(0.27)	(0.42)	(0.46)
Predicted immigrant inflow rate (pp)	0.17	0.71	0.44
	(0.12)	(0.42)	(0.41)
N	47	47	94

Note: All variables are multiplied by 100. Standard deviations are reported in parentheses. The full set of controls is reported in Appendix A.

also exclude residents with a visa status classified as Special Permanent Residents. Special Permanent Residents are long-term foreign residents, primarily descendants of individuals who lived in Japan before or during World War II. In recent years, their population has been declining due to aging and naturalization. Consequently, changes in their numbers do not reflect recent immigration inflows.

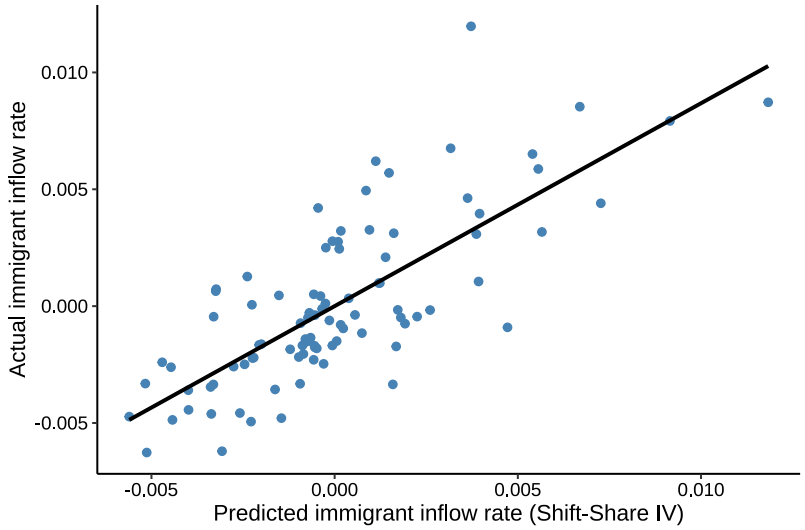
For the remaining variable, regional-level capital stock data is drawn from JIP Database, Research Institute of Economy, Trade and Industry (RIETI).

Descriptive statistics for key variables are reported in Table 6. Over the sample period, the native employment-to-population ratio declined, reflecting population aging. The aggregate wages increased approximately 2 percent over the entire period. The immigrant inflow rate rose particularly between 2015 and 2020, consistent with the trend shown in Figure 1. The predicted inflow rate, which corresponds to the shift–share instrumental variable, exhibits a similar pattern, indicating that the instrument captures the variation in the actual inflow rate well. In Appendix A, I provide summary statistics for the variables used in the main analysis.

Figure 3 plots the predicted immigrant inflow rate against the actual inflow rate. The strong positive correlation between these two variables suggests that the instrument has substantial predictive power for the observed inflows. Figure 4 summarizes reduced-form relationships between the predicted immigrant inflow rate and the labor market outcomes. As shown in Figure 4a, the predicted inflow rate is positively correlated with changes in the native employment-to-population ratio. Conversely, Figure 4b shows s negative relationship between the predicted inflow rate and the change in aggregate wages, although the estimated coefficient is not statistically significant. These visual patterns suggest that recent immigrant inflows may have affected the labor market outcomes in Japan.

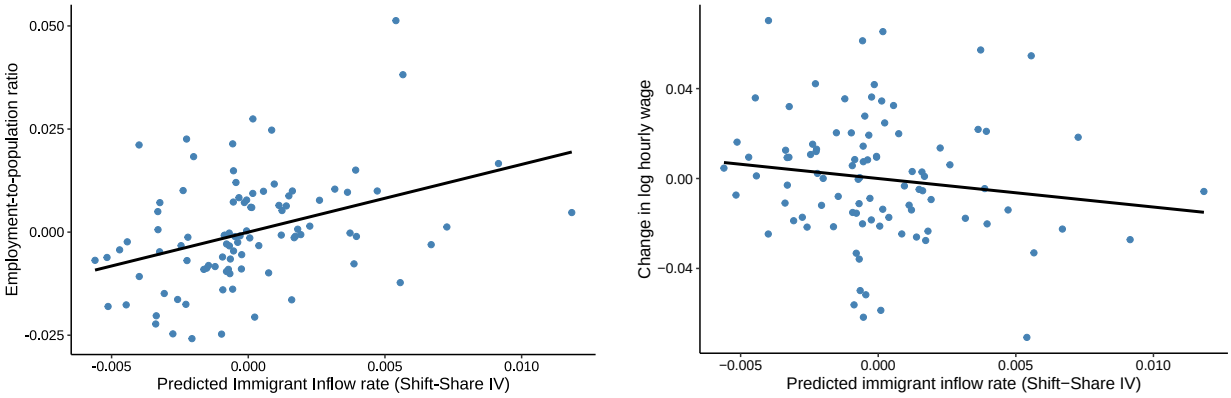
nationality and visa status to exclude short-term stayers. Since most inflows are concentrated among the working-age individuals, using national inflows over all ages should not weaken the first-stage estimation.

Figure 3: Predicted vs. Actual Immigrant Inflow Rate



Note: $N = 94(47 \times 2)$. A Regression model is estimated including year fixed effects. The Estimated coefficient and standard error are 0.868 and 0.083. Standard error is clustered at the prefecture level.

Figure 4: Predicted Immigrant Inflow Rate and Labor Market Outcomes



(a) Employment-to-population ratio

(b) Aggregate wage

Note: $N = 94\,(47 \times 2)$. Regression models are estimated including year fixed effects. Estimated coefficients and standard errors are 1.642 and 0.499 for panel (a), and -1.269 and 0.748 for panel (b). Standard errors are clustered at the prefecture level.

5 Estimation Results

In this section, I show the estimation result. I first assess the validity of the identification strategies. I then examine the overall effects of immigration on the labor market outcomes. Finally, I investigate heterogeneous effects across industries and explore the underlying mechanisms.

5.1 Validity of Identification Strategies

Table 7: First-Stage Estimation

	Dependent variable: Δm_{rt}			
	(1)	(2)	(3)	(4)
Δm_{rt}^{ssiv}	0.868***	0.692***	0.631***	0.624***
	(0.083)	(0.085)	(0.085)	(0.087)
Year fixed effects	✓	✓	✓	✓
Sum of initial shares		✓	✓	✓
Demographic controls			✓	✓
Log of capital stock				✓
N	94	94	94	94
R^2	0.745	0.762	0.833	0.833
F-stat	125.4	48.2	56.0	53.9

Note: $N = 94(47 \times 2)$. Standard errors are clustered at the prefecture level. Demographic controls include the share of college graduates, the share of manufacturing employment, the female employment share, the share of the population aged 65+. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

To assess the validity of the identification strategy, I examine the first-stage estimates and test for crowding-out effects. Table 7 reports the first-stage estimation results.[12] Column (1) includes only year fixed effects and it corresponds to the relationship illustrated in Figure 3. The estimated coefficient on the shift-share instrument is positive and highly significant.

In column (2), I additionally control for the sum of the immigrant shares to ensure that the variation in the shift–share IV comes from differences in the composition of migrants across locations, avoiding comparisons driven by variation in overall immigrant intensity. While the estimated coefficient becomes smaller in magnitude, it remains positive and statistically significant. Column (3) includes several demographic controls, and column (4) further includes the log of capital stock. After controlling for several variables, both the estimated coefficients and standard errors remain highly stable, indicating that the first-stage relationship is robust to alternative specifications. The baseline estimate in column (4) im-

[12] I do not use any weights in my estimation because the Census data cover the entire population and there is no sampling uncertainty. In addition, wages from the BSWS are already aggregated using sampling weights to recover population averages, so additional weighting is unnecessary.

Table 8: 2SLS Regression of Crowding-Out Effects

	Dependent variable			
	ΔN_{rt}	Outflow	Inflow	Within Pref.
Δm_{rt}	0.428	−0.013	−0.059	0.592
	(0.569)	(0.436)	(0.503)	(0.863)
Year fixed effects	✓	✓	✓	✓
Sum of initial shares	✓	✓	✓	✓
Demographic controls	✓	✓	✓	✓
Log of capital stock	✓	✓	✓	✓
N	94	94	94	94
R^2	0.832	0.135	0.433	0.411

Note: $N = 94(47 \times 2)$. ΔN denotes the growth rate of the native population. Inflow and Outflow measure movement of natives and early-settled immigrants between prefectures over 5 years. Within Pref. captures within-prefecture movement of these groups. These variables are divided by the entire population in $t-5$. Standard errors are clustered at the prefecture level. Demographic controls include the share of college graduates, the share of manufacturing employment, the female employment share, the share of the population aged 65+. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

plies that the instrument explains approximately 62 percent of the variation in the actual immigrant inflows.

Next, I investigate potential crowding-out effects. As discussed earlier, if natives and early-settled immigrants relocate in response to new immigrant inflows, estimated effects may be attenuated. I first examine the effects of immigrant inflows on the native population growth rate. The first column of Table 8 reports the corresponding estimates. The estimated coefficient is positive but not statistically significant, providing no evidence that the native population systematically relocate away from prefectures experiencing large immigrant inflows.

Because the Population Census records five-year retrospective information on place of residence, I further analyze inflow and outflow patterns of natives and early-settled immigrants between prefectures. Although the estimated coefficients are negative, their magnitudes are small and not statistically significant. Another concern is that these groups relocate within prefectures. The fourth column assesses whether such within-prefecture movement can be observed. The estimated coefficient is positive but not statistically significant.

These results suggest that population adjustments through either inter-prefectural migration or within-prefecture movement are limited, supporting the use of prefectures as the geographic unit of analysis.

5.2 Overall Effects

Having established that the identification assumptions are empirically plausible, I proceed to examine the overall effects of immigration on native employment and aggregate wages. Table 9 reports the estimation results for changes in the native employment-to-population

Table 9: 2SLS Regression of Employment-to-Population Ratio

	Dependent variable: ΔL_{rt}^N			
	(1)	(2)	(3)	(4)
Δm_{rt}	1.892***	1.831**	1.259*	1.239*
	(0.526)	(0.833)	(0.736)	(0.727)
Year fixed effects	✓	✓	✓	✓
Sum of initial shares		✓	✓	✓
Demographic controls			✓	✓
Log of capital stock				✓
N	94	94	94	94
R^2	0.424	0.418	0.565	0.561

Note: $N = 94(47 \times 2)$. Standard errors are clustered at the prefecture level. Demographic controls include the share of college graduates, the share of manufacturing employment, the female employment share, the share of the population aged 65+. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

ratio. In column (1), the estimated coefficient is positive and statistically significant. The result remains positive and statistically significant in column (2). After controlling for a rich set of region-level variables, the coefficient continues to be positive and is marginally significant.

The baseline estimate in column (4) implies that a one percentage-point increase in the immigrant inflow rate is associated with approximately 1.24 percentage-point increase in the native employment-to-population ratio over the five year period. Evaluated at the average immigrant inflow rate of 0.46 percentage points, this corresponds to an increase of about 0.57 percentage points. Given that the native employment-to-population ratio declined by roughly four percentage points over the sample period, the estimate suggests that immigrant inflows partially offset the secular downward trend in native employment.

To assess the plausibility of the baseline results, I apply the same empirical model to alternative measures of native employment outcomes. The first column of Table 10 reports the effect on the growth rate of native employment. The estimated coefficient is positive and marginally significant. The second column of the table shows the estimate of the native employment-to-labor-force ratio. The estimated coefficient is similar in magnitude to the employment growth rate. In the third column, I regress the immigrant inflow rate on the labor-force-to-population ratio. The coefficient is positive but insignificant, suggesting that the increase in immigrants does not affect labor-force participation. The fourth column reports the results of the native unemployment rate. The negative coefficient suggests that immigrant inflows reduce the native unemployment rate over this period. These additional results indicate that immigration primarily affects natives already participating in the labor market, rather than through operating labor market entry or exit.

Next, I examine the effects on wages. Table 11 reports estimation results for the aggregate wages. The estimated coefficient in column (1) is negative but not statistically significant. After including several controls, the estimated coefficients become closer to zero and remains

Table 10: 2SLS Regression of Other Employment Outcomes

	Dependent variable			
	Emp.Growth	Emp/LF	LF/Pop	Unemployment
Δm_{rt}	1.858^{*}	1.817^{*}	0.799	-0.608^{**}
	(1.104)	(1.051)	(0.723)	(0.246)
Year fixed effects	✓	✓	✓	✓
Sum of initial shares	✓	✓	✓	✓
Demographic controls	✓	✓	✓	✓
Log of capital stock	✓	✓	✓	✓
N	94	94	94	94
R^2	0.506	0.516	0.492	0.881

Note: $N = 94(47 \times 2)$. Standard errors are clustered at the prefecture level. Demographic controls include the share of college graduates, the share of manufacturing employment, the female employment share, the share of the population aged 65+. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

statistically insignificant. These results provide little evidence that immigration has adverse effects on the aggregate wages.

Goldsmith-Pinkham et al. (2020) propose several diagnostics to assess the validity of the shift-share instrument. Because the shift-share design can be interpreted as an analogy to a difference-in-differences framework with respect to the shares, a natural diagnostic is a pre-trends test. Figure 5 presents the results of this test, in which I regress the native employment-to-population ratio on the instrument for each interval. The estimates show no evidence of differential pre-trends prior to the immigration shock, providing partial support for the validity of the identification strategy.[13]

5.3 Heterogeneous Effects

The baseline results show that immigrant inflows increase native employment and have no statistically significant effect on aggregate wages. While these overall effects are informative, they do not shed light on the underlying mechanisms. As I show in Section 2, foreign workers are concentrated in specific sectors. I therefore examine heterogeneous effects across industries to better understand how immigration affects native labor market outcomes.

Let $i = 1, \dots I$ denote industries. By linearity, the aggregate change in employment-to-population can be decomposed into

[13]For the calculation of native employment in 1990 and 1995, I impute the number by subtracting foreign employment from total employment because the Censuses do not separately report native employment. This procedure generates only minor measurement error since response rates were nearly 100 percent during this period and the immigrant share was less than one percent.

Table 11: 2SLS Regression of Aggregate Log Hourly Wage

	Dependent variable: $\Delta \log w_{rt}$			
	(1)	(2)	(3)	(4)
Δm_{rt}	-1.461^{*}	-0.256	-0.310	0.178
	(0.848)	(1.683)	(1.867)	(1.868)
Year fixed effects	✓	✓	✓	✓
Sum of initial shares		✓	✓	✓
Demographic controls			✓	✓
Log of capital stock				✓
N	94	94	94	94
R^2	0.115	0.148	0.140	0.191

Note: $N = 94(47 \times 2)$. Standard errors are clustered at the prefecture level. Demographic controls include the share of college graduates, the share of manufacturing employment, the female employment share, the share of the population aged 65+. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

$$\begin{aligned}\Delta L_{rt} &= \sum_{i=1}^{I} \frac{L^N_{rit} - L^N_{rit-5}}{N_{t-5}} \\ &= \sum_{i=1}^{I} \Delta L^N_{rit}.\end{aligned}$$

where L^N_{rit} denotes native employment in industry i, and ΔL^N_{rit} is the five-year change in the native employment-to-population ratio for each industry.

Using this decomposition, I estimate industry-specific responses to immigration by estimating the following regression separately for each industry:

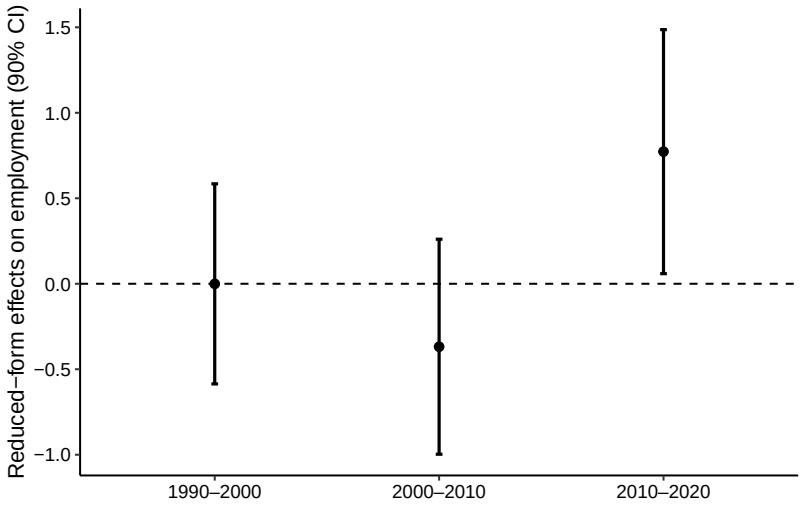
$$\Delta L^N_{rit} = \beta_i \Delta m_{rt} + X'_{rt_0}\gamma_i + \delta_{it} + \varepsilon_{rit}.$$

To examine sector-specific effects, part of the existing literature instead uses sector-specific immigration shocks Δm_{rit}, and estimates pooled models across industries with industry-time fixed effects.[14] However, I continue to use the overall regional immigration shocks Δm_{rt} when estimating industry-specific outcomes. This choice is motivated by economic theory and the interpretability of the estimated parameters.

Theoretically, empirical strategies that rely on sector-specific shocks fail to capture general equilibrium effects. The labor market outcomes in each industry are observed only after workers have reallocated across sectors in response to immigration shocks. Consequently, employment and wage adjustments depend not only on shocks to the industry but also on shocks affecting other sectors. Estimations based on sector-specific shocks thus fail to recover

[14]For example, Card (2001), Dustmann and Glitz (2015) adopt this approach.

Figure 5: Pre-trends Test for Employment-to-Population Ratio



Note: The figure presents reduced-form estimates of the employment-to-population ratio for pre-and post-immigration shocks. All specifications include the full set of baseline controls and year fixed effects.

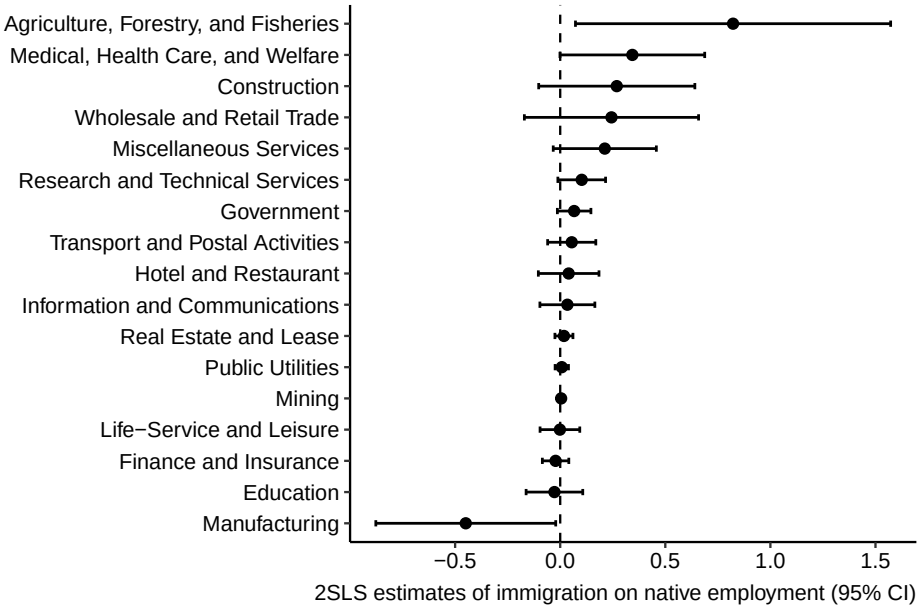
the total impact of immigration. In the next section, I introduce a theoretical framework that clarifies how native workers in each industry respond to aggregate shocks and how these responses jointly determine the distribution of native employment.

Furthermore, the estimated parameter using sector-specific shocks is difficult to interpret. As shown in Dustmann et al. (2016), the estimated coefficients in those models answer the question: holding the total immigration shock, how does an immigrant inflow into one sector affect outcomes in that sector relative to other sectors within the same region? This relative interpretation obscures absolute effects. For instance, even if employment increases in all industries, a sector receiving disproportionate share of inflows may yield a negative coefficient simply because its employment growth rate is smaller relative to other sectors. In addition, because these models mechanically partial out aggregate shocks, the resulting estimates are not informative about the total impact of immigration on labor market outcomes.

Figure 6 plots the second-stage estimates separately for each industry. The estimated effects exhibit substantial heterogeneity across industries. Industries that have recently received immigrant inflows, such as primary industries, health care service, and construction, display positive employment effects. These patterns are consistent with complementarity between native and immigrant workers, particularly in sectors facing severe labor shortages due to limited native labor supply.

One plausible mechanism behind the positive employment effects in the primary and construction sectors is task-based complementarity between immigrant and native workers (Peri and Sparber, 2009). Immigrants are often employed in physically demanding on-site tasks, which may increase demand for complementary activities such as transportation of outputs, operation of machinery, and site coordination. In many cases, these complementary tasks require formal certifications or licenses as well as language proficiency and are therefore more likely to be performed by native workers. A similar mechanism may operate in the

Figure 6: Industry-Specific Effects on Native Employment



Note: This figure reports industry-specific 2SLS estimates of the effect of immigration on the native employment-to-population ratio. All specifications include the full set of baseline controls and year fixed effects.

health care sector, where increased employment of immigrant care workers expands the demand for native workers in administrative coordination, specialized transportation, and clerical management. This interpretation is corroborated by the occupation-level analysis in Appendix B, which demonstrates positive native employment responses, especially in transportation and machine operation.

In contrast, manufacturing, an industry with a historically high concentration of immigrant workers, exhibits a negative employment effect. One possible interpretation of the negative effect is that manufacturing firms adjust production techniques endogenously in response to immigration. As I show in Section 2, immigrants have been absorbed predominantly into manufacturing and manual-intensive jobs since the 1990s. This historical pattern may have generated persistence in production organization, leading firms to rely on immigrant-intensive manual tasks instead of adjusting through labor-saving technologies such as automation (Lewis, 2011). Such endogenous adjustment in task allocation could make manufacturing a relatively less complementary sector for native workers compared to other industries.

Table 12 reports selected results for some industries. The first column presents the effects for the primary sector, which exhibits the largest positive increase. The second column shows the result for the health care service sector in which the estimated effect is positive but modest. The third column reports the effect for the expanding sectors defined as the sum of three industries with the largest point estimates. Fourth and fifth columns compare non-manufacturing and manufacturing sectors. While employment in manufacturing declines following immigrant inflows, the magnitude is small and is offset by positive employment

Table 12: 2SLS Regression of Employment-to-Population Ratio by Industry

	Dependent variable: ΔL_{rit}				
	Primary	Health Care	Expanding	Non-Manufacturing	Manufacturing
Δm_{rt}	0.822**	0.343*	1.092**	2.168**	−0.449**
	(0.372)	(0.171)	(0.455)	(0.967)	(0.213)
Year fixed effects	✓	✓	✓	✓	✓
Sum of initial shares	✓	✓	✓	✓	✓
Demographic controls	✓	✓	✓	✓	✓
Log of capital stock	✓	✓	✓	✓	✓
N	94	94	94	94	94
R^2	0.711	0.838	0.803	0.816	0.768

Note: $N = 94(47 \times 2)$. Expanding sectors include agriculture, forestry, and fisheries; medical, health care, and welfare; and construction. Standard errors are clustered at the prefecture level. Demographic controls include the share of college graduates, the share of manufacturing employment, the female employment share, the share of the population aged 65+. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

responses in other industries.

5.4 Reallocation Mechanism

The previous subsection documents pronounced heterogeneity in employment effects across industries. One important question is whether workers leaving manufacturing are absorbed into expanding sectors or instead are displaced from the labor market.

Because the Population Census does not report workers' job transitions, I use the Employment Status Survey (ESS) to complement my empirical analysis. The ESS is a nationally representative household survey conducted every five years, covering approximately 440,000 households and all household members aged 15 or older. The survey records each individual's labor force status as of October 1 in each survey year.

I use the ESS from 2012, 2017, and 2022. The ESS reports both the industry of respondents' previous jobs and that of their current jobs, which allows me to examine inter-industry transition patterns of workers.[15] Although the ESS does not distinguish between native and immigrant workers, it provides rich information on overall worker reallocation across industries. In addition, due to data availability, I restrict the sample to individuals aged 15 and older.

Using the ESS, I examine how workers employed in the manufacturing sector change industries over five-years. If workers transition from manufacturing to expanding sectors, this pattern would suggest reallocation effects rather than displacement effects. To clarify the underlying mechanisms, I construct the following two measures:

[15]The ESS captures transitions only among individuals who remain employed over the five-year interval. However, because I find no effect of immigration on labor force participation rates, this sample restriction is unlikely to affect the interpretation of the results.

Table 13: 2SLS Regression of Reallocation Patterns

	Net Reallocation Rate (ΔNRR_{rt})		Destination Share (π_{rt})
	Expanding sectors	Other sectors	Expanding sectors
Δm_{rt}	0.711*	0.043	3.276**
	(0.370)	(0.662)	(1.625)
Year fixed effects	✓	✓	✓
Sum of initial shares	✓	✓	✓
Demographic controls	✓	✓	✓
Log of capital stock	✓	✓	✓
N	94	94	94
R^2	0.402	0.406	0.723

Note: $N = 94(47 \times 2)$. Expanding sectors include agriculture, forestry, and fisheries; medical, health care and welfare; and construction. Standard errors are clustered at the prefecture level. Demographic controls include the share of college graduates, the share of manufacturing employment, the female employment share, the share of the population aged 65+. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

$$\Delta NRR_{rt} = \frac{\sum_{h \in H}[Flow(Manu \to h)_{rt} - Flow(h \to Manu)_{rt}]}{L^{manu}_{rt-5}}$$

$$\pi_{rt} = \frac{\sum_{h \in H} Flow(Manu \to h)_{rt}}{\sum_{i \in I} Flow(Manu \to i)_{rt}}$$

where H is a subset of industry I.

The first measure ΔNRR_{rt} captures the net reallocation rate of workers between manufacturing and industries in H divided by the number of manufacturing workers in region r at time $t-5$. A positive value of ΔNRR indicates that outflows from manufacturing to industries in H exceed inflows from those industries into manufacturing over five years.

The second measure π_{rt}, called destination share, captures the share of outflows from manufacturing that are directed toward industries in H. This measure assesses whether workers leaving manufacturing are more likely to transition into sectors in H. An increase π_{rt} implies that the distribution of exiting workers shifts toward the expanding sectors.

As a baseline specification, I define H to include the primary sector; medical, health care, and welfare sector; and construction exhibit the largest point estimates and have recently absorbed substantial immigration inflows. In the estimation, I use the same empirical specification as in the industry-level analysis.

Table 13 summarizes the estimation results for both measures. The first column of the table shows a positive and marginally significant effect. The estimate implies that in regions experiencing average immigrant shocks, the net reallocation rate from manufacturing to expanding sectors is 0.33 (0.71×0.46) percentage points of total manufacturing employment in $t-5$. The second column reports estimates for the remaining sectors. The estimated

coefficient is close to zero and statistically insignificant, suggesting that worker reallocation is concentrated on the expanding sectors rather than spread across industries.

In the third column, I examine how the distribution of outflows from manufacturing changed over time. The estimated coefficient is positive and statistically significant. Evaluated at the average increase in the immigrant inflow rates, manufacturing workers are 1.5 (3.3×0.46) percentage-points more likely to transition into the expanding sectors. Because transition shares across sectors sum to one, an increase in the share transitioning to one sector mechanically reduces the shares allocated to other sectors. I therefore report results only for expanding sectors.

These results provide suggestive evidence that the decline in manufacturing employment documented in the previous subsection reflects sectoral reallocation rather than displacement from the labor market. Prefectures experiencing larger immigrant inflows exhibit higher net reallocation rates from manufacturing toward the expanding sectors, and outflows from manufacturing are increasingly directed to these sectors. Furthermore, the absence of net reallocation toward non-expanding sectors provides additional support for this interpretation. Overall, the findings are consistent with the reallocation mechanism in which manufacturing workers transition toward the sectors with growing labor demand.

6 Theoretical Framework

In this section, I introduce a simple multi-sector specific factors model to analyze the short-run labor market effects of immigration. [16] Let $i = 1, \ldots, I$ denote industries. I assume that each industry i produces output using a production function

$$Y_i = F_i(L_i^N, L_i^M),$$

where L_i^N and L_i^M denote native and immigrant labor inputs respectively.[17] The production function $F_i(\cdot)$ is assumed to be twice continuously differentiable, strictly increasing in both arguments,

$$\frac{\partial F_i}{\partial L_i^N} = MPL_{N,i} > 0, \qquad \frac{\partial F_i}{\partial L_i^M} = MPL_{M,i} > 0,$$

and strictly concave to ensure interior solution.

I consider a small open economy in which output prices p_i are exogenous and determined in world markets. Goods and labor markets are assumed to be competitive. To focus on short-run labor market adjustment, I abstract from capital, which is plausibly fixed in the short run. Under these assumptions, firms in each industry take prices as given and choose labor inputs to maximize profits.

[16] Dustmann and Schönberg (2025) show that much of the immigration literature relies on nested CES production functions in skill-based analyses. In contrast, this paper adopts a specific factors model to highlight industry-level adjustments and short-run sectoral reallocation. This framework is particularly suitable given that the empirical analysis employs five-year differences.

[17] While Braun and Kvasnicka (2014) assume that native and immigrant workers are close substitutes due to the fact that expellees share very similar characteristics with natives, I explicitly distinguish between native and immigrant workers. In the case of Japan, native and immigrant workers differ along several dimensions, such as language proficiency and institutional knowledge. This assumption allows more flexible patterns of substitutability and complementarity across industries.

For simplicity, I assume that all regions share identical production technologies and factor endowments. I further assume that native workers are perfectly mobile across industries within a region, whereas immigrant workers face limited mobility across industries in the short run.[18] Furthermore, I assume full employment of native workers and that immigrants are exogenously allocated across sectors.

Equilibrium Conditions

Under the assumptions described above, the equilibrium is characterized by the following conditions. The first-order condition for native labor implies

$$w_i = p_i \frac{\partial F_i(L_i^N, L_i^M)}{\partial L_i^N}.$$

Because native workers are mobile across industries, equilibrium wages must be equalized across sectors:

$$w_i = w \qquad \text{for all } i.$$

The full employment condition of native workers implies the aggregate resource constraint:

$$\sum_{i=1}^{I} L_i^N = L^N$$

Immigrant labor is assumed to be sector-specific and allocated exogenously across industries:

$$L_i^M = \mu_i L^M, \qquad \sum_{i=1}^{I} \mu_i = 1$$

Comparative Statics

I now analyze the effects of an exogenous increase in the total supply of immigrant labor L^M on equilibrium wages and native employment. Totally differentiating the native wage condition yields

$$\begin{aligned} d\log w &= \frac{\partial \log MPL_{N,i}}{\partial \log L_i^N} d\log L_i^N + \frac{\partial \log MPL_{N,i}}{\partial \log L_i^M} d\log L_i^M \\ &= \kappa_i d\log L_i^N + \xi_i d\log L_i^M \end{aligned}$$

where κ_i and ξ_i are defined as

$$\kappa_i \equiv \frac{\partial \log MPL_{N,i}}{\partial \log L_i^N} < 0 \qquad \xi_i \equiv \frac{\partial \log MPL_{N,i}}{\partial \log L_i^M}$$

[18] This assumption reflects institutional and legal background that govern Japan's labor market. In Japan, immigration policy typically ties foreign workers to specific residency statuses and restricts their activities to particular sectors, which constrains short-run mobility across industries.

The parameter κ_i captures the diminishing marginal productivity of native labor. The parameter ξ_i represents the cross-elasticity, which determines whether immigrant and native workers are complements ($\xi_i > 0$) or substitutes ($\xi_i < 0$) in production.

Since immigrant labor is assumed to expand proportionally across all industries, the change in sectoral immigrant employment is equivalent to the aggregate shock: $d \log L_i^M = d \log L^M$. Substituting this into the differentiated wage condition,

$$d \log w = \kappa_i d \log L_i^N + \xi_i d \log L^M$$

The aggregate native labor market-clearing condition requires that the total supply of native labor remains constant:

$$\sum_{i=1}^{I} dL_i^N = 0 \iff \sum_{i=1}^{I} \lambda_i d \log L_i^N = 0$$

where $\lambda_i \equiv L_i^N / L^N$ represents the employment share of industry i in the total native employment. Combining these expressions yields the general equilibrium effect on the aggregate wages and sectoral native employment:

$$\begin{aligned} d \log w &= \left(\frac{\sum_{j=1}^{I} \lambda_j \xi_j / \kappa_j}{\sum_{j=1}^{I} \lambda_j / \kappa_j} \right) d \log L^M \\ &= \bar{\xi} d \log L^M \end{aligned}$$

and

$$\begin{aligned} d \log L_i^N &= \frac{1}{\kappa_i} \left(\frac{\sum_{j=1}^{I} \lambda_j \xi_j / \kappa_j}{\sum_{j=1}^{I} \lambda_j / \kappa_j} - \xi_i \right) d \log L^M \\ &= \frac{1}{\kappa_i} (\bar{\xi} - \xi_i) d \log L^M \end{aligned}$$

where $\bar{\xi}$ is the economy-wide weighted average of the industry-specific complementarity parameters. Consequently, the elasticities of labor market outcomes with respect to an aggregate increase in immigrant labor are expressed as

$$\frac{d \log w}{d \log L^M} = \bar{\xi}, \quad \frac{d \log L_i^N}{d \log L^M} = \frac{1}{\kappa_i} (\bar{\xi} - \xi_i).$$

These expressions yield two main implications. First, the aggregate wage effect of immigration is governed by the weighted average of sectoral complementarity $\bar{\xi}$. As a result, aggregate wages may change little even when immigration generates sizable sector-specific impacts. Second, native employment reallocates across industries: native labor expands in sectors where immigrants are relatively complementary to natives compared to the average ($\xi_i > \bar{\xi}$), and contracts in sectors where they are less complementary ($\bar{\xi} > \xi_i$). Importantly, the equilibrium allocation depends on relative magnitude between ξ_i and $\bar{\xi}$ rather than on the absolute value of ξ_i. Moreover, the extent of reallocation is greater in industries with weaker diminishing marginal product of native labor.

Implication for Empirical Results

This model provides a clear interpretation of the mechanisms that I found in the empirical analysis. The framework yields three implications for the empirical findings.

First, the small and statistically insignificant aggregate wage effects observed in the data are consistent with the model's prediction that aggregate wages are governed by the economy-wide average degree of complementarity $\bar{\xi}$, not by a single sector's parameter. When some sectors exhibit positive complementarity ($\xi_i > 0$) while others exhibit substitutability ($\xi_i < 0$), these sectoral effects can offset each other in equilibrium, resulting in little change in aggregate wages.[19]

Second, the response of sectoral native employment to immigrant shocks is determined by an industry's degree of complementarity ξ_i relative to the economy-wide benchmark $\bar{\xi}$. Sectors with above-average complementarity ($\xi_i > \bar{\xi}$) expand and absorb native workers, whereas those with below-average complementarity ($\bar{\xi} > \xi_i$) experience a contraction in native employment. This mechanism offers a coherent interpretation of the observed heterogeneous effects: industries currently facing acute labor shortages, such as the primary sector, medical and health care services, and construction, are consistent with the case where $\xi_i > \bar{\xi}$. By contrast, manufacturing corresponds to $\bar{\xi} > \xi_i$ where immigrant labor may act as a relative substitute for the native worker in the short run.

Third, the model predicts reallocation rather than pure displacement: the contraction of low-complementarity sectors, such as manufacturing, serves as the general equilibrium counterpart to the expansion of high-complementarity industries. This theoretical mechanism is supported by evidence from the ESS analysis, which shows that native outflows from manufacturing are increasingly directed toward these expanding sectors. Moreover, the concentration of net worker reallocation in these industries suggests that labor market adjustment operates primarily through absorption in high-complementarity sectors.

7 Conclusion

In this paper, I examine the effects of immigration on local labor market outcomes in Japan over the period 2010–2020. Exploiting prefecture-level variation in immigrant inflows and using a shift-share instrumental variable design, I find that immigration increases native employment while having modest effects on aggregate wages. The IV estimates indicate that an average increase in the immigrant share is associated with a 0.57 percentage-point rise in the native employment-to-population ratio, suggesting that recent immigration has partially mitigated the secular decline in native employment driven by demographic aging.

Extending the analysis to the industry level, I document substantial heterogeneity in employment responses across sectors. Native employment expands in industries that have experienced recent immigrant inflows and face acute labor shortages, such as primary industries, medical, health care, and welfare, and construction, while employment declines in manufacturing, a sector with a historically high concentration of immigrant workers.

To determine whether these heterogeneous effects reflect native displacement or sectoral reallocation, I analyze worker transitions using the Employment Status Survey. The re-

[19] More precisely, the magnitude of the response also depends on κ_i and λ_i.

sults indicate that workers employed in manufacturing are increasingly transitioning into the expanding sectors. Prefectures experiencing larger immigrant inflows exhibit higher net reallocation rates from manufacturing toward these sectors, and outflows from manufacturing are disproportionately directed to them. These findings demonstrate that sectoral reallocation constitutes the primary adjustment mechanism in the Japanese labor market.

Moreover, these findings are rationalized by a simple multi-sector specific factors model. When the degree of complementarity between immigrants and native workers varies across industries, immigration induces general equilibrium reallocation of native workers toward sectors with relatively high complementarity. In this model, aggregate wage effects are determined by the economy-wide average degree of complementarity, and consequently the effects remain modest even in the presence of sizable sector-specific immigrant inflows.

Overall, the evidence suggests that recent immigration has facilitated a structural transformation in the Japanese labor market by reallocating native workers toward expanding sectors that face acute labor shortages. More broadly, this reallocation mechanism may be relevant for other developed economies confronting similar demographic transitions characterized by population aging and tightening labor markets.

Several questions remain for future research. First, my empirical analysis does not fully capture long-run adjustment mechanisms. Future work could investigate how firms and industries respond over longer horizons by focusing on market entry and exit, changes in production scale, and technological adoption. Second, a skill-based analysis may uncover different impacts of immigration for specific worker groups in Japan. Third, Japan has introduced several policies related to foreign workers. Analyzing policy-specific effects would be important for understanding how institutional settings shape labor market outcomes.

References

Abe, Y. (2000). A comparison of wage structures in the united states and japan: Results from cell mean regressions. *The Japanese Economic Review*, 51(2):252–267.

Altonji, J. G. and Card, D. (1991). The effects of immigration on the labor market outcomes of less-skilled natives. In Abowd, J. M. and Freeman, R. B., editors, *Immigration, Trade, and the Labor Market*, pages 201–234. University of Chicago Press, Chicago, IL. NBER Chapters, originally NBER Working Paper No. 3123.

Borjas, G. J. (1999). The economic analysis of immigration. In Ashenfelter, O. and Card, D., editors, *Handbook of Labor Economics*, volume 3, pages 1697–1760. Elsevier, Amsterdam. Pforzheimer Professor of Public Policy, Harvard University; Research Associate, NBER.

Borjas, G. J. (2003). The labor demand curve is downward sloping: Reexamining the impact of immigration on the labor market. *The Quarterly Journal of Economics*, 118(4):1335–1374.

Borusyak, K., Hull, P., and Jaravel, X. (2022). Quasi-experimental shift-share research designs. *The Review of Economic Studies*, 89(1):181–213.

Borusyak, K., Hull, P., and Jaravel, X. (2025). A practical guide to shift-share instruments. *Journal of Economic Perspectives*, 39(1):181–204.

Braun, S. T. and Kvasnicka, M. (2014). Immigration and structural change: Evidence from post-war germany. *Journal of International Economics*, 93(2):253–269.

Card, D. (2009). Immigration and inequality. *American Economic Review: Papers and Proceedings*, 99(2):1–21. Richard T. Ely Lecture.

Card, D. and Lewis, E. G. (2007). The diffusion of mexican immigrants during the 1990s: Explanations and impacts. In Borjas, G. J., editor, *Mexican Immigration to the United States*, pages 77–114. University of Chicago Press, Chicago, IL. NBER Chapters, National Bureau of Economic Research.

Card, D. E. (2001). Immigrant inflows, native outflows, and the local labor market impacts of higher immigration. *Journal of Labor Economics*, 19(1):22–64. Published by The University of Chicago Press.

Dustmann, C., Frattini, T., and Preston, I. P. (2013). The effect of immigration along the distribution of wages. *The Review of Economic Studies*, 80(1):145–173.

Dustmann, C. and Glitz, A. (2015). How do industries and firms respond to changes in local labor supply? *Journal of Labor Economics*, 33(3):711–750.

Dustmann, C. and Schönberg, U. (2025). Linking empirical evidence to theory: A framework for understanding immigration's labor market effects. In Dustmann, C. and Lemieux, T., editors, *Handbook of Labor Economics*, volume 6, pages 447–542. Elsevier.

Dustmann, C., Schönberg, U., and Stuhler, J. (2016). The impact of immigration: Why do studies reach such different results? *Journal of Economic Perspectives*, 30(4):31–56.

Dustmann, C., Schönberg, U., and Stuhler, J. (2017). Labor supply shocks, native wages, and the adjustment of local employment. *The Quarterly Journal of Economics*, 132(1):435–483.

Foged, M. and Peri, G. (2016). Immigrants' effect on native workers: New analysis on longitudinal data. *American Economic Journal: Applied Economics*, 8(2):1–34.

Goldsmith-Pinkham, P., Sorkin, I., and Swift, H. (2020). Bartik instruments: What, when, why, and how. *American Economic Review*, 110(8):2586–2624.

González, L. and Ortega, F. (2011). How do very open economies absorb large immigration flows? evidence from spanish regions. *Labour Economics*, 18(1):57–70.

Jaeger, D. A., Ruist, J., and Stuhler, J. (2019). Shift-share instruments and the impact of immigration. Working Paper 24285, National Bureau of Economic Research.

Kawaguchi, D., Kawata, K., and Toriyabe, T. (2021). An assessment of abenomics from the labor market perspective. *Asian Economic Policy Review*, 16(2):247–278.

Kawaguchi, D. and Toriyabe, T. (2024). Nonresponse bias of japanese wage statistics. *Journal of Official Statistics*, 40(1):57–121.

Lewis, E. (2011). Immigration, skill mix, and capital skill complementarity. *The Quarterly Journal of Economics*, 126(2):1029–1069.

Lewis, E. G. (2003). Local open economies within the u.s.: How do industries respond to immigration? Working paper, Federal Reserve Bank of Philadelphia.

Nakamura, J. (2010). Impacts of international migration on the labor market in japan. *Japan Labor Review*, 7(3):68–85. Summer 2010 issue.

Nakamura, J., Naito, H., Kambayashi, R., Kawaguchi, D., and Machikita, T., editors (2009). *Foreign Labor Force in Japan: Evidence from Economics*. Nihon Keizai Shinbun-sha, Tokyo. In Japanese. Title in Japanese: *Nihon no Gaikokujin Roudou Ryoku: Keizaigaku kara no Kensho*.

Peri, G. and Sparber, C. (2009). Task specialization, immigration, and wages. *American Economic Journal: Applied Economics*, 1(3):135–169.

Sasahara, A., Sui, Y., and Taguchi, E. (2023). Immigration, imports, and (im)mutable japanese labor markets. Technical Report DP2023-002, Institute for Economic Studies, Keio University. Discussion Paper.

A Data Appendix

A.1 Data Construction

Population Census

For the 2015 and 2020 Population Censuses, I use the tabulations in which age and nationality are statistically imputed. Because the response rate among foreign nationals has declined in recent surveys, the imputed tabulations provide more reliable estimates to construct the relevant variables.

Basic Survey on Wage Structure

I use the BSWS data that are recalculated under the 2020 classification to ensure comparability across survey years. Because the analysis relies on tabulated cell-level wages (five-year age bins × gender × firm size), prefecture-level log wages are constructed by taking logs at the cell level and aggregating using cell employment counts. This approach mitigates aggregation bias.[20]

A.2 Descriptive Statistics

Table 14: Descriptive Statistics

	N	Mean	Std. dev.
Dependent variables			
Employment change relative to population (pp)	94	-3.92	1.54
Change in log hourly wage (%)	94	2.45	2.98
Net reallocation rate (%)	94	0.94	0.77
Destination share (%)	94	15.4	4.94
Endogenous variable			
Immigrant inflow rate (pp)	94	0.46	0.46
Instrumental variable			
Predicted immigrant inflow rate (pp)	94	0.44	0.41
Controls			
Sum of initial shares (%)	47	1.23	0.64
Share of college graduates (%)	47	16.9	3.78
Share of manufacturing employment (%)	47	17.5	5.34
Employment rate among women (%)	47	60.1	4.14
Share of population aged over 65 (%)	47	24.6	2.63
Log of capital stock	47	16.7	0.78

[20] See Abe (2000) for a detail discussion of cell mean regressions using the BSWS.

B Occupation-Level Analysis

In this appendix, I report results of occupation-level analysis. Table 15 summarizes distribution of native and foreign workers by occupation. The occupational distribution of foreign workers mirrors the patterns observed in the industry-level analysis. Most immigrants are employed in manual processing occupations in manufacturing, whereas recent immigrant inflows are concentrated in laborer jobs in the primary sector and construction, as well as in high-skilled jobs.

Table 15: Distribution of Native and Foreign Employment by Occupation

	Among Natives			Among Foreigners		
Occupation	2010	2020	2010–2020	2010	2020	2010–2020
Administrative and Managerial	2.53	2.10	-0.43	2.57	1.67	-0.90
Professional and Technical	15.37	18.41	3.03	14.29	15.03	0.74
Clerical	19.67	21.07	1.40	8.06	8.40	0.34
Sales	14.31	12.34	-1.97	8.22	7.58	-0.64
Service	12.15	12.14	-0.01	14.28	12.10	-2.17
Security	1.91	1.99	0.08	0.21	0.18	-0.03
Agricultural, Forestry and Fishery	4.16	3.38	-0.77	2.80	3.35	0.55
Manufacturing Process	14.80	13.19	-1.61	37.92	37.43	-0.49
Transport and Machine Operation	3.73	3.51	-0.23	1.99	1.75	-0.24
Construction and Mining	4.78	4.38	-0.40	3.05	4.92	1.87
Carrying, Cleaning, Packaging	6.59	7.49	0.89	6.61	7.57	0.96

Note: The table reports the distribution of native and foreign employment across occupations for each group and year. Within each group and year, entries sum to 100. Values for 2010 and 2020 are expressed in percent, while the 2010–2020 column reports percentage-point changes. The sample includes individuals aged 15 and older. The data are drawn from the 2010 and 2020 Population Censuses.

Table 16 shows foreign-to-native ratio for each occupation. A number of foreign workers are concentrated in physically intensive and manual-task occupations. This trend is in line with patterns observed in other countries.

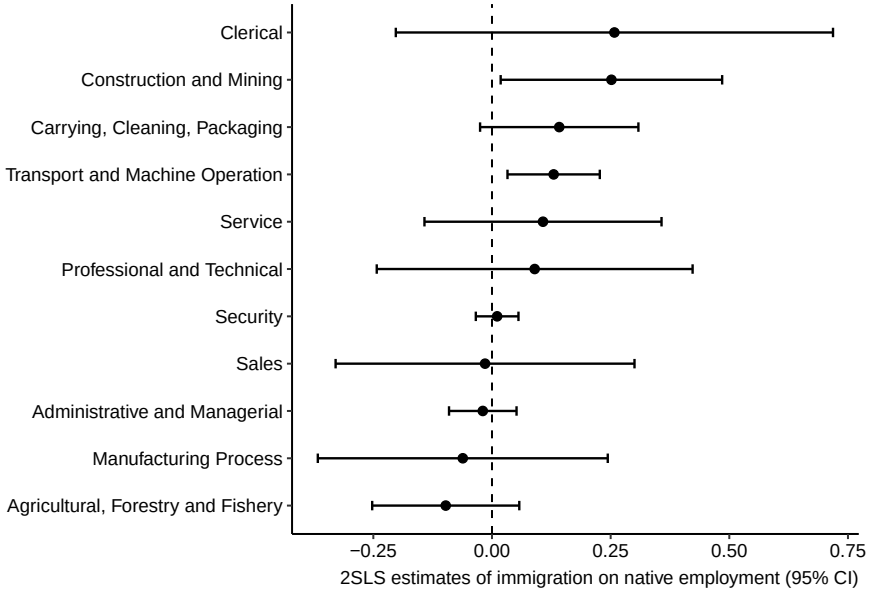
To examine heterogeneous effects across occupations, I estimate the same regression as in the industry-level analysis separately for each occupation. The results are summarized in Figure 7. The figure shows no negative effects on native employment across occupations. Instead, I find positive effects in several occupations, consistent with complementarity between native and immigrant workers in certain tasks.

Table 16: Distribution of Native and Foreign Employment by Occupation

	Foreign-to-Native ratio		
Occupation	2010	2020	2010–2020
Manufacturing Process	3.00	5.35	2.35
Construction and Mining	0.75	2.12	1.37
Agricultural, Forestry and Fishery	0.79	1.86	1.08
Carrying, Cleaning, Packaging	1.17	1.91	0.73
Service	1.37	1.88	0.51
Sales	0.67	1.16	0.49
Professional and Technical	1.09	1.54	0.45
Transport and Machine Operation	0.62	0.94	0.32
Administrative and Managerial	1.19	1.51	0.31
Clerical	0.48	0.75	0.27
Security	0.13	0.17	0.04

Note: The table reports the relative share of foreign-to-native employment by occupation. Values for 2010 and 2020 are expressed in percent, while the 2010–2020 column reports percentage-point changes between 2010 and 2020. The sample includes individuals aged 15 and older. The data are drawn from the 2010 and 2020 Population Censuses.

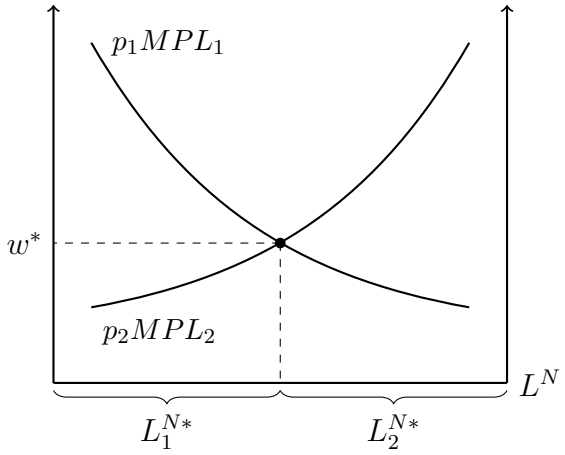
Figure 7: Occupation-Specif Effects on Native Employment



Note: This figure reports occupation-specific 2SLS estimates of the effect of immigration on the native employment-to-population ratio. All specifications include the full set of baseline controls described in the main text and year fixed effects.

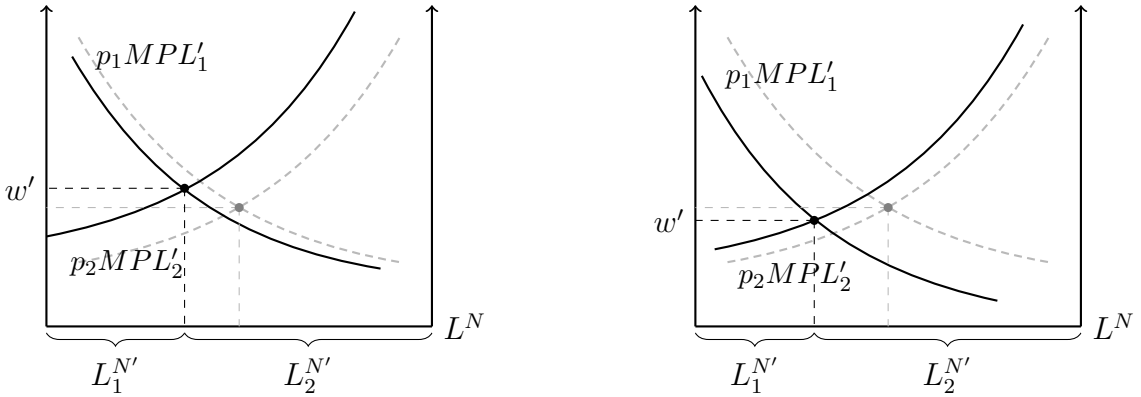
C Graphical Illustration of the Model

Figure 8: Labor Market Equilibrium with Symmetric Two Industries



This appendix provides intuition of the multi-sector specific factors model discussed in the main text. For simplicity, I just focus on a symmetric two-industry economy (i.e., $\kappa_1 = \kappa_2$ and $L_1^N = L_2^N$) in which native and immigrant workers are substitutes in industry 1 ($\xi_1 < 0$) and complements in industry 2 ($\xi_2 > 0$). In this environment, the equilibrium wage and the allocation of native workers are determined as in Figure 8.

Figure 9: Comparative Statics of Total Immigration Shocks



(a) $|\xi_1| < |\xi_2|$ (b) $|\xi_2| < |\xi_1|$

In this simple setup, the equilibrium response to an immigrant inflows depends on the relative magnitudes of ξ_1 and ξ_2. Figure 9a illustrates the case with $|\xi_1| < |\xi_2|$. In this case, the complementarity effect dominates the substitution effect, leading to a higher equilibrium wage. Conversely, Figure 9b shows the opposite case, in which the substitution effect dominates and the equilibrium wage declines. Importantly, in both cases native labor reallocates toward industry 2, where natives and immigrants are complementary. Overall, this simple two-sector example illustrates that the wage effect of immigration is generally ambiguous, while native workers are reallocated toward the complementary sector.