# Economic Impacts of Immigration in Japan

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神戸大学大学院経済学研究科

経済学専攻

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(日本における移民の経済効果)

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# Chapter 1

# Introduction

The economic impact of immigration[1] has been a hotly debated topic in the developed countries. As such, it has been studied extensively, especially in the Western world. On the other hand, Japan has maintained a conservative stance on immigration. Despite so, Japan has been slowly, but steadily accepted more immigrants in recent years. According to table 1.1, the immigration population has almost doubled from 2000 to 2019. The principle of the immigration policy has been about welcoming only high-skilled workers[2]. Regardless, less-skilled immigrants have been brought into Japan legally under different types of visas. Column 4 of table 1.1 calculates how much the growth in immigrants in each visa category contributes to the growth in immigrants of all visa categories. The numbers indicates that the less-skilled worker group has the largest growth[3]. In 2019, a new visa category was established to accept immigrant workers in specific industries. The targeted industries, and the fact that the visa was set up separately from other high-skilled visa categories show that it aimed at less-skilled immigrants. Thus, the increasing trend in immigration is expected to continue in the future and, hence, raises the need to estimate the impact that immigration has in Japan. This dissertation aims to do so in the following chapters.

[1]In Japan, foreign-nationals are referred to as foreigners. However, for consistency with the literature, this dissertation will refer to them as immigrants. See Roberts (2018) for more details.

[2]See Komine (2014) for detailed discussion about the history of Japanese immigration policy.

[3]International students are included in the less-skilled workers category due to their increasing participation in the Japanese labor market. In 2000, 7,923 international students were working (according to the "Foreign Employment Survey" by the Ministry of Health, Labour, and Welfare of Japan (MHLW) ), out of 114,761 international students recorded (from "Statistic on Foreign Nationals Residing in Japan by the Ministry of Justice Japan). On the other hand, in 2019, 318,278 international students were working, out of 345,791 international students recorded. In other words, the share of international students in the labor workforce has increased from 6.90% to 92.04%. Note that the numbers may not be comparative since they are from different surveys. However, it still illustrates the fact that a large number of international students participate in Japan's labor force.

Chapter 2 estimates the impact of immigrant population on bilateral trade between Japanese prefectures and foreign countries. Immigrants can increase trade value through two channels. First, immigrants can utilize knowledge of their home country to reduce bilateral trade costs and, in turn, improve trade. Second, immigrants bring with them preferences for goods from their home country. Thus, an increase in demand for goods from immigrants' country of origin leads to higher imports. Since imports is affected by both channels, immigrants are expected to have a larger effect on imports. The empirical results confirm this implication. Another way to test the hypothesis is to categorize traded goods into consumer goods and industrial goods. As expected, estimation results confirm that immigrant population has a larger trade effect on consumer goods. Finally, estimating the impacts on the margins of trade reveals that an increase in immigrant population improves trade through both the intensive (defined as trade of existing goods) and extensive (defined as the number of traded goods) margins, but mainly through the intensive margin.

Chapter 3 shifts the focus to local economic growth. Specifically, growth of regional output is disaggregated into growth of several factor inputs, using production function approach. The panel estimation implies that immigrant workers only positively affect the total number of workers. On the other hand, utilizing Geographically weighted panel regression (GWPR) shows that several of the economic effects induced by immigrants are masked. While the positive effects on labor force persist in most prefectures, local labor forces in the middle region do not benefit from an increase in immigrant workers. Capital-to-output ratio is negatively affected in many prefectures in the northern of Japan, which is the result of a positive impact on output growth, but not on capital growth. Both methods consistently indicate that an increase in immigrant workers expand the local labor force, without depressing wage. Using simple supply and demand theory, if the demand curve shifts to the right simultaneously when the supply curve shifts to right due to an increase in immigrant workers, then the wage level will remain unchanged. Finally, estimating the coefficients generated by GWPR on different groups of immigrants indicate that the economic impact of immigration correlates with the industrial structure of each prefecture.

One of the commonly debated topics when accepting immigrant workers is the impact they have on the native workers. Chapter 4 tries to answer this question by utilizing the anonymized version of Japanese Population Census microdata. A panel data for 47 prefectures (30 large cities) in 2005, 2010, and 2015 is constructed by aggregating workers by skill groups, year, and prefecture (city). To avoid the "downgrading" effect, skill group is defined as industry-occupation combination, instead of education-experience. The results indicate a negative effect on the number of native workers at city-level but not at prefecture-level, implying that native worker responses to an increase in competition due to immigration by moving to nearby cities in the same prefecture. To better understand the impact on the natives, workers are further grouped into regular and temporary workers. Interestingly, regular workers are negatively affected by immigration, but not temporary workers. This discrepancy might be due to the characteristics of the employment contract. Since regular workers have better employment protection and possibly higher wage insensitivity, firms can become more profitable by replacing them with immigrant workers, who are more likely to accept lower wage and harsher working conditions. On the other hand, the number and the wage of temporary workers can be easily adjusted. Thus, while an increase in temporary immigrant workers do not affect the employment of their native counterparts, it is possible that the wage has been adjusted. However, it is not possible to confirm this hypothesis due to data availability. Finally, in contrast with previous literature, there is no evidence that immigration negatively affects the inflow of native workers.

Based on the above results, chapter 5 proposes policy changes that aim at integrating the current immigrants into the society. Specifically, I propose 1) supporting immigrants in acquiring Japanese language skills, and 2) ensuring that children of immigrant receive sufficient education. The purposes are to alleviate the "downgrading" effect, as well as to cultivate high-skilled workers. Proper integration policy is essential in reaping the expected economic outcomes, and also to avoid future social problems. Finally, the dissertation ends by surveying research on another important effect of immigration: the fiscal impact. While an increase in immigrants raises tax revenue, it also raises spending on social benefits. Hence, it is important for welfare states to measure the impact of immigration on the public budget.

## Tables and Figures

**Table 1.1:** The number of immigrants in 2000 and 2019

| Visa category | 2000 (1) | 2019 (2) | Change in the number of immigrants (3) | Contribution to the total growth rate (%) (4) |
|---|---|---|---|---|
| **High-skilled workers** | 95,576 | 399,125 | 303,549 | 22.67 |
| Professor | 6,744 | 7,354 | 610 | 0.05 |
| Artist | 363 | 489 | 126 | 0.01 |
| Business manager | 5,694 | 27,249 | 21,555 | 1.61 |
| Legal/Accounting | 95 | 145 | 50 | 0.00 |
| Medical services | 95 | 2,269 | 2,174 | 0.16 |
| Researcher | 2,934 | 1,480 | -1,454 | -0.11 |
| Instructor | 8,375 | 13,331 | 4,956 | 0.37 |
| Engineer/Specialist in humanities/International services | 51,270 | 271,999 | 220,729 | 16.48 |
| Intra-company transferee | 8,657 | 18,193 | 9,536 | 0.71 |
| Skilled labor | 11,349 | 41,692 | 30,343 | 2.27 |
| Highly-skilled professional | 0 | 14,924 | 14,924 | 1.11 |
| **Less-skilled workers** | 114,761 | 758,976 | 644,215 | 48.11 |
| Nursing care | 0 | 592 | 592 | 0.04 |
| Technical intern | 0 | 410,972 | 410,972 | 30.69 |
| Specific skilled worker | 0 | 1,621 | 1,621 | 0.12 |
| International student | 114,761 | 345,791 | 231,030 | 17.25 |
| **Other** | 1,383,664 | 1,775,036 | 391,372 | 29.23 |
| Entertainment | 53,847 | 2,508 | -51,339 | -3.83 |
| Religious activities | 4,976 | 4,285 | -691 | -0.05 |
| Journalist | 349 | 220 | -129 | -0.01 |
| Cultural activities | 3,397 | 3,013 | -384 | -0.03 |
| Training | 36,199 | 1,117 | -35,022 | -2.62 |
| Dependent | 72,878 | 201,423 | 128,545 | 9.60 |
| Designated activities | 30,496 | 65,187 | 34,691 | 2.59 |
| Permanent resident | 145,336 | 793,164 | 647,828 | 48.38 |
| Spouse of Japanese national | 279,625 | 145,254 | -134,371 | -10.03 |
| Spouse of permanent resident | 6,685 | 41,517 | 34,832 | 2.60 |
| Long-term resident | 237,607 | 204,787 | -32,280 | -2.45 |
| Special permanent resident | 512,269 | 312,501 | -199,768 | -14.92 |
| **Total** | 1,594,001 | 2,933,137 | 1,339,136 | 100.00 |

Note: The number of immigrants by visa categories in 2000 and 2019 are shown in columns (1) and (2), respectively. The change in the number of immigrants in column (3) is calculated by subtracting column (2) from (1). Column (4) show how the change in the number of immigrants in each visa category contributes to the total change in the number of immigrants, which can be obtained by dividing column (3) by the change in the total number of immigrants.
Source: ”Statistics on Foreign Nationals Residing in Japan” and ”Statistics on Foreigners Registered in Japan” from MOJ

# Chapter 2

# Impact of Immigrants on Trade

## 2.1 Introduction

Recent literatures have established that immigrants can reduce trade costs with their country of origin and thereby improve bilateral trade. However, "how" immigrants can affect trade remains debatable. One explanation states that immigrants can improve both the intensive and extensive margins of trade by reducing variable trade costs. If immigrants can reduce fixed trade costs, then only the extensive margin improves. The empirical literatures on this mechanism have primarily focused on exports rather than imports. Furthermore, these studies have analyzed immigrants' impact on trade in "open border" countries such as the US (Gould, 1994; Herander and Saavedra, 2005; White, 2007) and European countries (Combes et al., 2005; Girma and Yu, 2002; Hatzigeorgiou and Lodefalk, 2015), without considering closed border countries like Japan. According to The World Bank (n.d.), immigrant-to-total population ratios in Japan, the US, and Italy were 1.6%, 14.5%, and 9.7%, respectively. Thus, it is unclear whether such small immigrant population will have positive impacts on trade similar to past literatures.

This study examines the relationship between immigrants and trade in Japan. Specifically, it attempts to (i) explain the relationship between immigrants and trade in an economy with strict migration laws, (ii) discuss the impact of immigrants on trade of different categories of goods, and (iii) quantify the effects of immigrants on intensive and extensive margins for both exports and imports.

To achieve these objectives, gravity equation is estimated using trade and immigrant data for 47 prefectures of Japan and 160 other countries between 2006 and 2014. Trade data are further categorized into Consumer Goods and Industrial Goods to compare the effects between the two groups. Intensive margins are studied using the same gravity model, but it only includes goods with a positive trade value for the entire period. However, to quantify the effects on extensive margins, the gravity equation is estimated using the Poisson pseudo-maximum-likelihood (PPML) estimator, considering the number of imported (exported) goods as the dependent variable. Additionally, following past literatures, this study adopts the instrumental variable (IV) method to address the problem of immigration endogeneity.

The models yield three important results, which are also presented in Luong (2023). First, an increase in immigrant population by 10% increases the imports (exports) by 4.49% (3.03%). For robustness checks, the model is re-estimate with different dependent variable: imports (exports) as a share of the prefecture's total imports (exports) or as a share of the prefecture's gross domestic product (GDP). Further tests are conducted by removing each dummy variable, excluding China, or excluding Tokyo. All the tests return significant and similar coefficients with the main findings. Thus, on average, immigrants share a positive relationship with trade value.

Second, when the trade data is categorized into Consumer Goods and Industrial Goods, immigrants have a more substantial effect on the former. This trend is observed for both imports and exports. Consumer Goods consist of Food & Direct Consumers, Consumer Non-durable Goods, and Consumer Durable Goods; while Industrial Goods consists of Industrial Supplies and Capital Equipment. These results show that immigrants can reduce trade costs for Consumer Goods more effectively. One possible explanation is that the information provided by immigrants is more valuable in the context of trading such goods.

Third, an increase in immigrant counts improves both the intensive and extensive margins for imports and exports. That is, an increase in immigrants leads to a higher trade value for the existing imported (exported) goods as well as a higher variety of imported (exported) goods. This implies that immigrants can reduce both fixed and variable trade costs. Robustness tests are conducted (except for extensive margins, which is tested using different variables). These tests generate robust results.

This study will be the first to analyze the effects of immigrant communities on bilateral trade in an open market but a closed-border economy such as Japan. Another significant contribution concerns the mechanisms through which immigrants affect trade. Specifically, there is evidence that immigrants increase both the intensive and extensive margins of trade. Most of the current literature has focused on the relationship between immigrants and exports. This study extends this line of empirical research by considering the case of imports as well.

The remainder of this chapter is organized as follows. Section 2.2 summarizes the past contributions regarding the use of the gravity equation to study the relationship between immigrants and bilateral trade. Section 2.3 presents the theoretical foundation of the gravity equation, the corresponding empirical model, and the strategy for IV estimation. Section 2.4 presents the estimation results and their implications. Section 2.5 presents the main findings of the study. Finally, Section 2.6 concludes the chapter.

## 2.2 Literature Review

The gravity model has been empirically successful in identifying the determinants of bilateral trade, such as GDP, free trade agreement (FTA) membership, and geographic distance. Immigration is also identified as a determinant of trade. Studies using various analytical methods have reported a positive relationship between trade and immigration. When immigrants enter a host country, they can influence trade through two channels: the home bias effect and business and social network effect. According to the home bias effect, immigrants' consumption habits differ from those of the natives. As goods from their country of origin may not be available or may be available at high prices, immigrants are incentivized to purchase such goods from their country of origin, effectively increasing imports from the host country (Gould, 1994; White, 2007). Mazzolari and Neumark (2012) study the effects of immigrants on a variety of goods in the host country to find that an increase in the number of immigrants leads to an increase in the number of ethnic restaurants, suggesting that immigrants are more likely to consume goods from their countries of origin.

The latter channel explains immigrants' abilities to lower trade costs (Head and Ries, 1998; Herander and Saavedra, 2005; Peri and Requena-Silvente, 2010; Rauch and Trindade, 2002; Rauch, 2001; Wagner et al., 2002). Immigrants can lower communication barriers in the context of trade because they understand the language of their country of origin. Another advantage is that they understand the culture and consumption habits of their country of origin, allowing for better business opportunities. Moreover, immigrants know whom to trust and how to conduct business in their country of origin; this is because they are better connected with its local businesses and are familiar with its rules and laws. Combes et al. (2005) extensively study social and business network effects. They analyze the impact of immigrant stocks (social networks) and production plant networks (business networks) on the inter- and intra-regional trade flows in 94 French regions. By accounting for plant networks, the authors attempt to capture business-related information provided by immigrants. The study reveals that both immigrant stocks and plant networks have positive and significant effects on trade, and a larger effect on the latter, implying the importance of immigrants' social and business networks.

Two conclusions can be drawn based on these arguments. First, both channels positively influence trade volumes. Second, apart from the business and social network effects, the home bias effect implies that immigrants can contribute toward an increase in imports. Rauch (2001) argues that the second conclusion explains the higher elasticity of imports compared to exports. White (2007) reaches the same conclusion by studying the effects of immigrants on US trade.

This mechanism can be examined from a different perspective by examining the impact of immigrants on fixed and variable trade costs. Chaney (2008) derives a theoretical model demonstrating that lowering variable trade costs can lead to an increase in both the intensive (trade value of existing goods) and extensive (trade of new goods) trade margins. The author also shows that lowering fixed trade costs can only increase the extensive trade margins. Thus, whether immigrants reduce only fixed trade costs or both fixed and variable trade costs can be determined by analyzing the link between immigration and both margins. Several studies have attempted to study this mechanism. Using US data for two periods, Coughlin and Wall (2011) define intensive margin as the trade that occurs in both periods and the extensive margin as the probability of entering or exiting a market. The authors find a positive impact of immigration on both intensive and extensive trade margins.

Using slightly different definitions of extensive margin (as the number of exported goods) and intensive margin (as the average value of exported goods), Kang (2018) shows that the immigrant population in South Korea improves both the intensive and extensive margins of exports. Parsons and Vézina (2018) exploit a natural experiment in the US history and find that Vietnamese immigrants help stimulate the extensive margin of exports (i.e., the number of industries with a positive trade value with Vietnam). Hatzigeorgiou and Lodefalk (2015) find that the immigrant population in Sweden facilitates higher exports only through extensive margins. Using micro data on individual trade in Spain, Peri and Requena-Silvente (2010) show that immigrant populations substantially improve exports, mostly through extensive margins.

Additionally, immigrants have a greater effect on certain types of goods than the others. Gould (1994) finds that pro-trade effects are stronger for consumer-manufactured goods than producer-manufactured goods. By categorizing the imports of 78 commodities into five groups of goods, Dunlevy and Hutchinson (1999) find significant immigrant-link effects in processed foodstuffs, semi-manufacturers, and manufacturers of consumption groups, linking this to the home-bias effect of immigrants. The authors repeat the analysis on the individual commodities to find significant positive effects for 35 commodities. Rauch and Trindade (2002) have studied the impact of the Chinese network on international trade and confirmed that the highest effects are associated with differentiated goods. They divide all goods into heterogeneous and homogeneous categories and argue that because homogeneous goods possess a reference price, buyers and sellers make purchase decisions based on this price. However, the differentiated goods have no reference prices. Hence, the information provided by immigrants is more critical in trading heterogeneous goods. Hatzigeorgiou (2010) uses a large dataset of 75 economies to obtain similar results. These studies indicate that if the information provided by immigrants is valuable, the effects should be the strongest for differentiated goods because such goods differ among suppliers.

Although the gravity model is usually estimated at the country level, many studies have extended it to the regional level. Compared to the country level, data from small spatial units (state or province level) are used to better control for unobserved heterogeneity and deal with the bias caused by the Modifiable Areal Unit Problem (MAUP) (Dunlevy, 2006; Peri and Requena-Silvente, 2010; Wagner et al., 2002). The

MAUP, similar to Simpson's paradox (Samuels, 1993), occurs when a trend either disappears or reverses when the observed data are grouped together. Additionally, trade can be positively correlated with immigration policies, which are usually set at the national level (Steingress, 2018). However, the actual implementation of immigration policies may vary depending on the local governments. As such, focusing on the prefecture level instead of the national level can not only help minimize MAUP, but also allow one to exploit the variation in the implementation of immigration policies between prefectures.

In summary, the literature consistently demonstrates the positive effects of immigrants on trade. Splitting the effects of trade into intensive and extensive margins makes it easier to identify the factors affecting trade. The magnitude depends on the value of the information provided by immigrants to the host country. Specifically, this relationship is more significant for differentiated goods.

## 2.3 Data and Methodology

### 2.3.1 Theoretical model

The gravity model is derived by following Anderson and Van Wincoop (2003). If $c_{ij}$ represents the consumption of goods exported from country $i$ to country $j$, the constant elasticity of substitution (CES) utility function of a representative consumer in $j$ is

$$\left(\sum_i \alpha_i^{\frac{1-\sigma}{\sigma}} c_{ij}^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}} \tag{2.1}$$

subjects to the budget constraint

$$Y_j = \sum_i p_{ij} c_{ij} \tag{2.2}$$

$\alpha_i$ is the CES preference parameter, $\sigma > 1$ is the elasticity of substitution among different goods, $Y_j$ is the total output value of $j$, and $p_{ij}$ represents the price at which consumers in country $j$ pay for the goods imported from country $i$. $p_{ij}$ can be further decomposed into $p_{ij} = p_i t_{ij}$, where $p_i$ denotes the factory-gate price in country $i$, and $t_{ij}$ denotes the iceberg-type trade costs (Samuelson, 1952). The demand function can be solved immediately. If the world's total output value is defined as $Y \equiv \sum_j Y_j$, then the total value of goods exported from country $i$ to country $j$ is as follows:

$$X_{ij} = \frac{Y_i Y_j}{Y} \times \left[\frac{t_i j}{\Pi_i P_j}\right]^{1-\sigma} \tag{2.3}$$

where $\Pi_i^{1-\sigma} = \sum_j \left(\frac{t_{ij}}{P_j}\right)^{1-\sigma} \frac{Y_j}{Y}$ and $P_j^{1-\sigma} = \sum_i \left(\frac{t_{ij}}{\Pi_j}\right)^{1-\sigma} \frac{Y_i}{Y}$ represent the price index of for countries $i$ and $j$, respectively. Equation 2.3 relates the trade flow between countries $i$ and $j$ to the economic mass ($Y_i$ and $Y_j$), multilateral resistance terms ($\Pi_i$ and $P_j$), and trade costs ($t_{ij}$).

Following Felbermayr et al. (2015), the determinants of trade costs are geographical distance and information on trading opportunities between countries $i$ and $j$. Since immigrants can reduce trade costs between countries $i$ and $j$ by using the knowledge obtained from their country of origin, information on trading opportunities can be written as a function of immigrant stocks from country $i$ residing in country $j$. Geographical distance is expected to increase trade costs, and immigrant stocks are expected to positively affect the availability of information on trading opportunities, thereby reducing trade costs.

### 2.3.2 Empirical model

Following Bratti et al. (2014), Equation 2.2 is estimated empirically by taking logarithm of the variables on both sides, and dummies are included to control for unobserved heterogeneity. Specifically,

$$\begin{aligned} \ln(1 + X_{ijt}) = \beta_1 \ln(1 + N_{ij,t-1}) + \beta_2 \ln d_{ij} + \beta_3 \ln(Y_{i,t-1} Y_{j,t-1}) \\ + \beta_4 \ln(Openness_i) + \delta_{ct} + \theta_{rt} + \mu_{cr} + \varepsilon_{ijt} \end{aligned} \tag{2.4}$$

where $X_{ijt}$ denotes bilateral trade (exports or imports) between countries $i$ and prefecture $j$ at time $t$. $N_{ij,t-1}$ represents the stock of immigrants from country $i$ residing in prefecture $j$ at time $t-1$. $d_{ij}$ is the geographic distance between $i$ and $j$. $Y_{i,t-1}$ and $Y_{j,t-1}$ are the GDP of country $i$ and prefecture $j$, respectively, at time $t-1$. Following Harrigan (1996) and Head and Ries (1998), $Openness_i$, measured as the ratio between the total trade to the world and country $i$'s GDP, is included to measure the world market integration level. Thus, a higher level Openness indicates that the country has a greater willingness to trade. $\delta_{ct}$ is a continent-year dummy, $\theta_{rt}$ is a region-year dummy, and $\mu_{cr}$ is a country-pair dummy, where $c$ indicates the continent of country $i$ and $r$ indicates the region in which prefecture $j$ is located. Instead of using GDPs in the same period $t$ as the trade value in accordance with the structural model, lagged GDPs are used instead to consider the possibility of a problem of endogeneity existing between the trade value and GDPs. The method is adopted following Bratti et al. (2014). Similarly, immigrant stocks are also lagged for one period.

No trade problem also needs to be addressed, which is more likely to happen at prefecture level than on national level. To retain zero-trade data, a constant of 1 is added to $X_{ijt}$ (Artal-Tur et al., 2012; Dunlevy, 2006; Peri and Requena-Silvente, 2010). Similarly, a constant of 1 is added to $N_{ij,t-1}$ to include all cases where trade is occurring with country $i$, but no immigrants from that country are present in prefecture $j$.

Following the literature, exporter-time, importer-time, and country-pair dummies are included (Baier and Bergstrand, 2007; Olivero and Yotov, 2012). However, the specification is very demanding as it absorbs most of the variations in the data(Bratti et al., 2014). As a result, region-year dummies permit variation between prefectures while controlling for unobserved heterogeneity. Similarly, continent-year dummies are included. Finally, region-continent dummies are used to control for unobserved heterogeneity between trade pairs.

### 2.3.3 Intensive and extensive margins of trade

The trade data are disaggregated in the 9-digit Harmonized System (HS9). Intensive margins can be measured by re-estimating the above gravity model using the data of goods displayed a positive trade value between 2006 and 2014.

To measure the impact on extensive margins, we use the number of traded goods as a proxy, following Parsons and Vézina (2018) and Kang (2018). Unlike intensive margin, PPML estimator is used instead. PPML is suitable because the dependent variable is count data with many zeros, and it may suffer from an overdispersion problem (variance is greater than the mean). Additionally, Pfaffermayr (2019) finds that PPML method suffers from downward bias. Therefore, province, continent, and year dummies are used instead to reduce the number of dummies.

### 2.3.4 IV estimation

In the previous section, immigrant stocks are lagged by one period to minimize endogeneity concerns. Nonetheless, IV is still used to better control for the problem of endogeneity. Hatzigeorgiou and Lodefalk (2015) have proposed using Denmark's immigrant stocks as instruments for Sweden's immigrant stocks because both countries share many similarities in immigrant population structure, cultural heritage, and population. Additionally, the authors argue that neighboring countries' immigrant stocks influence the country's trade of interest. However, this method is not applicable for Japan.

Alternatively, instruments based on historical settlement patterns is adopted (Bahar and Rapoport, 2018; Bratti et al., 2014; Hatzigeorgiou and Lodefalk, 2015; Peri and Requena-Silvente, 2010). This instrument is based on the assumption that immigrants tend to settle in areas where there exists a community of immigrants of the same nationality. The instrument is calculated using the following procedure. First, using the distribution of immigrants across prefectures in 1995, the share of immigrants to the total number of immigrants in 1995 for each combination of country $i$ and prefecture $j$ is obtained. Next, we multiply this share with the national-level immigrant stocks to obtain the constructed immigrant stocks for each period from 2006 to 2014. According to this calculation, the constructed immigrant stocks are correlated with the actual immigrant stocks in 1995 but should not be correlated with the bilateral trade observed in the same period.

### 2.3.5 Data

Most of the data used in this study are publicly available. The data cover 160 countries and 47 prefectures between 2006 and 2014. Japan's immigration and trade data are provided by the MOJ and Japan Customs, respectively. Both are available on the Portal Site of Official Statistics of Japan (e-Stat). In this study, immigrants are defined as foreigners with work or long-term visas. Foreigners that are not included in this study include those who come to Japan for "tourism, business, visiting friends or relatives, etc., that does not include remunerative activities" (Ministry of Foreign Affairs of Japan (MOF), 2020). The variable of interest is the stock of immigrants from a country of origin (country $i$) to a prefecture in Japan (prefecture $j$).

[**Table 2.1**]

Table 2.1 shows the top 10 countries of origin with the highest number of immigrants in 2014. These 10 countries account for 89.6% of all immigrants in Japan. Comparing the 2014 ranking (first column from the left) to the 2006 ranking (first column from the right) gives an overall picture of the composition of immigrants by country of origin over time. Of these 10 countries, the Vietnamese and Nepalese communities have seen the largest increase in population, while the Chinese have overtaken Koreans to become the largest migrant population.

Trade data are only recorded at the customs level; therefore, the trade value for each prefecture must be calculated. The trade value is redistributed depending on the prefecture's GDP ratio within the group managed by a specific custom. For example, Osaka Customs Headquarters manages trade coming to and from Osaka, Kyoto, Wakayama, Nara, Shiga, Fukui, Ishikawa, and Toyama. Therefore, Osaka's export (import) value is calculated by multiplying total exports (imports) through this custom by Osaka's GDP ratio[1]. Next, the trade data, originally in yen, is converted to US dollars using the exchange rate provided by the United Nations Commodity Trade Statistics Database. This process is performed separately for annual exports and imports.

GDP of the prefectures is taken from the Japanese Cabinet Office, while GDP of countries are taken from the World Bank's database. However, since prefectures' GDP are originally in the Japanese yen, the numbers needed to be converted to US dollars. First, the GDP ratio of each Japanese prefecture to the total GDP is calculated using Japanese Cabinet Office data. The ratio is then multiplied by Japan's GDP, taken from the World Bank's database, which is originally in US dollars.

The geographical distance between countries i and prefecture j is calculated using the Great Circle Distance and the coordinates of the capital city of country i and the

[1] The trade data for each prefecture has to be calculated since trade data is not available at the prefecture level, but only at the custom level.

prefectural government office of prefecture j. The coordinates of each country's capital city are provided by Mayer and Zignago (2011), whereas those of the prefectural government offices are provided by the Geospatial Information Authority of Japan.

Using the 2-digits, 4-digits, and 6-digits HS code classification by Japan Customs, trade data are categorized into Food & Direct Consumers, Industrial Supplies, Capital Equipment, Consumer Non-durable Goods, Consumer Durable Goods, and Others. For this study, the Others category is dropped, while the other five categories are grouped into Consumer Goods (Food & Direct Consumers, Consumer Non-durable Goods, Consumer Durable Goods) and Industrial Goods (Industrial Supplies, Capital Equipment).

## 2.4 Empirical Results

### 2.4.1 Baseline model

[**Table 2.2**]

Table 2.2 presents the coefficients and robust standard errors for the panel and IV estimations. The first-stage F-statistic suggests that the instruments are strong. The estimates are significant and negative for distance, implying that the transportation costs caused by distance can reduce trade between countries. In contrast, significant and positive signs for GDP imply that countries or prefectures that are large in terms of economic mass tend to trade more with each other. The positive Openness coefficients for both imports and exports imply that countries that are more integrated into the world economy will trade more with Japan. The effects of immigration on exports and imports are consistently positive in both estimates, confirming that immigration positively affects Japan's trade. After controlling for endogeneity, a 10% increase in the immigrant population leads to a 3.51% (1.74%) increase in imports (exports). All the results are as expected and consistent with those of previous studies.

### 2.4.2 Consumer goods and industrial goods

Table 2.3 presents the IV estimates for Consumer and Industrial Goods. The coefficients of immigrants are positive for the export and import of both categories and are higher for Consumer Goods than Industrial Goods. The same trend is observed for Industrial Goods, where the impact on imports exceeds that on exports. While this classification is similar to that of Rauch (1999), the major difference is that machinery is classified as a heterogeneous good. However, the results show that the relationship between immigrants and the trade of Consumer and Industrial Goods correspond to the relationship between homogeneous and heterogeneous goods. Specifically, because Consumer Goods differ significantly from each other (heterogeneous goods), immigrants can provide essential market information to induce more trade.

[**Table 2.3**]

### 2.4.3 Intensive and extensive margins of trade

Tables 2.4 and 2.5 display the IV estimation results for the effects of immigrants on the intensive and extensive margins of trade. Columns (1) and (2) show the impacts on imports and exports, respectively. The results show that immigrants positively and significantly affect the intensive margin but are higher for imports. Specifically, a 10% increase in immigrants leads to a 3.58% (1.58%) increase in the intensive margin of imports (exports). However, the trade creation effects are slightly higher for exports; a 10% increase in immigrants increases the extensive margin of exports (imports) by 1.39% (1.1%).

[**Table 2.4**]

[**Table 2.5**]

## 2.5 Discussion

### 2.5.1 Trade and migration in the gravity equation

The coefficients on immigrants are significant and positive for both imports and exports, suggesting that immigrants can reduce trade costs and promote trade volumes. Additionally, the effect is greater for imports (0.351) than for exports (0.174). Previous studies reported a similar trend (Bratti et al., 2014; White, 2007). This difference is consistent with the theory that imports are affected by both the home bias effect and business and network effects, whereas exports are only affected by the second channel. Another feasible hypothesis for Japan is that manufacturers produce products abroad and import them into the domestic market. Such companies are dubbed "Factoryless goods producers" (FGP) (see Morikawa (2016) for a detailed study on Japan's FGP). Ministry of Economy, Trade and Industry (2014) has noted this trend in its white paper on manufacturing industries, quoting the shrinking population as a concern. In other words, a decrease in trade costs and an increase in business opportunities abroad due to an increase in immigrant stocks make manufacturing more profitable abroad; thus, goods, even for domestic use, are being produced in foreign countries. This trend appears to be stronger for Consumer Goods than Industrial Goods. As stated above, the pattern is similar to that of heterogeneous and homogeneous goods; information is more important in facilitating the trade of the former goods.

This study finds evidence that immigration leads to higher intensive and extensive margins, which, in turn, lowers both fixed and variable trade costs. In other words, immigrants can open up new business opportunities, leading to a broader variety of goods to be traded and improving existing trade routes. As the literature has mainly focused on exports, finding concerning import is an important contribution. The results show that immigrants are better at improving the trade value of existing imported goods, compared to exported goods. On the other hand, immigrants are more likely to open new trade route for exported goods, comparted to imported goods.

Combining the baseline results with the effects on both margins of trade implies that the immigrant community in Japan improves trade mostly through intensive margins. Specifically, while immigration leads to higher import value for existing goods than exports, it leads to a slightly higher number of exported goods than imported goods. Moreover, the effects of immigrants on the overall trade and intensive margins are of similar magnitude. These results suggest that while immigrants help open up new trade opportunities, the overall trade value has significantly increased by improving the trade of existing goods.

### 2.5.2 Trade and migration in the traditional framework

The empirical results obtained from estimating the gravity equation emphasize that bilateral trade depends on the countries' economic size and trade costs, which is assumed to be a function of immigrant stocks. However, the gravity equation does not explain the pattern of trade by evaluating the relative price effects like in traditional trade analysis. Following Gaston and Nelson (2013), this section attempts to explain the theory behind the complementary relationship between immigration and trade, using the Hecksher-Ohlin-Samuelson (HOS) model.

First, the classic case of the HOS model is considered. There are 2 countries (home, foreign) that produce 2 goods (food, cloth) using 2 factors of production (labor, capital). For clarity, food is labor-intensive goods, and cloth is capital-intensive goods. Then, free trade between countries with different factor endowments will equalize not only the good prices, but also the real factor prices, even though the factors are immobile between countries (Samuelson, 1949). The reverse is also true, as proven by Mundell (1957): under similar HOS assumptions, if there is a gap between good prices between home and foreign, then factor mobility will result in the allocation similar to free trade. Figure 2.1 below expresses the above ideas. The horizontal axis denotes the real factor prices ratio $\omega = \frac{w}{r}$, where $w$ is the wages, and $r$ is the rental rate. The vertical axis denotes the good prices ratio $P = \frac{p_f}{p_c}$, where $p_f$ and $p_c$ are the prices of food and cloth, respectively. The superscripts H and F denote whether the ratios belong to home or foreign country. At the autarky position, both countries will have different $P - \omega$ combinations. When free trade or free factor mobility is allowed, good prices and factor prices ratio will converge to the equilibrium allocation $P^*$ and $\omega^*$. In this case, free trade and immigration are substitutes.

[**Figure 2.1**]

It is possible to derive a complementary relationship between free trade and immigration by changing some of the assumptions. Specifically, both countries are assumed to possess identical initial factor endowments. Furthermore, home country will have a Hicks-neutral superior technology in producing food (labor-intensive good). In other words, home country can produce more food than foreign country and, thus, food will have a lower price in home country. Figure 2.2 illustrates this assumption by representing the curve of home country lower than that of foreign country. Once free trade becomes possible, good prices are equalized at $P^*$. However, wages in home country will be higher than in foreign country, implying a higher marginal return of labor at home. Thus, home country will export the labor-intensive food. If free movement of labor is permitted at this point, labor will move from foreign to home country. As a result, home country will become abundant in labor, increasing its competitive advantage and, in turn, increasing trade.

[**Figure 2.2**]

On the other hand, free movement of labor will lead to the equalization of factor price ratio due to migration. Once free trade is introduced, countries will trade that they have a comparative advantage in, further increasing trade. As a result, under these set of assumptions, migration and trade are complements.

## 2.6 Conclusion

This study uses panel data from 47 prefectures in Japan and 160 trade partners to examine the relationship between immigrants and bilateral trade. First, on average, by reducing trade costs, immigrants improve both imports and exports to their countries of origin, and the magnitude is stronger for imports. The second finding is that the increase in trade is greater for consumer goods than industrial goods, implying the importance of the information provided by immigrants. Finally, immigrants lower both fixed and variable trade costs and, consequently, raise the trade value of existing goods and expand the variety of traded goods. One important policy implication of these findings is that immigration policies positively affect trade. Thus, by encouraging migration, the host country can exploit business and network effects to reduce bilateral trade costs and promote trade.

However, the trade enhancement effects may be more complex than an increase in the migrant population, leading to an increase in trade value. For example, while this study finds stronger effects on imports than on exports, Gould (1994) finds that immigrants from some countries lead to the opposite: an additional immigrant from Japan increases the import value by \$2,965 and export value by \$933 versus \$29,359 and \$47,708 for their counterparts from Singapore. Similarly, Hatzigeorgiou and Lodefalk (2015) find that immigrants only affect Sweden's exports and not its imports, citing that a large proportion of immigrants are refugees seeking shelter rather than employment. These two studies suggest that immigrants can have different trade improvement effects depending on their country of origin or migration purpose. However, this study fails to confirm these results because of missing data. Furthermore, Coughlin and Wall (2011) find a positive effect only for an extensive margin of exports, suggesting that firms may substitute exports with FDI. Overall, while immigrants can improve welfare by enhancing trade, further studies are needed to identify, for instance, the link between immigrants and the movement of capital or the heterogeneous effects of immigration. Thus, immigration policies can be further refined to achieve different economic objectives.

# Tables and Figures

**Table 2.1:** Japan's immigrant population by country of origin (top 10)

| **Ranking in 2014** | **Country of origin** | **Number of immigrants in 2014** | **Percentage of total immigrants in 2014** | **Growth from 2006 to 2014 (%)** | **Ranking in 2006** |
|---|---|---|---|---|---|
| 1 | China | 654,651 | 31.5% | 16.7% | 2 |
| 2 | Korea | 500,451 | 24.1% | -16.3% | 1 |
| 3 | Philippines | 217,533 | 10.5% | 12.4% | 4 |
| 4 | Brazil | 175,343 | 8.4% | -44.0% | 3 |
| 5 | Vietnam | 99,822 | 4.8% | 207.3% | 8 |
| 6 | America | 51,185 | 2.5% | -0.3% | 6 |
| 7 | Peru | 47,963 | 2.3% | -18.3% | 5 |
| 8 | Thailand | 43,052 | 2.1% | 8.7% | 7 |
| 9 | Nepal | 42,341 | 2.0% | 439.8% | 10 |
| 10 | Indonesia | 30,196 | 1.5% | 21.5% | 9 |
| | Top 10 countries | 1,862,537 | 89.6% | | |
| | Total | 2,079,174 | 100% | | |

Source: "Statistics on Foreign Nationals Residing in Japan" and "Statistics on Foreigners Registered in Japan" from Ministry of Justice Japan

**Table 2.2:** Effect of immigrants on trade volume (using gravity model)

| | *Dependent variable:* | | | |
|---|---|---|---|---|
| | **OLS estimation** | | **IV estimation** | |
| | Imports | Exports | Imports | Exports |
| | (1) | (2) | (3) | (4) |
| $\ln(1 + N_{ij,t-1})$ | 0.472*** | 0.310*** | 0.351*** | 0.174*** |
| | (0.008) | (0.007) | (0.018) | (0.018) |
| $\ln(distance_{ij})$ | −0.698*** | −0.769*** | −1.016*** | −1.054*** |
| | (0.042) | (0.034) | (0.060) | (0.059) |
| $\ln(Y_{i,t-1}Y_{j,t-1})$ | 1.199*** | 1.066*** | 1.238*** | 1.201*** |
| | (0.007) | (0.005) | (0.011) | (0.011) |
| $\ln(Openess_{jt})$ | 1.012*** | 1.244*** | 0.960*** | 1.271*** |
| | (0.017) | (0.014) | (0.019) | (0.018) |
| Observations | 60,160 | 60,160 | 60,160 | 60,160 |
| $R^2$ | 0.733 | 0.800 | 0.695 | 0.664 |
| F-statistic | | | 16,481 | 16,481 |

Note: The independent variable is the natural log of imports plus 1 in columns (1), (3), and log of exports plus 1in columns (2), (4). Robust standard errors are reported in parentheses. Columns (1) and (2) show the OLS estimates, while columns (3) and (4) show the 2SLS results, where the IV is the imputed immigrants. Region-continent, region-year, and continent-year dummies are included in all estimations. Robust standard errors are reported in parentheses. *p<0.1; **p<0.05; ***p<0.01

**Table 2.3:** Effects of immigrants on the trade of Consumer and Industrial Goods

| | *Dependent variable:* | | | |
|---|---|---|---|---|
| | **Imports** | | **Exports** | |
| | Consumer Goods | Industrial Goods | Consumer Goods | Industrial Goods |
| | (1) | (2) | (3) | (4) |
| $\ln(1 + N_{ij,t-1})$ | 0.682*** | 0.583*** | 0.590*** | 0.162*** |
| | (0.014) | (0.014) | (0.012) | (0.013) |
| $\ln(distance_{ij})$ | −0.755*** | −0.147*** | −0.315*** | −1.087*** |
| | (0.055) | (0.054) | (0.039) | (0.050) |
| $\ln(Y_{i,t-1}Y_{j,t-1})$ | 0.765*** | 1.143*** | 0.565*** | 1.210*** |
| | (0.010) | (0.010) | (0.008) | (0.009) |
| $\ln(Openess_{jt})$ | 0.598*** | 1.322*** | 1.030*** | 1.259*** |
| | (0.019) | (0.014) | (0.014) | (0.018) |
| Observations | 56,870 | 57,662 | 56,541 | 60,160 |
| $R^2$ | 0.639 | 0.682 | 0.689 | 0.663 |
| F-statistic | 15,207 | 15,352 | 14,907 | 16,576 |

Note: The independent variable is the natural log of imports plus 1 in columns (1), (2), and log of exports plus 1 in columns (3), (4). Robust standard errors are reported in parentheses. Region-continent, region-year, and continent-year dummies are included in all estimations. Robust standard errors are reported in parentheses. See text for the categorization of consumer goods and industrial goods. *p<0.1; **p<0.05; ***p<0.01

**Table 2.4:** Effects of immigrants on intensive margin

| | *Dependent variable:* | |
|---|---|---|
| | **Imports** | **Exports** |
| | (1) | (2) |
| $\ln(1+N_{ij,t-1})$ | 0.358*** | 0.158*** |
| | (0.015) | (0.016) |
| $\ln(distance_{ij})$ | −0.191*** | −0.757*** |
| | (0.056) | (0.052) |
| $\ln(Y_{i,t-1}Y_{j,t-1})$ | 1.058*** | 1.144*** |
| | (0.014) | (0.012) |
| $\ln(Openess_{jt})$ | 1.168*** | 1.194*** |
| | (0.020) | (0.019) |
| Observations | 29,544 | 37,688 |
| $R^2$ | 0.649 | 0.640 |
| F-statistic | 7,317 | 9,627 |

Note: The independent variable is the natural log of aggregated trade value of goods with positive trade in all periods. Robust standard errors are reported in parentheses. 2SLS estimator is used, where the IV is the imputed immigrants. Region-continent, region-year, and continent-year dummies are included in all estimations. Robust standard errors are reported in parentheses. See text for the definitions of intensive margin. *p<0.1; **p<0.05; ***p<0.01

**Table 2.5:** Effects of immigrants on extensive margin

| | *Dependent variable:* | |
|---|---|---|
| | **Number of imported goods** | **Number of exported goods** |
| | (1) | (2) |
| $\ln(1 + N_{ij,t-1})$ | 0.110*** | 0.139*** |
| | (0.007) | (0.004) |
| $\ln(distance_{ij})$ | −0.436*** | 0.008 |
| | (0.025) | (0.018) |
| $\ln(Y_{i,t-1}Y_{j,t-1})$ | 0.560*** | 0.401*** |
| | (0.008) | (0.004) |
| $\ln(Openess_{jt})$ | 0.444*** | 0.479*** |
| | (0.013) | (0.010) |
| Observations | 60,160 | 60,160 |
| Pseudo $R^2$ | 0.784 | 0.784 |
| F-statistic | 17,629 | 17,629 |

Note: The independent variable is the number of traded goods in each period. Robust standard errors are reported in parentheses. PPML-IV estimator is used, where the IV is the imputed immigrants. Region, continent, and year dummies are included in all estimations. Robust standard errors are reported in parentheses. See text for the definitions of extensive margin. *p<0.1; **p<0.05; ***p<0.01

**Figure 2.1:** Substitution relationship between migration and trade in HOS framework

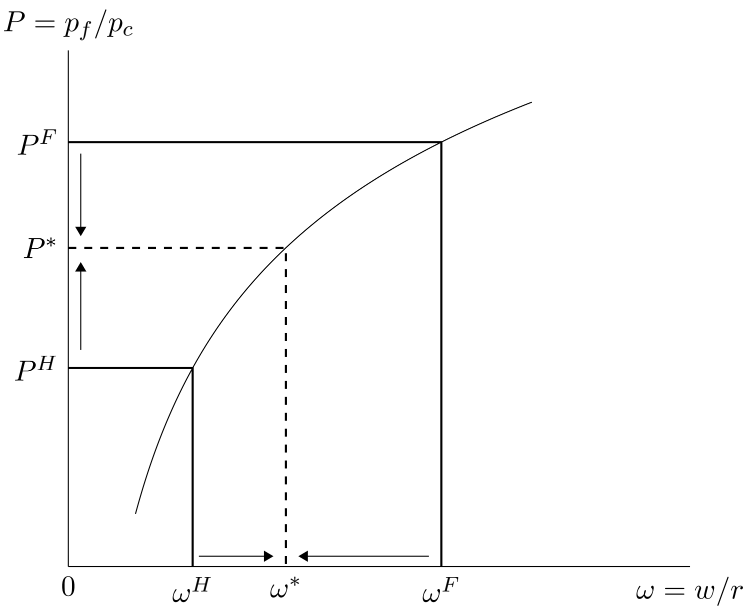
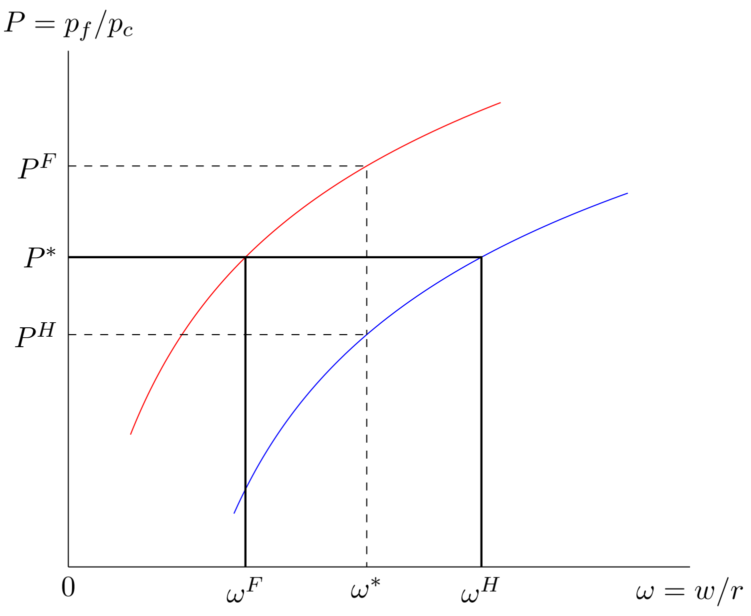



**Figure 2.2:** Complementary relationship between migration and trade in HOS framework



# Chapter 3

# Does immigration cause prefectures' economy to diverge? Evidence from Geographically Weighted Panel Regression

## 3.1 Introduction

The economic impacts of immigration have been studied extensively and produced mixed results. Additionally, most researches have been using Western countries, which are relatively open towards immigration, as their subjects. On the other hand, Japan provides a much more unique case of immigration. While its native population has been ageing fast and has experienced negative growth rates in recent years, the immigrant population has been growing steadily. A closer look at the data provided by the Ministry of Health, Labour and Welfare (MHLW) shows that of the 125% increase in immigrant workers between 2010 and 2018, "Technical Intern" and "International Student" contributed 36.7% and 25.6%, respectively. Thus, half of the increase in immigrant workers seem to be low skilled workers, showing how Japan has been easing the restrictions towards low skilled immigrant workers (Komine, 2018). Additionally, Japan stated that one of its concerns when accepting immigration is whether it will reduce job opportunities of Japanese workers (MHLW, 2002). Thus, there is a need to quantify the effects of immigrants in Japan to serve as a guide for future policy. In measuring the economic impacts of immigration, most papers have been trying to identify the average effects on local economies. However, the immigrants may have varying economic impacts, depending on the characteristics of the local economy.

In this chapter, we try to analyze the heterogeneous impacts of immigrant workers [1] across local economies. Specifically, gross domestic production (GDP) is decomposed into several input components using the production function. Then, we estimate immigrant workers' effects on each component using Geographically Weighted Panel Regression (GWPR). The method generates different estimates for each local economy, reflecting the heterogeneous effects of the workers.

Data on production inputs such as capital stock, immigrant workers, and total employment of 47 Japan prefectures from 2009 to 2018 are extracted from government data. Furthermore, average wage, worked hours, and the number of immigrant workers can be extracted from MHLW.

Applying the GWPR method produces interesting results on the distinct impacts of immigrant workers between prefectures. Specifically, immigration negatively affects the capital-to-output ratio in some selected prefectures. Capital-to-output ratio is further separated into the difference between the growth of capital and the growth of output. We find that immigration is positively correlated with capital stock and output in selected prefectures. However, focusing on prefectures that have their capital-to-output ratio negatively affected by immigration, the negative correlations can be explained by the positive link between immigration with output growth but not with capital growth. Furthermore, immigrant workers positively impact total employment and output but not capital stock in some selected prefectures. These results suggest that, in Japan, immigration increases output by raising the labor input, not capital input. In other words, the marginal productivity of labor is higher in these prefectures than others.

While many of the coefficients generated by the GWPR method are insignificant, the spread of coefficients carries valuable information on the heterogeneous effects of immigration across prefectures. Using these coefficients as independent variables and regressing them on the number of immigrants from different education and industry groups reveal interesting results. Specifically, highly educated immigrants enhance the

[1] Immigrant worker here is defined similar to the "Foreign Employment Survey" by MHLW. Specifically, immigrant workers are non-Japanese national who are being employed, and do not hold special permanent, diploma, or official visas. Additionally, non-Japanese nationals in Japan are referred as foreigners, or foreign workers in official documents.

positive impacts on total employment, while their less educated counterparts lessen the magnitude. These results suggest that, to some degree, the highly educated group expresses a comparatively more prominent complementary relationship with the native workers. Another possibility is that native workers are more likely to improve their education to avoid competing with less educated immigrant workers. Nonetheless, the overall effect on total employment remains positive. On the other hand, highly educated immigrants lower the positive effects' magnitude on capital stock, while the less educated ones enhance them. Since the data on capital only records physical capital stock, it is possible that highly educated immigrants improve human capital rather than physical capital.

Grouping immigrant workers into primary, secondary, and tertiary industries shows that prefectures with more immigrant workers working in the secondary industry have higher capital stock's coefficients, while a higher number of immigrants in the primary and tertiary industries lower them. Since the secondary industry is usually capital intensive (e.g., machinery, manufacturing plants), higher immigrants in this industry provide the prefectures with an opportunity to expand the industry further, thus raising the demand for capital.

The positive effects immigrant workers have on total employment are enhanced by a higher count of immigrants in the primary industry but are lessened by a higher count of immigrants in the secondary industry. These results are consistent with the industrial structure of Japan's prefecture. Maps generated by GWPR show that immigrants have positive and significant effects on the capital stock of prefectures that are relatively more focused on the secondary industry. In comparison, prefectures that lean more toward the primary industry experience positive and significant effects on total employment.

Our study has two significant contributions. First, we contribute to the development of the GWPR method. Second, we identify the pattern of economic impacts of immigrants on the local economy. The rest of this chapter is organized as follows. Section 3.2 reviews previous studies on the link between immigration and economic growth, and the GWPR method. Section 3.3 describes the production function approach, measure of immigration, GWPR method, and data used. Sections 3.4 and 3.5 present and discuss the results. Section 3.6 provides concluding remarks.

## 3.2 Literature Review

### 3.2.1 Immigrant

Immigrants' impact on domestic market performance has been a hot research topic, especially on labor market outcomes. The answer to how native workers react to immigrant workers has been mixed. In his book, Borjas (2014) summarizes many related researches to provide a foundation on how to analyze the impact of immigration on the native labor market. However, Card and Peri (2016) describe the overall tone of the book toward immigration as "uniformly dismal", saying that it is only "half the story". In many of his works, Peri (2011) and Peri (2012) shows that the negative impacts of immigrants on wage or employment level of their native counterparts are nonsignificant. The author provides evidence that immigrant workers and native workers are imperfect substitutes for each other, since both possess different skill sets. Thus, native workers will move to other occupations where they have a comparative advantage over immigrant workers (Peri and Sparber, 2009).

The correlation between immigration and capital input has not been a focus in this field. Theoretically, neoclassical growth model predicts that capital-to-GDP ratio will stay constant in the long term. Hence, a net positive inflow of immigration, which increases the destination countries' population, should not affect the capital-to-GDP ratio. Empirically, Peri (2012) confirms this long-term pattern by analyzing data between 1960 and 2006. In short-term trend, Lewis (2011) uses data between 1988 and 1993 to show that least-skilled immigrant workers and automation machinery are substitutes.

Overall, immigrants are found to have a positive correlation with productivity. Using the production function approach, Peri (2012) finds that immigrants improve total factor productivity of the receiving U.S. states. Using Canadian firm-level data, Gu et al. (2020) find a positive correlation between immigrant workers and labor productivity, defined as the ratio between value-added output and labor input. The authors find the relationship is stronger for less-skilled immigrants. One channel through which immigrants can improve productivity is by inducing technological progress, which in turn depends on innovative activities. Using data on the H-1B visa program, Kerr and Lincoln (2010) find that cities with higher H-1 B admission rates lead to higher patent counts from Chinese and Indians.

On the other hand, empirical research on immigration in Japan is minimal. Mitani (1993), using the Japanese Census, studied the impacts of immigrant workers on Japanese women part-time laborers. The study finds a negative relationship between the number of immigrant workers and the number of Japanese women workers only in manufacturing industries, but nonsignificant overall. The author also finds a positive impact of immigrant workers on wages across industries, except for manufacturing industry. Another paper by Ohtake and Ohkusa (1993) find that while immigrant workers are substitutes for capital and non-regular workers, they are complements of regular workers. Korekawa (2015) studies the assimilation [2] of Chinese and Brazilian immigrant workers in Japan using the 2010 Census. The study finds that when compared with Japanese men, the economic achievements of Chinese men are similar, but lower for Brazilian men. Additionally, high economic achievements among Chinese men are further enhanced for those with higher education, while the adverse effects among Brazilian men are alleviated if they are less educated and are married to a Japanese national.

### 3.2.2 Geographically weighted panel regression

GWPR is an extension of Geographically weighted regression (GWR) by allowing data to vary over time. GWR is written in detail by Fotheringham et al. (2002). The method allows regression coefficients to vary spatially by running different regressions for each region. In each regression, regions are weighted by their proximity to other regions using distance decay function. Applications of GWR include Benson et al. (2005) and Farrow et al. (2005), in which the determinants of poverty are spatial non-stationary, suggesting that policy aiming at reducing poverty should be designed to target specific areas. Huang and Leung (2002) study the regional industrialization in Jiangsu province and find that the determinants can vary differently in signs and significant levels between northern, southern, and central regions. In regional growth, Partridge et al. (2008) find that the determinant factors of employment growth vary

[2] Assimilation is defined as the probability of working as Administrative and Managerial workers, or as Profession and engineering workers.

between U.S. nonmetropolitan. Similarly, Lewandowska-Gwarda (2018) reaches a similar conclusion when analyzing Poland's regional unemployment data.

GWPR is first proposed by Yu (2010) and developed further by Yu et al. (2021). The latter finds that the development of high-speed rail system benefits rural regions or areas with lower access to the rail system. The paper concludes that the benefits of the rail system diminish for regions with better accessibility. Other application of GWPR includes the study of weather conditions on agricultural yield (Cai et al., 2014). Specifically, the authors find weather's effect on corn yields in different U.S. states can be either positive or negative. The average effect estimated by traditional OLS fails to capture this pattern.

To the authors' knowledge, neither GWR nor GWPR has been used to study the heterogeneous effects of immigrants on macroeconomic indicators.

## 3.3 Data and Methodology

### 3.3.1 Production function method

The production function method in this study is similar to that of Peri (2012). Assume each prefecture $p$ at year $t$ has the following production function

$$Y_{pt} = A_{pt} K_{pt}^{\alpha} (h_{pt} N_{pt} \phi_{pt})^{1-\alpha} \tag{3.1}$$

where $Y_{pt}$ is the total production, $K_{pt}$ captures aggregate private physical capital, $h_{pt}$ indicates average worked hours per person, $A_{pt}$ measures total factor productivity, $\alpha$ is the elasticity of substitution between capital and labor, $L_{pt}$ represents the total number of workers, and $\phi_{pt}$ is a wage index. Next, output per worker is defined as $y_{pt} = \frac{Y_{pt}}{L_{pt}}$, and equation (3.1) is rewritten as follows

$$y_{pt} = \frac{Y_{pt}}{L_{pt}} = A_{pt}^{\frac{1}{1-\alpha}} \left(\frac{K_{pt}}{Y_{pt}}\right)^{\frac{\alpha}{1-\alpha}} h_{pt} \phi_{pt} \tag{3.2}$$

Finally, we rewrite equation (3.2) in terms of growth rate by taking the logarithm derivative with respect to time to obtain

$$\hat{Y}_{pt} = \hat{L}_{pt} + \hat{y}_{pt} = \hat{L}_{pt} + \left(\frac{1}{1-\alpha}\right)\hat{A}_{pt} + \left(\frac{\alpha}{1-\alpha}\right)\hat{\frac{K_{pt}}{Y_pt}} + \hat{h}_{pt} + \hat{\phi}_{pt} \tag{3.3}$$

According to equation (3.3), total production value for each prefecture increases due to an increase in total employment $\hat{L}_{pt}$ or of an increase in output per worker $\hat{y}_{pt}$. The last equality states that an increase in $\hat{y}_{pt}$ can be further broken down into four parts: total factor productivity $\hat{A}_{pt}$, capital-to-output ratio $\hat{\frac{K_{pt}}{Y_pt}}$, average hours worked $\hat{h}_{pt}$, and wage index $\hat{\phi}_{pt}$.

Following Peri (2012), equation (3.4) below is estimated to analyze how immigration affects each term on the right-hand side of equation (3.3)

$$\hat{\delta}_{pt} = \eta_t + \eta_p + \beta\hat{\theta}_{pt} + \varepsilon_{pt} \tag{3.4}$$

where $\hat{\theta}_{pt}$ will be replaced with total employment $\hat{L}_{pt}$, total factor productivity $\hat{A}_{pt}$, capital-to-output ratio $\hat{\frac{K_{pt}}{Y_pt}}$, average hours worked $\hat{h}_{pt}$, and wage index $\hat{\theta}_{pt}$. $\eta_t$, $\eta_p$, and $\varepsilon_{pt}$ are time-fixed effects, individual-fixed effects, and random error, respectively. Finally, $\hat{\theta}_{pt}$ is a measure of change in immigrant workers between two periods.

### 3.3.2 Measure of immigrant workers' change

To capture the change in the immigrant labor force between two periods, one can follow Borjas (2003), Borjas (2006), and Borjas (2014) and use the ratio of immigrant workers to total employment $r_{pt}$, defined as

$$r_{pt} = \frac{F_{pt}}{N_{pt} + F_{pt}} \tag{3.5}$$

where $F$ is the number the immigrant workers, and $N$ is the number of native workers. Then, the change of immigrant workers between periods $\hat{\theta}$ in equation (3.4) can be measured as the ratio of immigrant workers between two periods

$$\hat{\theta}_{pt} = r_{pt} - r_{p,t-1} \tag{3.6}$$

However, Card and Peri (2016) point out that such specification cannot correctly capture the effect of immigrant flow. Applying the first order Taylor expansion on

$\hat{\theta}_{pt}$ shows that [3]

$$\hat{\theta}_{pt} \approx (1 - r_{p,t-1})\frac{\Delta F_{pt}}{L_{p,t-1}} - r_{p,t-1}\frac{\Delta N_{pt}}{L_{p,t-1}} \tag{3.7}$$

where $L_{pt} = F_{pt} + N_{[i]t}$ is the sum of immigrant workers and native workers, $\Delta F_{pt} = F_{pt} - F_{p,t-1}$ is the change in immigrant workers' number, and $\Delta N_{pt} = N_{pt} - N_{p,t-1}$ is the change in native workers' number. Equation (3.7) shows that $\hat{\theta}_{pt}$ is the weighted average of the change in immigrant workers and of the change in native workers. Thus, $\hat{\theta}_{pt}$ depends not only on the change of immigrant labor but also on the change of native labor. The negative sign of the second term in equation (3.7) highlights another problem. If, for instance, a demand shock leads to a positive correlation between economic indicators and the native labor force in a prefecture. Then, equations (3.5) and (3.7) indicate a negative bias in coefficient $\beta$.

To construct a variable that can correctly account for the change in the immigrant labor force, we first define the growth rate of total employment of prefecture $p$

$$\frac{L_{pt} - L_{p,t-1}}{L_{p,t-1}} \tag{3.8}$$

where the numerator can be written in terms of immigrant and domestic workers

$$\frac{(F_{pt} + N_{pt}) - (F_{p,t-1} + N_{p,t-1})}{L_{p,t-1}}$$

By grouping immigrant workers and domestic workers variables,

$$\frac{(F_{pt} - F_{p,t-1}) - (N_{pt} - N_{p,t-1})}{L_{p,t-1}} = \frac{\Delta F_{pt} + \Delta N_{pt}}{L_{p,t-1}} \tag{3.9}$$

the growth rate of labor market size consists of the growth rate of immigrant and domestic workers. Thus, $\frac{\Delta F_{pt}}{L_{p,t-1}}$ can be used to capture only the impact of the immigrant labor force. This is also the first term on the RHS of equation (3.7) without multiplying the weights. Constructing our explanatory variable this way is also consistent with Peri (2012) and Card and Peri (2016).

[3]See Appendix A.1 for the full Taylor expansion

### 3.3.3 Geographically weighted panel regression

Geographically Weighted Regression (GWR) is used to estimate the spatially varying coefficients using cross-section data (Fotheringham et al., 2002). GWPR extends this method by utilizing panel data. Thus, both methods are similar in the estimation procedures. First, we will present the basics of GWR.

$$y_j = x_j\beta_i + \varepsilon_j \tag{3.10}$$

where $i, j = 1, 2, 3, ..., n$ index the geographic location, $y_j$ is the dependent variable, $x_j$ is the independent variable, and $\varepsilon_j$ is the error. Different from linear regression, where we have only one unique coefficient for each independent variable, GWR produces different coefficients for each at each geographic location. In other words, if our sample size is $n$, GWR will produce $n$ coefficients. In matrix form, coefficients of GWR can be estimated as follow

$$\hat{\beta}_i = [X^T W(i) X]^{-1}[X^T W(i) Y] \tag{3.11}$$

where $W(i)$ is an $n \times n$ diagonal weighting matrix of the form

$$W(i) = \begin{bmatrix} w_1(i) & 0 & \cdots & 0 \\ 0 & w_2(i) & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & w_n(i) \end{bmatrix} \tag{3.12}$$

where $w_n(i)$ is the weight assigned to data point n while estimating the model at location $i$.

Equation (3.11) states that, at each location $i$, $\hat{\beta}_i$ can be estimated using the Weighted Least Square method, and the weighting matrix follows equation (3.12). However, instead of having a constant weight matrix, it will vary according to each location $i$. The weighting scheme is based on the proximity between $i$ and other data points. Specifically, higher weight is assigned to data points geographically closer to $i$. Many kernel functions can be used to achieve this result. For this chapter, we use the bi-square decay function defined as follows

$$w_n(i) = \begin{cases} \left(1 - \left(\frac{d_n(i)}{b}\right)^2\right)^2 & if|d_n(i)| < b \\ 0 & otherwise \end{cases} \tag{3.13}$$

where $b$ is the bandwidth.

Equation (3.13) assigns weight at a decaying rate depending on how far $n$ is from $i$, and assigns weight equal to zero for any points further than a threshold dictated by bandwidth $b$.

There are two types of bandwidths: fixed bandwidth and adaptive bandwidth. The former will result in similar bandwidth for every location. However, irregularly spaced geographical units exist since some prefectures can be smaller than others. This problem can lead to the extreme case where only one data point is used, thus leading to a perfect fit. To remedy this problem, adaptive bandwidth is preferable. Instead of producing a similar optimal bandwidth for all locations, adaptive bandwidth determines the dataset size to be used at each location. Next, to calculate the appropriate bandwidth, golden-section search optimization method is used to search for the optimal bandwidth b that minimizes the following cross-validation score (CV-score)

$$\sum_{n}^{i}[y_i - \hat{y}_{\neq i}(b)]^2 \tag{3.14}$$

Finally, we extend to GWPR by simply stacking cross-section data over $T$ periods. Specifically, assuming there are $t$ periods, then equation (3.10) becomes

$$y_{jt} = x_{jt}\beta_i + \varepsilon_{jt} \tag{3.15}$$

The coefficient $\hat{\beta}_i$ can still be estimated using equation (3.11), where the matrix $X$ and $Y$ will have $(n * t) \times 1$ dimension, and the weight matrix $W(i)$ will have $(n * t) \times (n * t)$ dimension as follow

$$X = \begin{bmatrix} X_{11} \\ \vdots \\ X_{1t} \\ X_{2t} \\ \vdots \\ X_{nt} \end{bmatrix} \tag{3.16}$$

$$Y = \begin{bmatrix} Y_{11} \\ \vdots \\ Y_{1t} \\ Y_{2t} \\ \vdots \\ Y_{nt} \end{bmatrix} \tag{3.17}$$

$$W(i) = \begin{bmatrix} W_{11}(i) & \cdots & 0 & 0 & \cdots & 0 \\ \vdots & \ddots & \vdots & \vdots & \ddots & \vdots \\ 0 & \cdots & w_{1t}(i) & 0 & \cdots & 0 \\ 0 & \cdots & 0 & w_{2t}(i) & \cdots & 0 \\ \vdots & \ddots & \vdots & \vdots & \ddots & \vdots \\ 0 & \cdots & 0 & 0 & 0 & w_{nt}(i) \end{bmatrix} \tag{3.18}$$

Since geographical distances between regions do not change over time, the kernel function (3.13) can be used to get the weight matrix[4]. CV-score can be estimated by extending equation (3.14) to

$$\sum_{t}^{k} \sum_{n}^{i} [y_{i,t} - \hat{y}_{\neq i,t}(b)]^2 \tag{3.19}$$

Time- and individual-fixed effects are also included to control for time-variant and time-invariant unobservable. All the above estimations are done using R (R Core Team, 2022). The codes are based on the package gwpr (Gaboriault et al., 2020), and modified using lfe (Gaure, 2022), plm (Croissant and Millo, 2018), and GWmodel (Gollini et al., 2015) packages.

[4]This also implies that $w_{11}(i) = w_{12}(i) = \cdots = w_{1t}(i)$. In other words, at location $i$, the weights of location indexed as 1 are constant over time.

### 3.3.4 Data

We consider the data from 47 prefectures in Japan between 2009 and 2018. Data on gross regional product (GRP), the number of workers, and private capital stock can be taken from the Gross Prefectural Account of the Cabinet Office. Capital utilization rate is taken from the Ministry of Economy, Trade and Industry. From the MHLW, data on the number of immigrant workers (Foreign Employment Survey) and average hours worked per person (Monthly Labor Survey), and wage data (Basic Survey on Wage Structure) can be extracted.

To construct capital stock for each prefecture, two problems need to be addressed: (a) the most recent data for capital stock and capital utilization rate is only available until 2017, and (b) the capital utilization rate is only available on the national level. We solve the first problem by interpolating the capital stock in 2018 by using the capital stock in 2017 and the coefficient obtained from the following linear regression

$$k_t = \delta k_{t-1} + \varepsilon_t \tag{3.20}$$

The procedure is done separately for each prefecture.

Next, to construct the capital utilization rate for each prefecture, monthly capital utilization rates of the manufacturing and service industries are averaged to get the annual rate for both industries separately. Then, the weighted average of both rates is calculated, where the weight of the manufacturing (service) industry is the ratio between the GRP value of the manufacturing (service) industry and the sum of both industries' GRP. Following these steps, each prefecture's capital utilization rate differs depending on its manufacturing and service industry size. Then, the capital utilization rate for 2018 is interpolated similarly to capital stock. Finally, capital stock is multiplied by the capital utilization rate to obtain $K_{pt}$.

Total factor productivity $A_{pt}$ is not observable. However, it can be calculated by rewriting equation (3.1) to

$$A_{pt} = \frac{Y_{pt}}{K_{pt}^{\alpha}(h_{pt}N_{pt})^{1-\alpha}} \tag{3.21}$$

Thus, $A_{pt}$ is obtainable after we decide on the value of parameter $\alpha$. Following

Takizawa (n.d.), the elasticity of output to capital $\alpha$ is calculated on the national level as follows

$$\alpha = 1 - \frac{(w + T)}{Y} \tag{3.22}$$

where $w$ is the compensation of employees, $T$ is the taxes on production and imports. Both $w$ and $T$ are available from the Gross Prefecture Product of the Cabinet Office.

Wage index in each prefecture is constructed by first combining the data on ordinary and part-time workers to get the wage indexes for all industries. Then, we combine these indexes to obtain the wage index for each prefecture. Specifically, for ordinary workers, scheduled hours worked and overtime worked hours are summed up and multiplied by 12 to get the total worked hours annually in each industry. Similarly, for part-time workers, the total worked hours annually in each industry is calculated by multiplying the average worked days per month by the average worked hours per day and by 12. Annual earning (including bonus) is then divided by the total worked hours to get the average earning per hour. Afterwards, the average earning per hour of ordinary and part-time workers are combined using weighted average, where the weights are the ratio between total worked hours of ordinary workers (part-time workers) to total worked hours of both types of workers. Finally, the average earning per hour for each prefecture is again obtained using weighted average, where the weights are now the ratio between the total worked hours of each industry and the total worked hours of all industries.

Following the above procedure, the wage index $\theta_{pt}$ can be thought of as the average earnings per hour in each prefecture. However, one drawback of using the Basic Survey on Wage Structure is that the data does not include workers from "Agriculture and Forestry" and "Fisheries" since earnings in these sectors fluctuate significantly due to seasons or weather conditions. Nevertheless, the survey still includes valuable information on wages because it covers most parts of the economy.

## 3.4 Empirical Results

### 3.4.1 Panel regression

Before looking at the results of GWPR, we first present the baseline result using panel regression. Weighted least square estimator, where each prefecture is weighted by its labor market size, is adopted from Peri (2012). Individual and time fixed effects are included, and standard errors are clustered by prefecture. Table 3.1 shows the regression results. Each column represents different specifications: column (1) is the basic result, column (2) and (3) tests whether the results are sensitive to the periods chosen, column (4) shows the result of 2SLS, and column (5) re-estimates the weighted OLS with change in immigrant ratio as the independent variable. Each row is the coefficient for each of the macroeconomic indicators. For brevity, only the coefficients for the immigration variable are presented. In overall, the results in columns (1) to (3) indicate a positive impact of immigrants on total employment. Recall that the independent variable represents the change of total employment, resulting from a change in foreign workers. Thus, coefficient around 2 suggests that increasing foreign workers by 1 will expand the local labor force size by 2, implying demand-driven bias. Additionally, coefficient larger than 1 also indicates that immigrants do not crowd out native workers.

On the other hand, immigrant workers have a negative but insignificant effect on output per worker. The negative correlation is the result of a negative impact on capital-to-output ratio and total factor productivity, but a positive impact on average worked hours, and wage index. Note that the impacts on $\hat{y}$ and its components are all statistically insignificant.

[**Table 3.1**]

Immigration and economic indicators can simultaneously affect each other: higher number of immigrant workers can improve the economy of the region, which, in turn, attracts more immigrant workers. This demand-driven bias can lead to an overestimation of the immigrant coefficients. A common reconciliation approach is to use instrumental variable based on past settlements of immigrants. For this chapter, immigrant populations are first categorized into 13 groups: China, North and South

Korea, Philippines, Nepal, Vietnam, rest of Asia, Africa, Europe, Brazil, rest of South America, U.S., rest of North America, and others. Then, using the immigrant population in 2006 as our base, year-on-year national growth rate for each group is applied to that group in each prefecture in all subsequent years. Finally, immigrants are summed across groups to obtain the imputed immigrant population. Following these steps, our instrumental variable depends only on the past settlement that is not included in our regression, and does not depend on the local economy.

The results are presented in column (4). Weak instrument diagnostic test using F-statistic indicates that the instrument is appropriate. Compared to weighted OLS, immigrants show smaller and insignificant impacts on total employment. The impacts on $\hat{y}$ and all its component remain insignificant.

In the previous section, we provided mathematical proof that using the immigrant ratio may bias the results. Column (5) attempts to prove it empirically. First, the impact of immigrants on the local economy is similar in almost all indicators, albeit with a much smaller magnitude. The results show that immigrant has very little impact on the local labor market, which is consistent with many researches that use the immigrant ratio as independent variable. Surprisingly, the correlation between immigrants and output per capital is positive and significant at the 10% level. The effect is a combination of negative impacts on capital-to-output ratio, and positive impacts on total factor productivity, total worked hours, and wage index. The coefficient for capital-to-output ratio is significant at the 5% level.

### 3.4.2 Geographically weighted panel regression

First, we present a simple spatial autocorrelation test using Moran's I. The calculation steps of Moran's I in panel data are written in detail by Beenstock and Felsenstein (2019). The weight matrix is defined simply as the inverse of distance between prefectures. Table 3.2 indicates that we can reject the null hypothesis of no spatial autocorrelation in two out of six models: output per worker and capital-to-output ratio. For this chapter, we decide to use GWPR instead of any other spatial models since it can generate different coefficients for each prefecture, which allows a better understanding of the impact of immigration on the local economy.

[**Table 3.2**]

The weight matrix can be calculated using different kernel functions. In order to select the appropriate function, we compare the corrected Akaike Information Criterion (AICc) in Table 3.3 for bi-square, tri-square, and gaussian kernel functions. Overall, the bi-square kernel function produces the lowest AICc value. However, the differences seem negligible. For this chapter, GWPR will be estimated using the bi-square kernel function.

[**Table 3.3**]

Finally, GWPR results are presented in the following structure: the left-side map indicates the coefficient $\beta$, while the right-side map indicates the t-value. The impact of immigrant workers on $\hat{L}, \hat{y}, \frac{\hat{K}}{Y}, \hat{A}, \hat{h}, \hat{\theta}$ are shown in Figures 1, 2, 3, 4, 5, and 6, respectively.

According to Figure 1, immigrants positively affect total employment in all prefectures but are only significant in some prefectures. Prefectures from regions other than the Chubu and Kansai regions enjoy the benefits of additional immigrant workers. In Figure 2, while indicating positive effects on output per worker, the effects are insignificant. Coefficients for the capital-to-output ratio, as shown in Figure 3, are spread from negative to positive. The significant coefficients are concentrated on prefectures of the Tohoku region and Hokkaido prefecture. In Figure 4, the impacts on total factor productivity are negative and insignificant across prefectures. Finally, Figures 5 and 6 show that immigrants positively affect the average worked hours and wage index. However, both are insignificant across prefectures.

GWPR indicates that immigrants' impact on the capital-to-output ratio can be significant in some regions. To better understand the relationship, we separate the ratio into the growth rate of capital, and the growth rate of output, as below

$$\left(\frac{\alpha}{1-\alpha}\right)\frac{\hat{K_{pt}}}{Y_pt} = \left(\frac{\alpha}{1-\alpha}\right)\hat{K}_{pt} - \left(\frac{\alpha}{1-\alpha}\right)\hat{Y}_{pt} \tag{3.23}$$

The decomposition is important in understanding how immigrants influence capital input. According to equation (3.23), three patterns can lead to a negative capital-to-output ratio: (a) the growth rate of capital is negative, while that of remains constant; (2) the growth rate of output is positive, while that of capital remains constant; and (3) both growth rates are positive, but output grows at a faster rate. The results of re-estimating GWPR separately on the growth rates of capital and output are shown in Figure 7 and Figure 8, respectively. Immigrants can positively and significantly affect the capital stock of most prefectures in the Chubu and Kansai regions. Furthermore, immigrants have a positive effect on output in the northern part of Japan.

[**Figure 3.1**]

[**Figure 3.2**]

[**Figure 3.3**]

[**Figure 3.4**]

[**Figure 3.5**]

[**Figure 3.6**]

[**Figure 3.7**]

[**Figure 3.8**]

The coefficients generated by the GWPR method imply that immigrants affect each prefecture differently. We take one step further from previous literature and regress these coefficients on different groups of immigrants. Specifically, using publicly available statistics from the 2010 Census, the immigrant working population (15-64 years old) is categorized into three groups: highly educated (those who finish vocational school, have a college degree or higher), and less educated (those with highs school education or less, or are attending school). International students are included since they are also vital to the labor force[5]. They are categorized as less educated because they are only allowed to work 28 hours per week and cannot work as regular employees. The findings are presented in Table 3.4. For brevity, we focus on the coefficients that demonstrate the heterogeneous impacts of immigrants on the

[5]According to MHLW, in 54.95% of foreign workers in Accommodation, and Food Services are international students.

local economy, which are the total employment, capital stock, and output. Columns (1), (3), and (5) of the top panel use the 2010 Census to construct the three immigrant variables, while columns (2), (4), and (6) use the 2020 Census[6]. The bottom panel categorizes immigrants into three industry groups: primary industry, secondary industry, and tertiary industry[7]. The dependent variables are the coefficients of total employment, capital, and output generated by the GWPR method above.

The results indicate that highly educated immigrants are correlated with higher total employment's coefficients, but lower capital stock's coefficients. On the contrary, the less educated group is correlated with lower total employment's coefficients, but higher capital stock's coefficients. On the other hand, grouping immigrants into industry groups reveal another interesting trend. An increase in immigrant workers in the primary industry is correlated with higher total employment's coefficients, but lower capital stock's coefficients. An increase in immigrant workers in the secondary industry, however, is correlated with lower coefficients' magnitude of total employment and GP, but higher coefficients' magnitude of capital stock. Finally, immigrant workers in tertiary industry lower the magnitude of capital stock's coefficients but have insignificant effects on the coefficients of total employment and output.

[**Table 3.4**]

## 3.5 Discussion

GWPR method reveals the differentiated effects of immigrants on capital-to-output across prefectures. Separately estimating the effects on capital and output shows the negative and significant coefficients in selected prefectures are because immigration increases output but not capital. Furthermore, the distribution of the capital coefficients indicates that an increase in immigration raises the capital stock of the Kansai and part of the Chubu region. One possible explanation is that these prefectures focus more on the manufacturing industry (Table A.1 in Appendix A.2).

[6]While Japan Census is conducted every 5 years, education retainment is asked every 10 years (e.g., 2000, 2010, 2020). As a result, while this study does not cover the 2020 period, 2020 Census is used instead of 2015 Census as a robustness check.

[7]Different from education retainment, categorizing using industry groups use only immigrants who are actually employed.

As a result, an increase in immigration may lead to an increase in investment in physical capital (e.g., factories, machinery, etc.).

Interestingly, immigration does not bring the same benefit to Tokyo. The reason might be that Tokyo is concentrated with technology-based firms, where human capital and non-physical capital are much more important. Nonetheless, most of the capital stock's coefficients are positive, suggesting that immigration and physical capital are not substitutes for each other.

Combining the results of Figures 3.1, 3.7 and 3.8 show two notable trends. First, prefectures that experience higher physical capital stock from immigration do not see higher output due to immigration. Second, Hokkaido prefecture and prefectures from the Tohoku, Shikoku, and Kyushu regions benefit from a larger labor force due to higher immigration. However, only Hokkaido prefecture and part of the Tohoku region see increased output due to higher immigration. Using the production function, output can be increased through two channels: an increase in capital input or labor input. The above results indicate that, in Japan, while immigration can lead to a higher physical capital stock and a larger labor force, only the labor channel is significant enough to increase output. Furthermore, the second trend also implies higher marginal productivity of labor in Hokkaido prefecture and part of the Tohoku region. The magnitude of the significant coefficients suggests that the expansion of the local labor force is not only because of immigration but also because of a positive net migration by natives. Specifically, if a local labor market has an additional new immigrant worker, the total number of workers in the region should increase by one, assuming that the number of native workers remains constant. Coefficients greater than one indicate that an additional immigrant attracts more than one worker. Therefore, the magnitude of these coefficients suggests that immigration has a crowd-in effect in some prefectures.

The coefficients mapped out in Figure 3.5 do not vary much, suggesting that the immigrants' impacts on average worked hours are similar across prefectures. Moran's I tests fail to reject the null hypothesis further confirm the results. While immigrant workers positively affect the wage index, they are neglectable. The insignificant might be the results of the combined effects of immigrants on different types of workers. However, due to data limitations, we cannot further disentangle the wage effect of immigrants. Equivalently, Figure 3.4 also shows that immigrants exert negative but insignificant effects on TFP. The magnitude is also similar across prefectures.

The coefficients computed using GWPR, while insignificant in many cases, carry valuable information on how immigrants are heterogeneously affecting the local economies. Utilizing Census data in 2010 and 2020, we try to dig deeper into this phenomenon. Grouping immigrants by education suggests that, to some degree, highly educated immigrant workers have a complementary relationship with native workers, while their less educated counterparts may have a weaker complementary relationship. However, the aggregate effect on total employment is positive. One possible explanation is that since immigrants are more likely to work in low-paying jobs, they may have a substitute relationship with the native workers, especially the non-regular workers (similar to the results of Mitani (1993) and Ohtake and Ohkusa (1993)). Another possibility is the return to school effect, where natives are encouraged to complete high school (Hunt, 2017) or attain higher education to avoid competing with immigrants (Brunello et al., 2020).

The less educated group leads to higher capital stock's coefficients. The results confirm the possible link between highly educated immigrants and human capital. Since the data does not include human capital, if highly educated immigrants are better at utilizing their professional knowledge to improve human capital, an increase in highly educated immigrants has less impact on the physical capital stock. On the other hand, prefectures with a higher number of less educated immigrants see a greater positive impact on capital stock.

This point is further explored in the bottom panel of Table 3.4. The results suggest that an increase in immigrants working in the manufacturing industry (secondary industry) leads to greater magnitude of capital stock's coefficients. Since the manufacturing industry requires more physical capital stock, an increase in immigrants working in the industry raises the physical capital stock. Figure 3.7 also confirms this point, as immigration positively and significantly impacts the capital stock of prefectures focusing on the manufacturing industry. For example, Aichi prefecture is one of the prefectures that experiences higher capital stock due to a higher number of immigrants. The prefecture has the most prominent secondary industry in terms of output value (Table A.1 in Appendix A.2). It also has the second largest immigrant worker population, next to Tokyo, but the largest immigrant worker population in the manufacturing industry (Table A.2 in Appendix A.2).

A higher number of immigrants working in the primary industry is linked to higher total employment's coefficients, but lower capital stock's coefficients. Since the primary industry is relatively more labor-intensive, prefectures looking for more immigrants to work in the primary industry may not be incentivized to invest in capital stock. This point is further confirmed in Figures 3.1, 3.7, and 3.8: higher immigrant counts in the primary industry lead to higher output due to an increase in total employment, not physical capital stock. According to the Prefectural Account published by Cabinet Office (Table A.1), seven prefectures fitting into this trend put greater focus on the primary industry than other prefectures.

While Japan has been relying on its native population to run its economy, ageing population and declining birth rate have put pressure on its working population. Thus, accepting immigration seems to be the only viable method to keep its economy running, at least in the short term. In fact, Japan has been expanding its immigration policy recently by being more open towards low skilled workers. In contrast with the theory that immigration increases labor supply and, thus, puts pressure on wages, the empirical results show that many prefectures see their workforce expanding, but no significant changes in wages. Using a simple supply-demand graph, if the demand curve shifts to the right at the same time the supply curve shifts due to immigration, then total employment increases while keeping wages at the same level (Figure 9). This case is possible especially in Japan, since it is experiencing a decline in working population, and immigration provides firms with labors and an opportunity for expansion.

[**Table 3.9**]

Another explanation for an immigration-induced increase in total employment without affecting wage is the skill specialization between immigrant and native workers. Specifically, if immigrant workers are more likely to perform manual-intensive tasks, then their native counterparts will move to tasks that require more communication skills (Peri and Sparber, 2009).

## 3.6 Conclusion

This chapter uses the production function approach and GWPR method to study the relationship between immigrant workers and the economic inputs of Japanese prefectures. The method allows one to explore the possible distinct effects across prefectures.

Immigrants are shown to negatively affect the capital-to-output ratio in northern Japan. Further analysis shows that the negative effects are due to the positive relationship between immigration and output. In other words, immigration drives output growth but not capital growth, thus lowering the capital-to-output ratio. Additionally, an increase in immigrants is correlated with higher output and total employment, but not with capital also shows that marginal productivity of labor is higher in northern Japan.

We also find evidence that highly educated immigrants dampen the positive effects on total employment but enhance the positive effects on capital stock. Immigrant workers in the labor-intensive primary industry exert greater impacts on total employment but lessen the magnitude of the impacts on capital stock. On the contrary, immigrants in the capital-intensive manufacturing industry are linked to higher capital stock's coefficients, but lower total employment's coefficients. Combining these results with the maps generated by GWPR shows that the economic impacts of immigrants depend on the industrial structure of the prefectures.

Overall, the empirical results show that expanding the immigration policy can benefit the Japanese economy without hurting its native workers. However, prefectures should encourage immigrant workers that best fit their industrial structure to maximize the benefits.

# Tables and Figures

**Table 3.1:** Impact of immigration on native workforce at prefecture level and city

| | Baseline model | 2011-2018 | 2010-2017 | 2SLS | Change in immigrant ratio as independent variable |
|---|---|---|---|---|---|
| Dependent variable | (1) | (2) | (3) | (4) | (5) |
| $\hat{L}$ | 2.288*** | 1.823*** | 2.305*** | 1.402 | 0.014 |
| | (0.590) | (0.621) | (0.581) | (1.355) | (0.010) |
| $\hat{y}$ | -1.322 | -1.975 | -1.037 | -3.466 | 0.031* |
| | (1.243) | (1.425) | (1.608) | (3.332) | (0.016) |
| Components of $\hat{y}$ | | | | | |
| $\left(\frac{\alpha}{1-\alpha}\right)\frac{\hat{K}}{Y}$ | -0.501 | -1.096 | -0.511 | -4.074 | -0.038** |
| | (1.773) | (1.863) | (2.031) | (5.400) | (0.016) |
| $\left(\frac{1}{1-\alpha}\right)\hat{A}$ | -3.177 | -2.045 | -0.650 | -4.584 | -0.033 |
| | (3.186) | (3.752) | (3.704) | (8.948) | (0.073) |
| $\hat{h}$ | 0.591 | 0.753 | 0.081 | -2.775 | 0.009 |
| | (0.747) | (0.756) | (0.721) | (1.863) | (0.009) |
| $\hat{\phi}$ | 2.191 | 0.971 | 0.608 | 6.114 | 0.085 |
| | (2.807) | (3.364) | (3.480) | (5.706) | (0.066) |
| F-statistic | | | | 33.520 | |
| Observations | 423 | 376 | 376 | 423 | 423 |

Note: The independent variable is a change in foreign workers as a percentage of initial total employment in (1)-(4), and is a change in immigrant ratio in (5). Each cell in columns (1) to (3) and (6) is the result of a different weighted least squares regression, where each prefecture is weighted by its total employment. Column (5) shows the result of 2SLS method, where IV is the imputed immigrants. Each regression includes time and individual fixed effects. Standard errors in parenthesis are clustered by prefecture. *p<0.1; **p<0.05; ***p<0.01

**Table 3.2:** Moran's I for panel regression

| | **Moran's I** | **p-value** |
|---|---|---|
| $\hat{L}$ | 0.380 | 0.352 |
| $\hat{y}$ | 1.537 | 0.062 |
| $\left(\frac{\alpha}{1-\alpha}\right)\frac{\hat{K}}{Y}$ | 2.487 | 0.006 |
| $\left(\frac{1}{1-\alpha}\right)\hat{A}$ | 0.722 | 0.235 |
| $\hat{h}$ | 0.859 | 0.195 |
| $\hat{\theta}$ | 1.137 | 0.128 |

**Table 3.3:** Corrected Akaike Information Criterion value of different GWPR models using different kernel functions

| | **Bi-square** | **Tri-square** | **Gaussian** |
|---|---|---|---|
| $\hat{L}$ | -2,989 | -2,982 | -2,982 |
| $\hat{y}$ | -2,123 | -2,122 | -2,123 |
| $\left(\frac{\alpha}{1-\alpha}\right)\frac{\hat{K}}{Y}$ | -2,034 | -2,028 | -2,038 |
| $\left(\frac{1}{1-\alpha}\right)\hat{A}$ | -1,582 | -1,582 | -1,686 |
| $\hat{h}$ | -2,621 | -2,620 | -2,617 |
| $\hat{\theta}$ | -1,235 | -1,172 | -1,212 |

**Table 3.4:** Effects of immigrants on the trade of Consumer and Industrial Goods

| | *Dependent variable:* | | | | | |
|---|---|---|---|---|---|---|
| | **Total employment** | | **Capital** | | **Output** | |
| | 2010 | 2020 | 2010 | 2020 | 2010 | 2020 |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| **Panel (a): Education** | | | | | | |
| Constant | 2.553*** | 2.481*** | 0.415* | 0.516** | 2.892*** | 3.084*** |
| | (0.234) | (0.245) | (0.220) | (0.241) | (0.792) | (0.773) |
| Highly educated | 0.0001*** | 0.00003*** | −0.0001*** | −0.00005*** | 0.00001 | 0.00002 |
| | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0001) | (0.0000) |
| Less educated | −0.0001*** | −0.00005*** | 00001*** | 0.0001*** | −0.00005 | −0.0001 |
| | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0001) | (0.0000) |
| **Panel (b): Industry** | | | | | | |
| Constant | 2.290*** | 2.000*** | 0.773*** | 0.907*** | 2.716*** | 2.628*** |
| | (0.243) | (0.253) | (0.257) | (0.280) | (0.848) | (0.872) |
| Primary industry | 0.0005** | 0.0004*** | −0.0005** | −0.0003* | 0.001 | 0.001 |
| | (0.0002) | (0.0001) | (0.0002) | (0.0001) | (0.0010) | (0.0004) |
| Secondary industry | −0.0001*** | −0.00005*** | 0.0001*** | 0.00005*** | −0.0001* | −0.0001** |
| | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0001) | (0.0000) |
| Tertiary industry | 0.00001 | 0.00001 | −0.00003*** | −0.00002*** | −0.00001 | −0.00001 |
| | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) |
| Observations | 47 | 47 | 47 | 47 | 47 | 47 |

The dependent variables are the coefficients generated by GWPR method for total employment in (1) and (2), capital in (3) and (4), output in (5) and (6). The independent variables in panel (a) are the number of highly educated immigrants and less educated immigrants. The independent variables in panel (b) is the number of immigrants working in primary industry, secondary indsutry, and tertiary indsutry. Weighted OLS is used, where weights for 2010 and 2020 are total employment from Census 2010 and Census 2020, seperately. Standard errors are in parenthesis. *p<0.1; **p<0.05; ***p<0.01

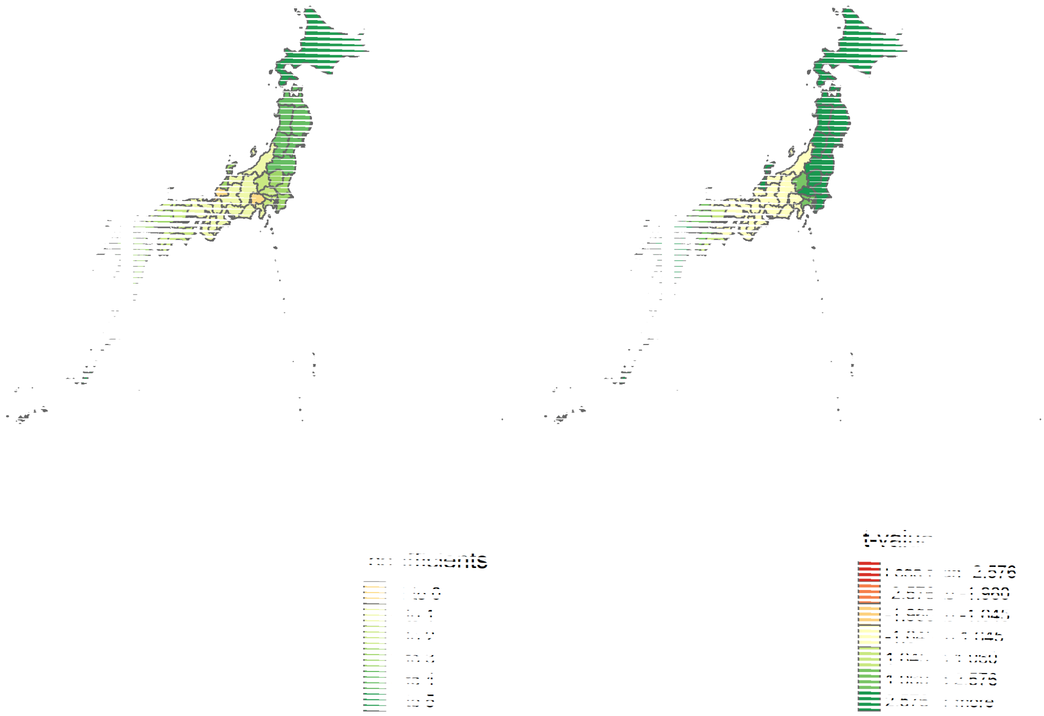


**Figure 3.1:** GWPR results of immigrants' effects on total employment

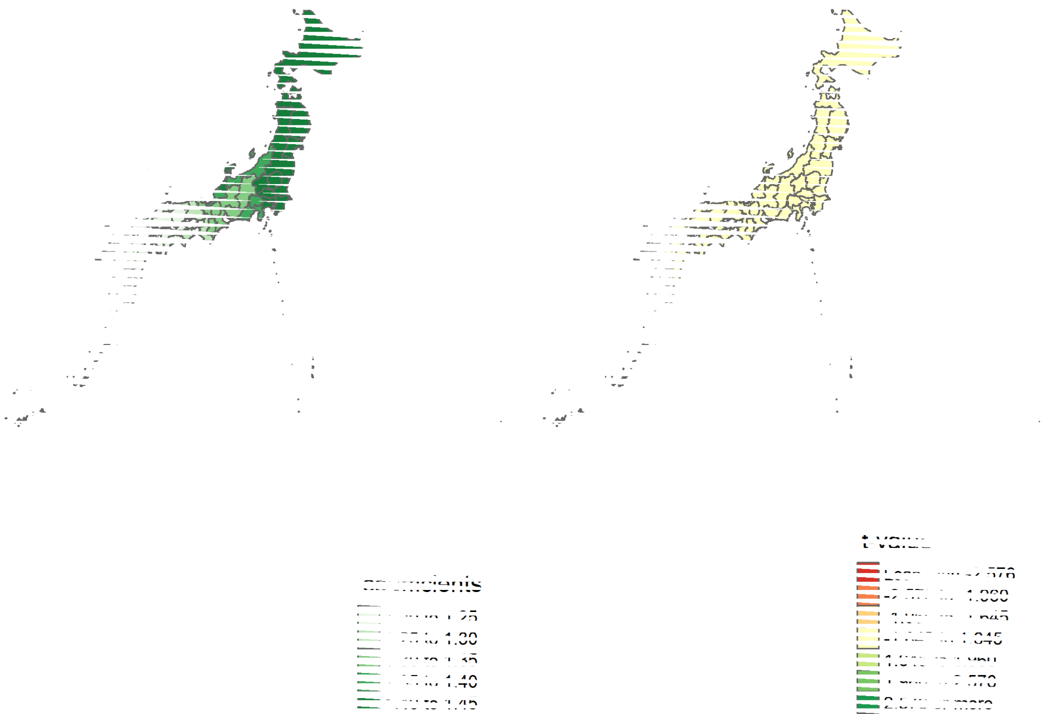


**Figure 3.2:** GWPR results of immigrants' effects on output per worker

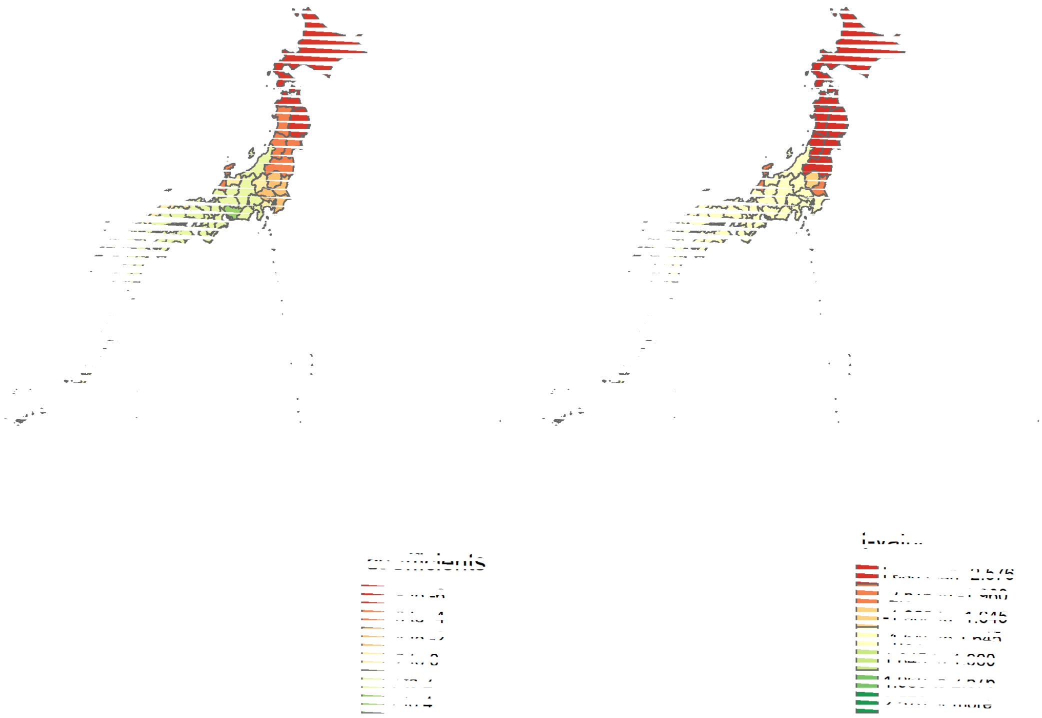


**Figure 3.3:** GWPR results of immigrants' effects on capital-to-output ratio

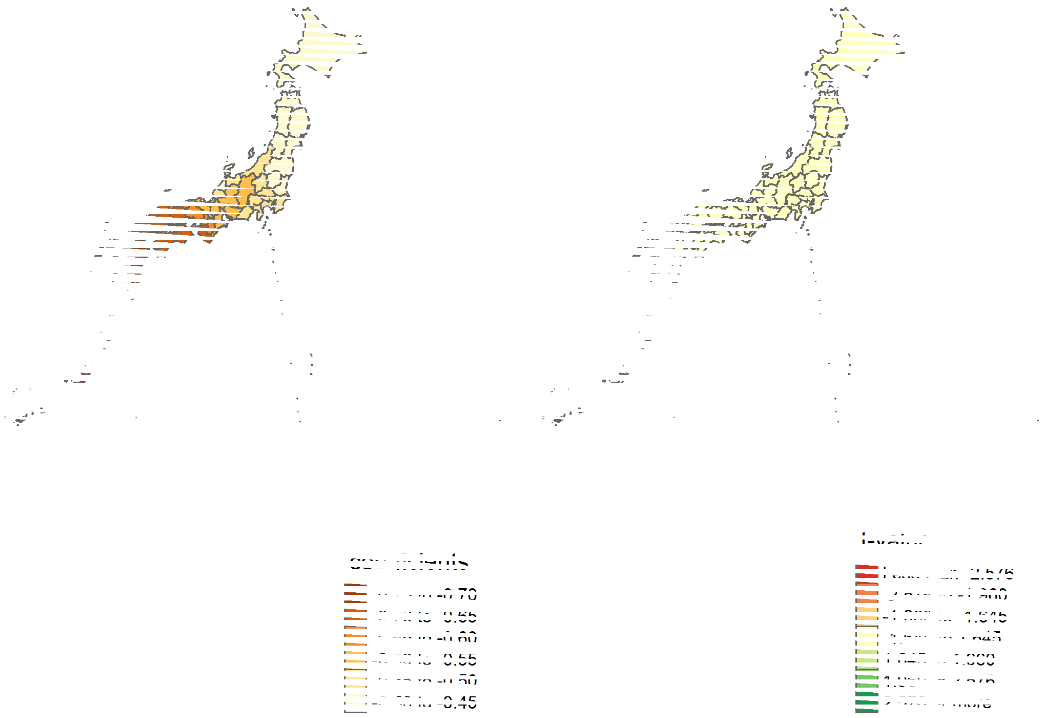


**Figure 3.4:** GWPR results of immigrants' effects on total factor productivity

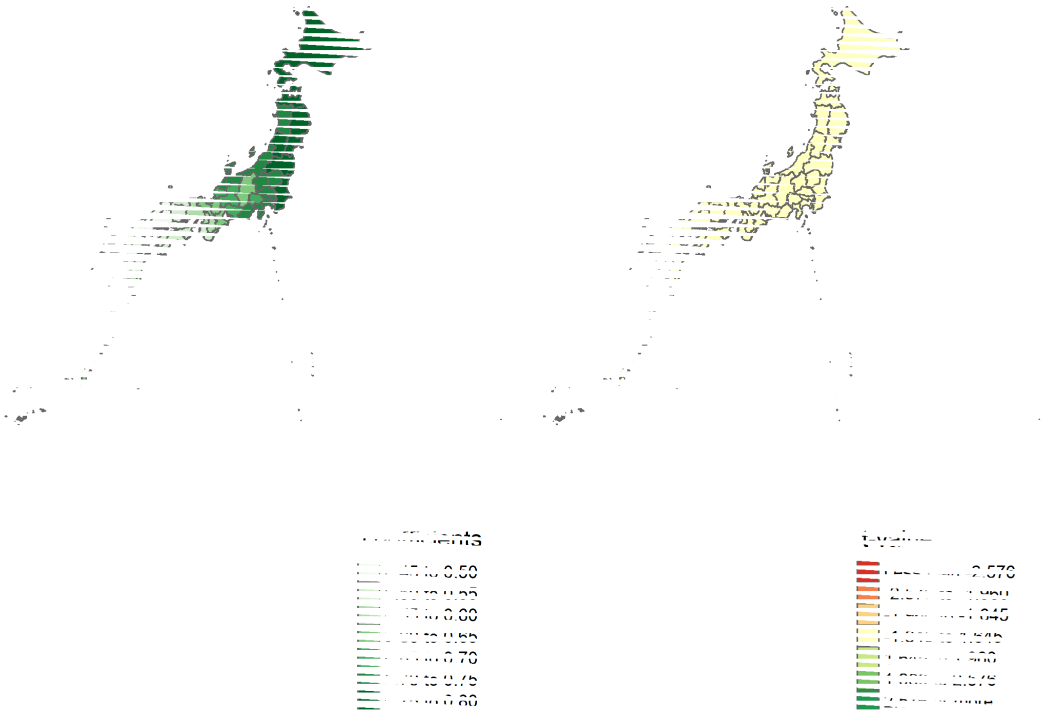


**Figure 3.5:** GWPR results of immigrants' effects on average worked hours

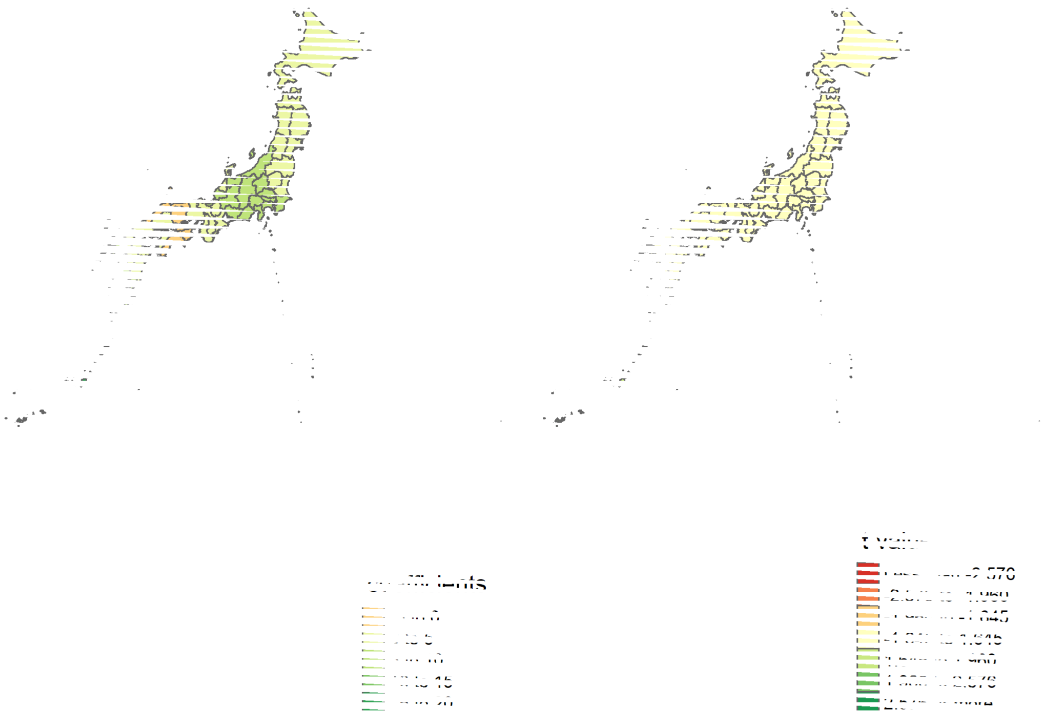


**Figure 3.6:** GWPR results of immigrants' effects on wage index

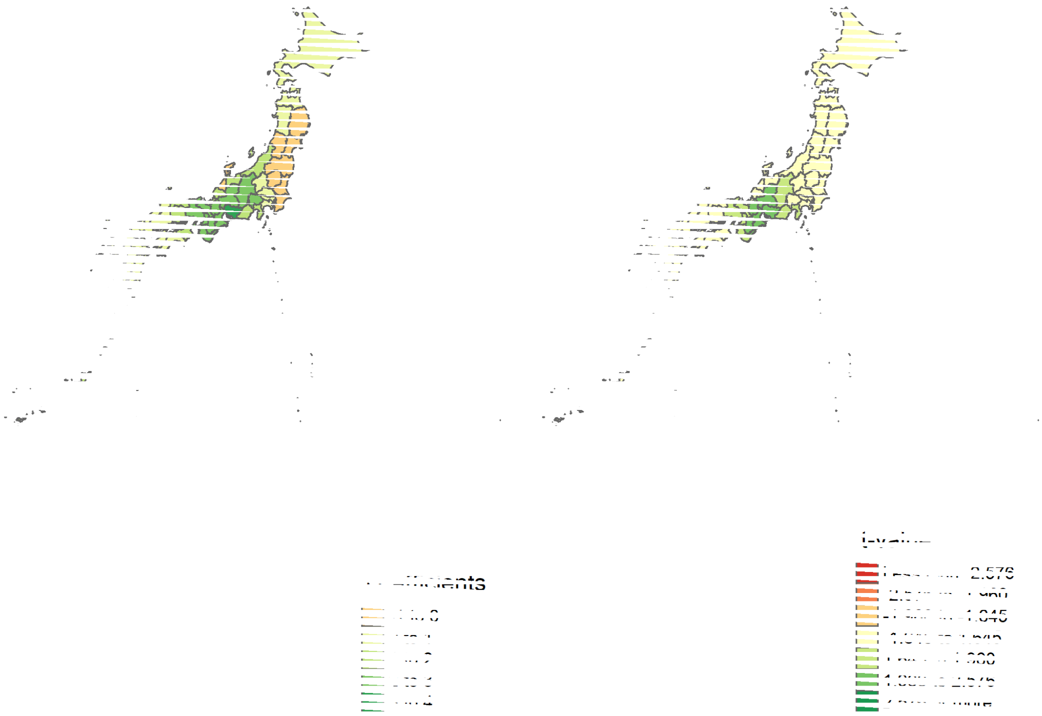


**Figure 3.7:** GWPR results of immigrants' effects on capital

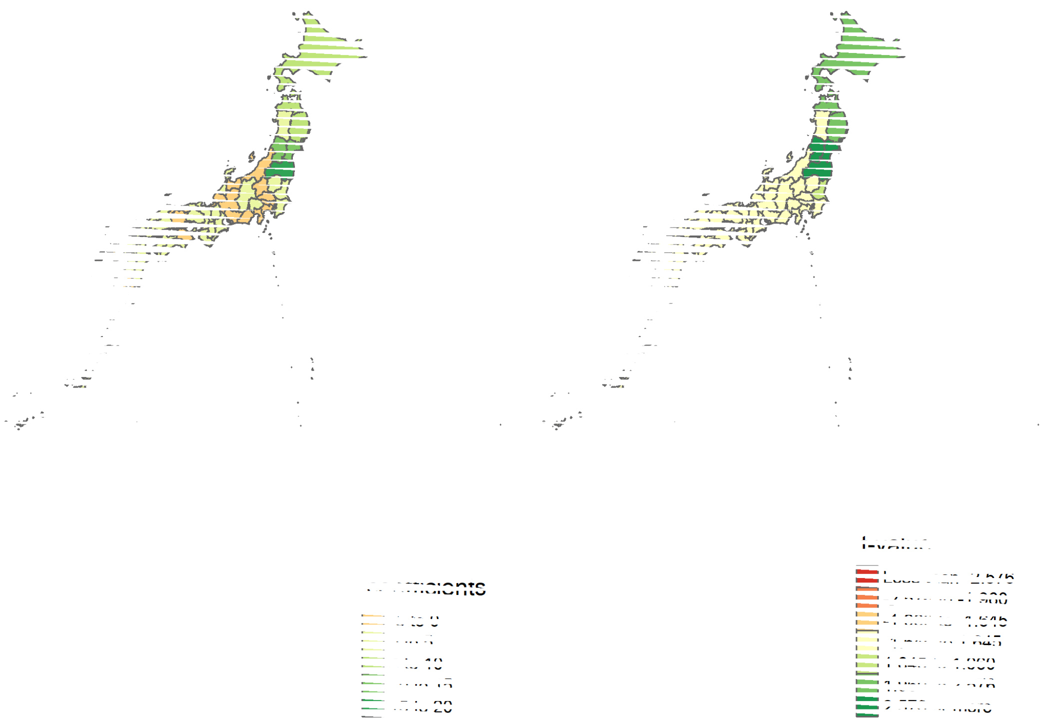


**Figure 3.8:** GWPR results of immigrants' effects on output

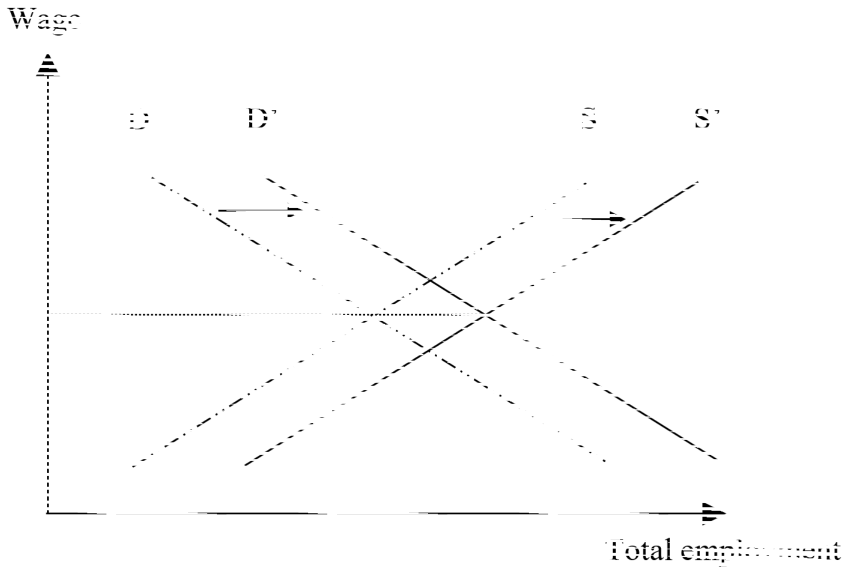



**Figure 3.9:** Illustration of an immigration-induced increase in total employment without change wage level

# Chapter 4

# Immigrant Workers and Native Labor Market

## 4.1 Introduction

Immigrants can have direct effects on the employment of native workers and, thus, have always been a hot topic of research. Many researches have been trying to study the effects on Western economies but with mixed results. Thus, it is unclear whether these implications can be carried over to countries with radically different immigration policies and, thus, different immigrant population characteristics. One such case is Japan. While its native working population has been on a decline, the immigrant population has been increasing. However, literature on the effects of immigrants on Japanese workers is still limited. This chapter tries to fill this gap by utilizing microdata from the anonymized Japanese Population Census (hereafter will be referred to as the Census) and determine the impacts of immigration on regional economies.

The model developed by Borjas (2006) is adopted to analyze the response of native workers to an increase in immigrant workers. While the original model enables one to study both the wage effects and employment effects, due to the characteristic of the Census, this chapter will focus solely on the effects of immigration on native's employment.

There are three main results from the analysis. First, immigration has a negative impact on the number of native workers at city level, but not at prefecture level. However, data at city level only covers 30 cities in 16 prefectures. Therefore, 47 prefectures are categorized into large prefectures group, which contain 16 prefectures contain cities with population larger than 500,000, and small prefectures group, which contain the other 31 prefectures. The impact of immigration is re-estimated at prefecture level using either the large or small prefectures groups. The negative and significant coefficients at city level all become insignificant. If immigrant workers are to replaced native workers, the negative relationship should somewhat remain at prefecture level. Thus, it implies that native workers respond to immigration by moving to another city within the same prefecture. The finding also rejects the claim that area-based estimations are uninformative.

Regular and temporary immigrant workers both negatively affect regular native workers at city level. Surprisingly, temporary native workers are unaffected by immigration. The finding implies that the temporary labor market absorbs the inflow of immigration without negatively affecting the native workers. In large prefectures group, an increase in regular immigrant workers has a positive effect on temporary native workers only when both male and female workers are included. The result implies that firms may be replacing regular native workers with regular immigrant workers due to the fact that immigrant workers are more likely to take jobs with lower wages and harsher work conditions. On the other hand, since the wage and employment of temporary workers can be easily adjusted, firms can hire additional immigrant workers without hurting the natives.

Due to data availability, it is not possible to study the impact of immigration on net-migration of native workers. Regardless, studying how native inflow responds to immigration still provides valuable implication. The results indicate that immigration reduces the inflow of temporary native workers at city level, but attracts temporary native workers in small prefectures group. The negative impact of immigration is relatively small compared to previous literature. Additionally, prefectures with relatively small populations may benefit from an increase in immigration, without harming the employment of native workers.

This chapter contributes to the limited research on the impact of immigration on Japanese native workers. The findings indicate that immigration may affect the flow of native workers between cities, but not their employment. Additionally, instead of education-experience, industry-occupation skill group is proposed to avoid the "downgrading effects" on immigrant workers.

The rest of this chapter is organized as follows. Section 4.2 reviews previous studies on the impact of immigration on native workers. Section 4.3 describes the model and data. Sections 4.4 and 4.5 present and discuss the results. Section 4.6 provides concluding remarks.

## 4.2 Literature Review

To understand the impact of immigrants on the labor market, one can assume immigration as a change in supply of homogeneous labor. Then, theoretically, an increase in immigrant workers will depress the wage of their native counterparts. However, the assumption is not useful practically since it always predicts a negative effect by immigration. Borjas (2003) resolves the problem by developing the skill-cell approach and assuming an imperfect substitute relationship between immigrants and natives. The model categorizes immigrant and native workers into different skill cells, using education level and experience. The idea is that immigrants and natives with the same education level are imperfect substitute since they have different experience level. The paper finds negative links between immigration and the wage and labor supply of competing US workers. The author later develops another model that can control for native adjustment to immigration when estimating at regional level (Borjas, 2006). The model also provides evidence of the negative relationship between immigration and wages and native employment. Details of this mode will be discussed in the latter section. The adverse impact of immigration on the local labor market is also identified in European countries. Dustmann et al. (2017) study the impact of commuting immigrant workers who do not have residence rights in German shortly after the fall of the Berlin wall. The author raises concerns whether the effect is long since the immigrants do not reside in the region, thus do not raise demand for local goods. Glitz (2012) also studies the German case by exploiting an immigration policy 1989 that distribute immigrants evenly between regions. Therefore, immigrant settlement decision does not correlate with the local economy conditions. The paper also concludes a short term negative effects on resident workers.

On the other hand, Peri and Sparber (2009) find the adverse wage effect of immigrants is miniscule in US. The employed model consists of an open economy with two goods, where each goods is produced either by low or high education. Furthermore, each education level performs manual and communication tasks to produce the goods. The 2-stage nested CES model provides evidence of specialization by immigrant and native workers. Specifically, immigrant workers will specialize in manual tasks, while native workers will move to perform more communication tasks. As a result, even among the less-educated natives, who should face high competition from immigration, experience modest wage impacts. Peri (2011) expands the nested CES model to a 4-stage model and finds no effect on wage of natives living in California. Ortega and Verdugo (2014) apply the model by Borjas (2003) to the French labor market and find that immigration improves wages and employment rates. The contrary results with the original paper are robust under different specifications, and when shift-share instrument variable is used. Cattaneo et al. (2015) utilize the longitudinal dataset of individuals and households in 15 European countries between 1994 and 2015 to analyze the immigration impact on individuals over time. They conclude that native workers benefit from inflow of immigrant workers. Specifically, immigrant workers increase the wage, and the probability of upward mobility, without harming the employment of native workers. Basten and Siegenthaler (2019) study the immigration effect on Switzerland labor market between 2002 and 2011 using national skill-cell approach. They find that an increase in foreign workers increase job opportunities for native workers. Additionally, there is evidence that native workers move to higher-skilled and better-paid occupations. Docquier et al. (2014) tackle the immigration issue differently by simulating the wage and employment effects on natives in OECD countries between 1990 and 2000. The simulation results indicate that, in general, immigrants' effects on native wage and employment range from insignificant to modestly positive. Mocetti and Porello (2010) investigate how native's mobility respond to immigration. The results show a substitute relationship between immigrants and less educated natives, but a complementary relationship between immigrants and highly educated natives. Since the complementary relationship concentrated among younger population, the authors conclude that immigration can help attract younger natives and, hence, mitigate aging population.

At the time of this writing, there has been no rigorous research on the impacts that immigration has on Japanese native workers. Nakamura et al. (2009) use simple linear regression to study several effects of immigration on Japanese local economy between 1985 and 2000. For example, regressing the dummy that equals 1 if an individual lives in different location 5 years earlier on immigrant share and controlling for individual fixed effects result in negative coefficients, meaning that immigration crowd-outs native workers. Among the natives with high school diploma, immigrant share increases by 1% will increase the chance of moving out of the region by 0.7%. In another regression, the authors verify the "return to school" effects (Hunt, 2017) among natives between 19 and 23. The results show that a higher immigrant share lead to a lower number of natives who are mainly working, and to a higher number of natives who are going to school. Thus, these imply that young natives respond to immigration by improving their education so as not to compete directly with immigrant workers.

Overall, in contrast with Western countries, study on the impact of immigration on Japanese labor market is still limited. Additionally, Japan's immigration policy has changed greatly since 2000. Thus, the above results on the impacts of immigration in Japan are outdated. As a result, this paper tries to identify the response of native workers to immigration using proper framework and more recent data.

## 4.3 Data and Methodology

### 4.3.1 Empirical model

The estimation uses in this chapter is adopted from Borjas (2006). The theoretical model is simplified by assuming that the number of native workers is fixed on the national level. If there are only native workers, and the distribution of native workers in each local economy is not at equilibrium, native workers will move between regions every period to adjust for the difference in wage. Immigration is incorporated into the model by assuming that each regions receives the same influx of immigrants every period, and that immigrants do not move internally. Thus, the function of wage in the region depends on the sum of native and immigrant workers. As each region receives new a new influx of immigrant workers, native workers will see their wage change and migrate to another regions in the next period if their current wage is lower than the national equilibrium[1].

Based on these assumptions, the author derives a theoretical model to link immigrant influx with native workers' wage and employment. Since the data used in this study does not cover workers' wage, it is only possible to estimate the effects that immigrants have on native's employment. Specifically, for skill group $i$, region $j$, and period $t$, I estimate the following empirical model

$$\ln N_{ijt} = \beta R_{ijt} + s_i + p_j + \pi_t + \zeta_{ij} + \psi_{it} + \rho_{jt} + \varepsilon_{ijt} \tag{4.1}$$

where $N_{ijt}$ is the number of native workers under 65. Let $M_{ijt}$ be the number of immigrants, $R_{ijt} = \frac{N_{ijt}}{N_{ijt}+M_{ijt}}$ is the share of immigrant. Skill group, region, and time fixed effects are included as $s_i$, $p_j$, and $\pi_t$, respectively. $\zeta_{ij}$, $\psi_i t$, and $\rho_j t$ represent the skill-region, skill-time, and region-time fixed effects. Equation 4.1 is estimated using weighted regression, where the weight is the number of native workers in each $(i, j, t)$ combination. The standard errors are clustered by skill-region $(i, j)$ cells.

Several robustness tests are also conducted. First, the total number of native and immigrant workers is used instead as dependent variable. Then, an increase in immigrant workers should increase or have no impact on the total number of workers. Second, following previous literature, control variables are included to take into account the labor market condition in the last period (Borjas et al., 1997; Borjas, 2006). The estimate results are justified if they do not change considerably after including the control variables. The control variables used in this chapter are the lag number of native workers and lag share of native workers 65 and above. While the former is in line with existing literature, I depart from the original study and include lagged share of native workers 65 and above, calculated as

$$o_{ijt} = \frac{N_{ijt}^{\geq 65}}{N_{ijt}^{\geq 65} + N_{ijt}^{<65}} \tag{4.2}$$

where $N_{ijt}^{\geq 65}$ is the number of native workers 65 and above, $N_{ijt}^{<65}$ is the number of native workers under 65. The variable is meant to take into account the recent aging population in Japan. If the number of new young workers is not enough to

[1] See the Appendix A.3 for the detailed derivation of the theoretical and empirical models

replenish the number of retired workers, the negative relationship between native workers (under 65) and immigrant workers might be exaggerated. While the year fixed effects can control the general aging population trend across Japan, the share of native workers 65 and above help controlling for different aging trend between prefectures. For this control variable to work as a proxy for aging population, the share of old native workers must have an increasing trend, which is shown in the next section.

### 4.3.2 Data

Anonymized data, representing 1% sample of the population, from the Japanese Population Census in 2000, 2005, 2010, and 2015 are obtained from the National Statistic Center. Since the data has gone through several data anonymization techniques and later further processes by the author, some of the results may show discrepancy with the statistics published by the Minister of Internal Affairs and Communication. Primarily, the analysis focuses on male workers aged 15-64, who are not working in the government sector. To better understand the impacts of immigrants on native workers' employment, the sample is further restricted to workers whose employment status are Regular, Temporary, and Managers and Directors, while Self-employed are Family Workers are excluded. Nationality of a person, recorded in the Census, is used to identify a person as natives or immigrants. Current place of living is recorded for all persons at prefecture level, but only identifiable for those living in cities with population larger than 500,000. Place of living five years earlier is not available in 2005.

The definition of skill group varies between research. Borjas (2006) defines skill group as a combination of education and experience. Other skill group classifications include industry and education level (Altonji and Card, 1991), occupation and education level (Card, 2001), or occupation and experience (Basten and Siegenthaler, 2019). For this chapter, a skill group is defined as a combination of industry and occupation instead. There are two reasons to adopt this definition. First, education-experience skill group imply that immigrants and native with similar education level are imperfect substitute since they have different experience level. However, "downgrading effects" on immigration upon arrival may place highly-educated immigrant workers in similar position to less-educated workers (Dustmann et al., 2013). The industry-occupation skill group eliminates this concern since it assumes workers with similar occupation and in the same industry are substitutes, disregarding education level. Second, the Census only records education attainment every ten years. Thus, only two out of four periods will be usable. Trying to control for labor market conditions in the previous period will further limit the analysis into one period.

Over the years, the number of industry classification has increased to account for new industry[2]. As a result, to maintain the number of industry constant over the years, industry classifications from 2005 to 2015 are aggregated to match the classification in 2000. Accordingly, there are seven industry classifications: 1) Agriculture, Forestry, Fisheries; 2) Mining, Construction; 3) Manufacturing, Electricity, Gas, Heat Supply and Water; 4) Information and Communications, Transport; 5) Wholesale and Retail Trade, Services; 6) Finance and Insurance; 7) Real Estate. Similarly, occupation classifications have also been increased and moved between groups[3]. After aggregating occupations so the groups remain constant over the years, three groups remain: 1) Managers and Officials, 2) Sales Workers, Services Workers, 3) Professional and Technical Workers, Clerical and Related Workers, Protective Service Workers, Agricultural, Forestry and Fisheries Workers, Workers in Transport and Communication Occupations, Production Process Workers and Labourers. Therefore, workers are categorized into 21 skill groups.

As mentioned in the previous section, the share of native workers 65 and above is used to control for the aging population. Table 4.1 below shows the rate of change of workforce aged 15-64, and 65 and above. The numbers indicate that the number of workers aged 15-64 steadily declines over the years, while the number of workers aged 65 and above greatly increases. This justifies the use of the share of workers 65 and above to control for aging population.

[**Table 4.1**]

[2] There are eight industry classifications in 2000, 12 in 2005, 14 in 2010 and 2015.
[3] There are seven occupation classification in 2000, 2005, and eight in 2010, 2015.

## 4.4 Empirical Results

### 4.4.1 Immigrants and native labor force

To maintain a consistent timeframe throughout the estimation, the data is limited to 2005, 2010, and 2015. Data in 2000 will be used to construct the control variable used in robustness checks. Table 4.2 shows the impact of immigration on native labor force. Panels I and II show the results on prefecture level, and city level, respectively. The estimation is conducted with only male workers, or when both male and female workers are included. The columns indicate regressions with different dependent variables. The rows numbered 1, 2, 3, 4 show the coefficients of the total number of immigrant worker share. The immigrant worker share is then separated into the share of regular immigrant worker and temporary immigrant worker. The impact on native worker is then re-estimated when both shares are included, and the coefficients are showed in regressions numbered 1a, 1b, 2a, 2b, 3a, 3b, 4a, and 4b. Panel I shows only a positive and significant impact of immigration on the temporary native workers when both male and female workers are included. When immigrant workers are furthered divided into regular and temporary, only the regular group show a positive and significant effects (lower significant level at 10%). Panel II indicates that immigration negatively impacts the total number of native workers, but the impact is mainly on the regular workers. Regular and temporary immigrant workers are both linked to the negative effects. However, the significant level is at 10% in the male sample, but only at 5% when both genders are included.

[**Table 4.2**]

Since the data at prefecture level covers all 47 prefectures, but at city level only covers 30 cities from 16 prefectures, the impact of immigration at different geographical levels may not be comparable. Therefore, table 4.3 below divides 47 prefectures into two groups of prefectures. The large prefectures group (panel I) contains the 16 prefectures that appear in previous estimation at city level, while the small prefectures group (panel II) contains the other 31 prefectures. In the male sample of panel I, regular immigrant workers negatively affect the number of regular native workers, but positively affect the number of temporary native workers. However, both coefficients are only significant at 10% level. In the male and female sample, immigration has a positive impact on the number of temporary native worker, mostly through an increase in regular immigrant workers. The trend is similar but more significant than when all 47 prefectures are included in the estimation. On the other hand, the coefficients in panel II are all positive, but they are all insignificant.

[**Table 4.3**]

### 4.4.2 Immigrants and native in-migration rate

In this section, the impact of immigration on the actual migration flow of natives is estimated, using the number of native workers moved between regions to construct the dependent variables. However, the anonymized version of the Census does not provide detail on the place of living five years earlier of a person, but only whether he or she is living the same region. Thus, it is only possible to calculate the inflow of natives, but not the outflow or the net inflow of natives. Regardless, finding out whether immigrant workers hinder or encourage the inflow of native worker can have important implications.

The in-migration rate of native labor is calculated as

$$v_{ijt} = \frac{IN_{ijt}}{\frac{N_{ijt}+N_{ij,t-1}}{2}} \tag{4.3}$$

where $IN_{ijt}$ is the number of native workers who lived in another region five years earlier. Since a person's place of living five years earlier is only recorded in 2000, 2010, and 2015, the analysis in this section is restricted to samples in 2010 and 2015.

Similar to the previous section, table 4.4 presents the impact of immigrant workers on the in-migration rate of native workers at prefecture and city level. Table 4.5 presents the same estimation in large prefectures groups and small prefecture groups.

[**Table 4.4**]

At prefecture level, immigration shows no significant effects on the inflow of native workers. At city level, temporary immigrant workers hinder the inflow of native workers, but the aggregate impact of temporary and regular immigrant workers is insignificant. The negative impact seems to affect mainly the temporary native workers. One difference between the male and male and female samples is that the share of all immigrant workers shows a negative coefficient in the latter sample.

[**Table 4.5**]

The results in table 4.5 show no significant impact of immigration on native inflow at prefecture level. For small prefectures, an increase in regular immigrant workers encourage the inflow of temporary native workers. However, the relationship is only found when both male and female workers are included.

### 4.4.3 Robustness

This section tests the sensitivity of the results in previous sections. Tables 4.6 and 4.7 shows the coefficients of immigrant share when control variables are included. For brevity, coefficients of the control variables are excluded. The results are similar to that in tables 4.2 and 4.3. Next, tables 4.8 and 4.9 uses the total number of immigrant and native workers as dependent variables. The results indicate that immigration increases the size of total labor workforce, or has no significant impact at all, which are the expected results. Similarly, sensitivity checks for in-migration rate of native workers are conducted in tables 4.10 and 4.11. The results are consistent with previous results.

[**Table 4.6**]

[**Table 4.7**]

[**Table 4.8**]

[**Table 4.9**]

[**Table 4.10**]

[**Table 4.11**]

## 4.5 Discussion

Panel I of table 4.2 shows the impact of immigration at prefecture level. When the sample includes both male and female workers, there is a positive effect of immigration on the temporary native labor force, mostly from an increase in regular immigrant worker. The effect becomes insignificant when temporary and regular native workers are aggregated. Since the ratio of temporary workers is relatively small compared to regular workers, the positive effect gets diluted. Additionally, in Japan, females are more likely to work as temporary workers. Thus, only when both males and females workers are included does the impact on temporary native worker becomes significant. Panels I and II of table 4.3 categorized the prefectures into 16 prefectures that have cities with population larger than 500,000 (large prefectures) and other 31 prefectures (small prefectures). Similar trends to panel I of Table 2 are found in the large prefectures group. While some coefficients in the male sample are significant, they are only significant at 10% and, thus, can be ignored. On the other hand, immigration shows no impact on the native labor force of the small prefectures group. Overall, an increase in temporary immigrant workers is linked to an increase in temporary native workers in prefectures with large population.

At city level, immigrant workers show a negative and significant impact on their native counterpart. The negative link is seen only with the regular native worker, but not with the temporary native worker. Additionally, an increase in regular immigrant worker might be the main reason for the decrease in native workers. There are several ways to explain the response of native workers at both prefecture and city level. First, native worker may response to an increase in immigrant workers with similar characteristic (from the same skill group) by moving to other skill groups, or moving to other regions. If the native responses by moving to other skill groups, then the effects at city level and large prefecture groups should express some similarity, since both samples cover the same 16 prefectures. However, the discrepancy between the two results shows that moving between skill groups might not have been the case. Therefore, the negative impacts of immigration at city level are more likely to be native moving to other cities but still within the prefecture. This implication is consistent with previous literature, as workers can easily move between small geographical units (city) than large geographical units (prefecture).

The above phenomenon can also be explained based on the characteristics of the employment contract (Edo, 2016). Compared to temporary worker, regular worker has better employment protection and possibly higher wage insensitivity. In other words, it is harder to adjust the number of workers under regular contract than that under temporary contract. Since immigrant workers are more likely to accept lower wages and harsher conditions, firm will be more profitable by replacing native workers with immigrant workers. On the other hand, similar effects are not observed for temporary native workers. This implies that firms absorb the increase in immigrant workers while keeping the employment level of native workers. Overall, the findings show that firm may be replacing regular native workers with immigrant workers. In contrast, temporary native workers experience an increase in job opportunities.

While it is not possible to obtain the out-migration rate and, thus, the net-migration rate of native workers, estimating the effect of immigration on the in-migration rate of native workers still carries valuable implication. The results indicate that an increase in temporary immigrant worker reduces the inflow of temporary native workers only at city level. At prefecture level, the impact is insignificant in large prefectures group, but positive in small prefectures group. In contrast with previous literature (Borjas, 2006; Mocetti and Porello, 2010), there is not enough evidence to conclude that immigration negatively affect the inflow on native workers. The positive sign in small prefectures group shows that prefectures with relatively small population may benefit from immigration, without harming native workers. The results of several robustness tests are similar to the main estimation, further validating the results and their implications.

This chapter contributes to the limited research on immigrant workers in Japan. The results show that native workers response negatively to immigration only in crowded cities. Specifically, the natives respond by moving between cities within the current prefecture they are living in. Different from previous literatures (Borjas, 2003; Borjas, 2014), skill group is defined as a combination of industry-occupation, instead of education-experience. This definition of skill group helps avoid the "downgrading effects" on immigration, in which immigrant workers may work in low-skilled jobs despite higher education level.

## 4.6 Conclusion

This chapter estimates the impact that immigration has on Japanese native workers. To achieve this objective, anonymized Japanese Population Census data in 2005, 2010, and 2015 are used. To avoid the "downgrading effects" on immigration, skill group is defined differently from previous literatures. Namely, a skill group is defined as a combination of industry and occupation, instead of education level and labor market experience.

From the findings, it is hard to definitively conclude that immigration has a negative impact on the native workers. While immigration has a strong and negative impact on their native counterparts at city level, it becomes insignificant at prefecture level. This evidence implies that native workers might have respond to an increase in immigrant workers by moving to nearby cities that are within the same prefecture. When workers are categorized into temporary and regular worker, immigrant workers are found to negative affect the regular workers, but not the temporary workers. In fact, when both male and female workers are included, the impact of immigration becomes positive and significant.

Estimating the effect of immigration on inflow of native workers review contrasting results with previous research. The evidence is not enough to conclude that immigrant reduce the inflow of male native workers. When both genders are included, the relationship between immigration and inflow of temporary native worker is negative at city level, but positive for small prefectures group.

# Tables and Figures

**Table 4.1:** Rate of change in the number of native workers aged 15-64, and 65 and

| | 15-64 | >64 |
|---|---|---|
| 2000-2005 | -5.6% | 9.4% |
| 2005-2010 | -7.9% | 23.1% |
| 2010-2015 | -5.0% | 38.8% |

**Table 4.2:** Impact of immigration on native workforce at prefecture level and city

| | *Dependent variable:* | | | | | |
|---|---|---|---|---|---|---|
| | All native worker | | Regular native worker | | Temporary native worker | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| I. Prefectures | | | | | | |
| 1. All immigrant worker share. Male | 0.185 | | -0.012 | | 1.861 | |
| | (0.564) | | (0.509) | | (1.352) | |
| 1a. Regular immigrant worker share. Male | | -0.062 | | -0.154 | | 1.490 |
| | | (0.600) | | (0.585) | | (1.206) |
| 1b. Temporary immigrant worker share. Male | | 0.764 | | 0.322 | | 2.730 |
| | | (0.810) | | (0.785) | | (2.472) |
| 2. All immigrant share. Male and female | 0.139 | | -0.144 | | 1.710** | |
| | (0.386) | | (0.383) | | (0.607) | |
| 2a. Regular immigrant worker share. Male and female | | -0.022 | | -0.225 | | 1.724* |
| | | (0.503) | | (0.488) | | (0.856) |
| 2b. Temporary immigrant worker share. Male and female | | 0.432 | | 0.004 | | 1.685 |
| | | (0.509) | | (0.736) | | (1.405) |
| II. Cities | | | | | | |
| 3. All immigrant worker share. Male | -1.008*** | | -1.066*** | | -0.408 | |
| | (0.205) | | (0.240) | | (0.620) | |
| 3a. Regular immigrant worker share. Male | | -0.919*** | | -0.980*** | | -0.190 |
| | | (0.209) | | (0.229) | | (0.591) |
| 3b. Temporary immigrant worker share. Male | | -1.856* | | -1.892* | | -2.511 |
| | | (0.932) | | (0.968) | | (2.332) |
| 4. All immigrant worker share. Male and female | -1.001*** | | -0.990*** | | -0.017 | |
| | (0.249) | | (0.300) | | (0.647) | |
| 4a. Regular immigrant worker share. Male and female | | -0.885*** | | -0.900** | | -0.019 |
| | | (0.292) | | (0.333) | | (0.735) |
| 4b. Temporary immigrant worker share. Male and female | | -1.969** | | -1.738** | | -0.007 |
| | | (0.798) | | (0.776) | | (2.322) |

Note: Standard errors in parentheses are clustered at the region-skill level. Weighted regression is used, where the weight is the number of native workers in the skill-region-year cell. The dependent variable is the total number of native worker in columns (1) and (2), the number of regular native worker in columns (3) and (4), the number of temporary native worker in columns (5) and (6). Regressions numbered 1, 2, 3, and 4 show the coefficients of the total number of immigrant share. Regressions numbered 1a, 1b, 2a, 2b, 3a, 3b, 4a, and 4b show the coefficients of regression that uses both regular immigrant worker share and temporary immigrant worker share as independent variables. The number of observations is 2,961 at prefecture level, and 1,890 at city level.
*p<0.1; **p<0.05; ***p<0.01

**Table 4.3:** Impact of immigration on native workforce in large prefectures and small prefectures groups

| | *Dependent variable:* | | | | | |
|---|---|---|---|---|---|---|
| | All native worker | | Regular native worker | | Temporary native worker | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| I. Large prefectures | | | | | | |
| 1. All immigrant worker share. Male | -0.277 | | -0.607 | | 2.230 | |
| | (0.567) | | (0.533) | | (1.304) | |
| 1a. Regular immigrant worker share. Male | | -0.508 | | -0.781* | | 2.663* |
| | | (0.570) | | (0.432) | | (1.377) |
| 1b. Temporary immigrant worker share. Male | | 1.138 | | 0.461 | | -0.425 |
| | | (1.353) | | (1.865) | | (7.023) |
| 2. All immigrant share. Male and female | -0.132 | | -0.447 | | 1.946** | |
| | (0.503) | | (0.609) | | (0.898) | |
| 2a. Regular immigrant worker share. Male and female | | -0.239 | | -0.660 | | 3.003** |
| | | (0.547) | | (0.634) | | (1.126) |
| 2b. Temporary immigrant worker share. Male and female | | 0.146 | | 0.106 | | -0.798 |
| | | (1.216) | | (1.604) | | (4.469) |
| II. Small prefectures | | | | | | |
| 3. All immigrant worker share. Male | 0.486 | | 0.422 | | 0.873 | |
| | (0.730) | | (0.679) | | (1.805) | |
| 3a. Regular immigrant worker share. Male | | 0.484 | | 0.498 | | 0.366 |
| | | (0.908) | | (0.915) | | (1.871) |
| 3b. Temporary immigrant worker share. Male | | 0.490 | | 0.305 | | 1.645 |
| | | (0.726) | | (0.677) | | (2.239) |
| 4. All immigrant worker share. Male and female | 0.386 | | 0.212 | | 1.388 | |
| | (0.573) | | (0.502) | | (1.451) | |
| 4a. Regular immigrant worker share. Male and female | | -0.238 | | -0.163 | | 1.081 |
| | | (0.805) | | (0.664) | | (1.753) |
| 4b. Temporary immigrant worker share. Male and female | | 0.589 | | 0.279 | | 1.807 |
| | | (0.477) | | (0.588) | | (1.518) |

Note: Standard errors in parentheses are clustered at the region-skill level. Weighted regression is used, where the weight is the number of native workers in the skill-region-year cell. The dependent variable is the total number of native worker in columns (1) and (2), the number of regular native worker in columns (3) and (4), the number of temporary native worker in columns (5) and (6). Regressions numbered 1, 2, 3, and 4 show the coefficients of the total number of immigrant share. Regressions numbered 1a, 1b, 2a, 2b, 3a, 3b, 4a, and 4b show the coefficients of regression that uses both regular immigrant worker share and temporary immigrant worker share as independent variables. The number of observations is 1,008 for large prefectures group, and 1,953 for small prefectures group. *p<0.1; **p<0.05; ***p<0.01

**Table 4.4:** Impact of immigration on in-migration rate of native workers at prefecture level and city level

| | *Dependent variable:* | | | | | |
|---|---|---|---|---|---|---|
| | All native worker | | Regular native worker | | Temporary native worker | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| I. Prefectures | | | | | | |
| 1. All immigrant worker share. Male | -0.113 | | -0.112 | | -0.001 | |
| | (0.195) | | (0.146) | | (0.080) | |
| 1a. Regular immigrant worker share. Male | | -0.052 | | -0.074 | | 0.022 |
| | | (0.147) | | (0.136) | | (0.072) |
| 1b. Temporary immigrant worker share. Male | | -0.242 | | -0.192 | | -0.050 |
| | | (0.479) | | (0.373) | | (0.135) |
| 2. All immigrant share. Male and female | -0.072 | | -0.049 | | -0.023 | |
| | (0.146) | | (0.122) | | (0.054) | |
| 2a. Regular immigrant worker share. Male and female | | -0.018 | | -0.041 | | 0.023 |
| | | (0.149) | | (0.140) | | (0.078) |
| 2b. Temporary immigrant worker share. Male and female | | -0.154 | | -0.061 | | -0.093 |
| | | (0.253) | | (0.197) | | (0.094) |
| II. Cities | | | | | | |
| 3. All immigrant worker share. Male | 0.033 | | 0.119 | | -0.085 | |
| | (0.189) | | (0.160) | | (0.074) | |
| 3a. Regular immigrant worker share. Male | | 0.201 | | 0.211 | | -0.011 |
| | | (0.185) | | (0.175) | | (0.066) |
| 3b. Temporary immigrant worker share. Male | | -0.967** | | -0.437 | | -0.530** |
| | | (0.425) | | (0.296) | | (0.202) |
| 4. All immigrant worker share. Male and female | -0.056 | | -0.104 | | -0.160** | |
| | (0.133) | | (0.132) | | (0.065) | |
| 4a. Regular immigrant worker share. Male and female | | 0.117 | | 0.196 | | -0.079 |
| | | (0.138) | | (0.151) | | (0.059) |
| 4b. Temporary immigrant worker share. Male and female | | -0.923* | | -0.356 | | -0.567** |
| | | (0.445) | | (0.322) | | (0.224) |

Note: Standard errors in parentheses are clustered at the region-skill level. Weighted regression is used, where the weight is the number of native workers in the skill-region-year cell. The dependent variable is the total number of native worker in columns (1) and (2), the number of regular native worker in columns (3) and (4), the number of temporary native worker in columns (5) and (6). Regressions numbered 1, 2, 3, and 4 show the coefficients of the total number of immigrant share. Regressions numbered 1a, 1b, 2a, 2b, 3a, 3b, 4a, and 4b show the coefficients of regression that uses both regular immigrant worker share and temporary immigrant worker share as independent variables. The number of observations is 2,961 at prefecture level, and 1,890 at city level. *p<0.1; **p<0.05; ***p<0.01

**Table 4.5:** Impact of immigration on in-migration rate of native workers in large prefectures and small prefectures groups

| | *Dependent variable:* | | | | | |
|---|---|---|---|---|---|---|
| | All native worker | | Regular native worker | | Temporary native worker | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| I. Large prefectures | | | | | | |
| 1. All immigrant worker share. Male | -0.035 | | -0.022 | | -0.013 | |
| | (0.118) | | (0.094) | | (0.126) | |
| 1a. Regular immigrant worker share. Male | | 0.054 | | -0.017 | | 0.071 |
| | | (0.131) | | (0.142) | | (0.113) |
| 1b. Temporary immigrant worker share. Male | | -0.459 | | -0.043 | | -0.416 |
| | | (0.519) | | (0.302) | | (0.289) |
| 2. All immigrant share. Male and female | -0.081 | | 0.026 | | -0.107 | |
| | (0.153) | | (0.130) | | (0.085) | |
| 2a. Regular immigrant worker share. Male and female | | -0.003 | | 0.041 | | -0.044 |
| | | (0.210) | | (0.187) | | (0.124) |
| 2b. Temporary immigrant worker share. Male and female | | -0.255 | | -0.006 | | -0.249 |
| | | (0.244) | | (0.173) | | (0.199) |
| II. Small prefectures | | | | | | |
| 3. All immigrant worker share. Male | -0.082 | | -0.108 | | 0.026 | |
| | (0.260) | | (0.251) | | (0.075) | |
| 3a. Regular immigrant worker share. Male | | -0.040 | | -0.047 | | 0.007 |
| | | (0.190) | | (0.228) | | (0.054) |
| 3b. Temporary immigrant worker share. Male | | -0.132 | | -0.181 | | 0.049 |
| | | (0.468) | | (0.410) | | (0.109) |
| 4. All immigrant worker share. Male and female | 0.017 | | -0.080 | | 0.096*** | |
| | (0.162) | | (0.170) | | (0.031) | |
| 4a. Regular immigrant worker share. Male and female | | 0.079 | | -0.078 | | 0.157** |
| | | (0.119) | | (0.151) | | (0.062) |
| 4b. Temporary immigrant worker share. Male and female | | -0.051 | | -0.082 | | 0.031 |
| | | (0.296) | | (0.293) | | (0.098) |

Note: Standard errors in parentheses are clustered at the region-skill level. Weighted regression is used, where the weight is the number of native workers in the skill-region-year cell. The dependent variable is the total number of native worker in columns (1) and (2), the number of regular native worker in columns (3) and (4), the number of temporary native worker in columns (5) and (6). Regressions numbered 1, 2, 3, and 4 show the coefficients of the total number of immigrant share. Regressions numbered 1a, 1b, 2a, 2b, 3a, 3b, 4a, and 4b show the coefficients of regression that uses both regular immigrant worker share and temporary immigrant worker share as independent variables. The number of observations is 1,008 for large prefectures group, and 1,953 for small prefectures group. *p<0.1; **p<0.05; ***p<0.01

**Table 4.6:** Robustness checks the impact of immigration on native workforce at prefecture level and city level by including control variables

| | *Dependent variable:* | | | | | |
|---|---|---|---|---|---|---|
| | All native worker | | Regular native worker | | Temporary native worker | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| I. Prefectures | | | | | | |
| 1. All immigrant worker share. Male | 0.218 | | 0.012 | | 1.925 | |
| | (0.574) | | (0.516) | | (1.374) | |
| 1a. Regular immigrant worker share. Male | | -0.033 | | -0.132 | | 1.541 |
| | | (0.606) | | (0.585) | | (1.234) |
| 1b. Temporary immigrant worker share. Male | | 0.809 | | 0.352 | | 2.825 |
| | | (0.831) | | (0.801) | | (2.502) |
| 2. All immigrant share. Male and female | 0.161 | | -0.134 | | 1.765** | |
| | (0.391) | | (0.389) | | (0.642) | |
| 2a. Regular immigrant worker share. Male and female | | -0.003 | | -0.221 | | 1.785* |
| | | (0.503) | | (0.488) | | (0.883) |
| 2b. Temporary immigrant worker share. Male and female | | 0.461 | | 0.025 | | 1.729 |
| | | (0.523) | | (0.748) | | (1.341) |
| II. Cities | | | | | | |
| 3. All immigrant worker share. Male | -0.985*** | | -1.052*** | | -0.417 | |
| | (0.209) | | (0.234) | | (0.630) | |
| 3a. Regular immigrant worker share. Male | | -0.900** | | -0.970*** | | -0.192 |
| | | (0.221) | | (0.229) | | (0.595) |
| 3b. Temporary immigrant worker share. Male | | -1.799* | | -1.830* | | -2.558 |
| | | (0.924) | | (0.959) | | (2.391) |
| 4. All immigrant worker share. Male and female | -0.994*** | | -0.995*** | | 0.003 | |
| | (0.257) | | (0.309) | | (0.658) | |
| 4a. Regular immigrant worker share. Male and female | | -0.882*** | | -0.908** | | -0.005 |
| | | (0.300) | | (0.342) | | (0.744) |
| 4b. Temporary immigrant worker share. Male and female | | -1.935** | | -1.718** | | 0.071 |
| | | (0.814) | | (0.806) | | (2.289) |

Note: Standard errors in parentheses are clustered at the region-skill level. Weighted regression is used, where the weight is the number of native workers in the skill-region-year cell. The dependent variable is the total number of native worker in columns (1) and (2), the number of regular native worker in columns (3) and (4), the number of temporary native worker in columns (5) and (6). Regressions numbered 1, 2, 3, and 4 show the coefficients of the total number of immigrant share. Regressions numbered 1a, 1b, 2a, 2b, 3a, 3b, 4a, and 4b show the coefficients of regression that uses both regular immigrant worker share and temporary immigrant worker share as independent variables. The number of observations is 2,961 at prefecture level, and 1,890 at city level. See text for details on control variables. For brevity, only immigration's coefficients are showed. *p<0.1; **p<0.05; ***p<0.01

**Table 4.7:** Robustness checks for the impact of immigration on native workforce between in prefectures and small prefectures groups by including control variables

| | *Dependent variable:* | | | | | |
|---|---|---|---|---|---|---|
| | All native worker | | Regular native worker | | Temporary native worker | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| I. Large prefectures | | | | | | |
| 1. All immigrant worker share. Male | -0.310 | | -0.692 | | 2.512* | |
| | (0.603) | | (0.574) | | (1.287) | |
| 1a. Regular immigrant worker share. Male | | -0.514 | | -0.833* | | 2.917* |
| | | (0.580) | | (0.450) | | (1.375) |
| 1b. Temporary immigrant worker share. Male | | 0.966 | | 0.186 | | -0.015 |
| | | (1.447) | | (1.968) | | (7.050) |
| 2. All immigrant share. Male and female | -0.167 | | -0.526 | | 2.074** | |
| | (0.537) | | (0.643) | | (0.868) | |
| 2a. Regular immigrant worker share. Male and female | | -0.259 | | -0.702 | | 3.073** |
| | | (0.553) | | (0.646) | | (1.156) |
| 2b. Temporary immigrant worker share. Male and female | | 0.071 | | -0.067 | | -0.543 |
| | | (1.287) | | (1.595) | | (4.215) |
| II. Small prefectures | | | | | | |
| 3. All immigrant worker share. Male | 0.492 | | 0.430 | | 0.864 | |
| | (0.765) | | (0.718) | | (1.806) | |
| 3a. Regular immigrant worker share. Male | | 0.518 | | 0.534 | | 0.379 |
| | | (0.945) | | (0.953) | | (1.875) |
| 3b. Temporary immigrant worker share. Male | | 0.453 | | 0.270 | | 1.603 |
| | | (0.766) | | (0.707) | | (2.263) |
| 4. All immigrant worker share. Male and female | 0.311 | | 0.143 | | 1.326 | |
| | (0.561) | | (0.497) | | (1.451) | |
| 4a. Regular immigrant worker share. Male and female | | 0.202 | | 0.129 | | 1.055 |
| | | (0.765) | | (0.629) | | (1.757) |
| 4b. Temporary immigrant worker share. Male and female | | 0.461 | | 0.162 | | 1.696 |
| | | (0.496) | | (0.603) | | (1.543) |

Note: Standard errors in parentheses are clustered at the region-skill level. Weighted regression is used, where the weight is the number of native workers in the skill-region-year cell. The dependent variable is the total number of native worker in columns (1) and (2), the number of regular native worker in columns (3) and (4), the number of temporary native worker in columns (5) and (6). Regressions numbered 1, 2, 3, and 4 show the coefficients of the total number of immigrant share. Regressions numbered 1a, 1b, 2a, 2b, 3a, 3b, 4a, and 4b show the coefficients of regression that uses both regular immigrant worker share and temporary immigrant worker share as independent variables. The number of observations is 1,008 for large prefectures group, and 1,953 for small prefectures group. See text for details on control variables. For brevity, only immigration's coefficients are showed. *p<0.1; **p<0.05; ***p<0.01

**Table 4.8:** Impact of immigration on the total workforce at prefecture level and city level

| | *Dependent variable:* | | | | | |
|---|---|---|---|---|---|---|
| | All worker | | Regular worker | | Temporary worker | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| I. Prefectures | | | | | | |
| 1. All immigrant worker share. Male | 1.203** | | 0.757 | | 3.999** | |
| | (0.563) | | (0.509) | | (1.583) | |
| 1a. Regular immigrant worker share. Male | | 0.936 | | 0.935 | | 2.117 |
| | | (0.599) | | (0.590) | | (1.228) |
| 1b. Temporary immigrant worker share. Male | | 1.830** | | 0.338 | | 8.416** |
| | | (0.794) | | (0.790) | | (3.503) |
| 2. All immigrant share. Male and female | 1.170*** | | 0.636 | | 3.257** | |
| | (0.385) | | (0.382) | | (0.724) | |
| 2a. Regular immigrant worker share. Male and female | | 0.989* | | 0.933* | | 2.323** |
| | | (0.503) | | (0.493) | | (1.058) |
| 2b. Temporary immigrant worker share. Male and female | | 1.501*** | | 0.097 | | 4.959*** |
| | | (0.513) | | (0.732) | | (1.325) |
| II. Cities | | | | | | |
| 3. All immigrant worker share. Male | -0.021 | | -0.124 | | 0.550 | |
| | (0.203) | | (0.236) | | (0.411) | |
| 3a. Regular immigrant worker share. Male | | 0.066 | | 0.061 | | -0.014 |
| | | (0.207) | | (0.235) | | (0.424) |
| 3b. Temporary immigrant worker share. Male | | -0.858 | | -1.905* | | 5.975** |
| | | (0.932) | | (0.966) | | (2.118) |
| 4. All immigrant worker share. Male and female | 0.001 | | -0.027 | | 0.983 | |
| | (0.249) | | (0.295) | | (0.604) | |
| 4a. Regular immigrant worker share. Male and female | | 0.115 | | 0.176 | | 0.445 |
| | | (0.293) | | (0.345) | | (0.733) |
| 4b. Temporary immigrant worker share. Male and female | | 0.959 | | -1.735** | | 5.491** |
| | | (0.799) | | (0.756) | | (2.410) |

Note: Standard errors in parentheses are clustered at the region-skill level. Weighted regression is used, where the weight is the number of native workers in the skill-region-year cell. The dependent variable is the total number of native worker and immigrant worker with different employment contract. Regressions numbered 1, 2, 3, and 4 show the coefficients of the total number of immigrant share. Regressions numbered 1a, 1b, 2a, 2b, 3a, 3b, 4a, and 4b show the coefficients of regression that uses both regular immigrant worker share and temporary immigrant worker share as independent variables. The number of observations is 2,961 at prefecture level, and 1,890 at city level. *p<0.1; **p<0.05; ***p<0.01

**Table 4.9:** Impact of immigration on the total workforce in large prefectures and small prefectures groups

| | *Dependent variable:* | | | | | |
|---|---|---|---|---|---|---|
| | All worker | | Regular worker | | Temporary worker | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| I. Large prefectures | | | | | | |
| 1. All immigrant worker share. Male | 0.728 | | 0.329 | | 3.632** | |
| | (0.567) | | (0.516) | | (1.268) | |
| 1a. Regular immigrant worker share. Male | | 0.497 | | 0.297 | | 2.957** |
| | | (0.568) | | (0.446) | | (1.285) |
| 1b. Temporary immigrant worker share. Male | | 2.145 | | 0.521 | | 7.770 |
| | | (1.350) | | (1.854) | | (6.098) |
| 2. All immigrant share. Male and female | 0.896* | | 0.420 | | 3.084*** | |
| | (0.510) | | (0.606) | | (0.972) | |
| 2a. Regular immigrant worker share. Male and female | | 0.777 | | 0.472 | | 3.334** |
| | | (0.547) | | (0.644) | | (1.303) |
| 2b. Temporary immigrant worker share. Male and female | | 1.204 | | 0.285 | | 2.436 |
| | | (1.233) | | (1.583) | | (4.487) |
| II. Small prefectures | | | | | | |
| 3. All immigrant worker share. Male | 1.512** | | 1.087 | | 3.607 | |
| | (0.724) | | (0.724) | | (2.098) | |
| 3a. Regular immigrant worker share. Male | | 1.473 | | 1.598* | | 1.405 |
| | | (0.911) | | (0.915) | | (1.993) |
| 3b. Temporary immigrant worker share. Male | | 1.570 | | 0.307 | | 6.695** |
| | | (0.710) | | (0.683) | | (3.163) |
| 4. All immigrant worker share. Male and female | 1.420** | | 0.916* | | 3.385* | |
| | (0.565) | | (0.522) | | (1.641) | |
| 4a. Regular immigrant worker share. Male and female | | 1.242 | | 1.346* | | 1.962 |
| | | (0.810) | | (0.655) | | (1.946) |
| 4b. Temporary immigrant worker share. Male and female | | 1.664*** | | 0.329 | | 5.330*** |
| | | (0.457) | | (0.594) | | (1.673) |

Note: Standard errors in parentheses are clustered at the region-skill level. Weighted regression is used, where the weight is the number of native workers in the skill-region-year cell. The dependent variable is the total number of native worker in columns (1) and (2), the number of regular native worker in columns (3) and (4), the number of temporary native worker in columns (5) and (6). Regressions numbered 1, 2, 3, and 4 show the coefficients of the total number of immigrant share. Regressions numbered 1a, 1b, 2a, 2b, 3a, 3b, 4a, and 4b show the coefficients of regression that uses both regular immigrant worker share and temporary immigrant worker share as independent variables. The number of observations is 1,008 for large prefectures group, and 1,953 for small prefectures group. *p<0.1; **p<0.05; ***p<0.01

**Table 4.10:** Robustness checks the impact of immigration on the in-migration rate if native workers at prefecture level and city level by including control variables

| | *Dependent variable:* | | | | | |
|---|---|---|---|---|---|---|
| | All native worker | | Regular native worker | | Temporary native worker | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| I. Prefectures | | | | | | |
| 1. All immigrant worker share. Male | -0.015<br>(0.181) | | -0.025<br>(0.142) | | 0.010<br>(0.081) | |
| 1a. Regular immigrant worker share. Male | | 0.027<br>(0.152) | | -0.004<br>(0.148) | | 0.030<br>(0.076) |
| 1b. Temporary immigrant worker share. Male | | -0.102<br>(0.425) | | -0.069<br>(0.325) | | -0.033<br>(0.130) |
| 2. All immigrant share. Male and female | -0.009<br>(0.142) | | -0.007<br>(0.125) | | -0.001<br>(0.050) | |
| 2a. Regular immigrant worker share. Male and female | | 0.017<br>(0.144) | | -0.014<br>(0.136) | | 0.032<br>(0.077) |
| 2b. Temporary immigrant worker share. Male and female | | -0.049<br>(0.217) | | 0.003<br>(0.189) | | -0.052<br>(0.095) |
| II. Cities | | | | | | |
| 3. All immigrant worker share. Male | 0.068<br>(0.177) | | 0.152<br>(0.154) | | -0.084<br>(0.070) | |
| 3a. Regular immigrant worker share. Male | | 0.197<br>(0.164) | | 0.213<br>(0.166) | | -0.017<br>(0.060) |
| 3b. Temporary immigrant worker share. Male | | -0.702*<br>(0.407) | | -0.213<br>(0.293) | | -0.489**<br>(-0.195) |
| 4. All immigrant worker share. Male and female | -0.028<br>(0.122) | | 0.126<br>(0.123) | | -0.153**<br>(0.066) | |
| 4a. Regular immigrant worker share. Male and female | | 0.113<br>(0.120) | | 0.195<br>(0.144) | | -0.081<br>(0.056) |
| 4b. Temporary immigrant worker share. Male and female | | -0.738*<br>(0.392) | | -0.222<br>(0.282) | | -0.516**<br>(0.210) |

Note: Standard errors in parentheses are clustered at the region-skill level. Weighted regression is used, where the weight is the number of native workers in the skill-region-year cell. The dependent variable is the total number of native worker in columns (1) and (2), the number of regular native worker in columns (3) and (4), the number of temporary native worker in columns (5) and (6). Regressions numbered 1, 2, 3, and 4 show the coefficients of the total number of immigrant share. Regressions numbered 1a, 1b, 2a, 2b, 3a, 3b, 4a, and 4b show the coefficients of regression that uses both regular immigrant worker share and temporary immigrant worker share as independent variables. The number of observations is 2,961 at prefecture level, and 1,890 at city level. See text for details on control variables. For brevity, only immigration's coefficients are showed. *p<0.1; **p<0.05; ***p<0.01

**Table 4.11:** Robustness checks for the impact of immigration on the in-migration rate of native workers between in prefectures and small prefectures groups by including control variables

| | *Dependent variable:* | | | | | |
|---|---|---|---|---|---|---|
| | All native worker | | Regular native worker | | Temporary native worker | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| I. Large prefectures | | | | | | |
| 1. All immigrant worker share. Male | 0.043 | | 0.046 | | -0.003 | |
| | (0.114) | | (0.087) | | (0.134) | |
| 1a. Regular immigrant worker share. Male | | 0.090 | | 0.015 | | 0.075 |
| | | (0.137) | | (0.156) | | (0.121) |
| 1b. Temporary immigrant worker share. Male | | -0.179 | | 0.194 | | -0.373 |
| | | (0.658) | | (0.425) | | (0.306) |
| 2. All immigrant share. Male and female | 0.001 | | 0.081 | | -0.080 | |
| | (0.130) | | (0.128) | | (0.082) | |
| 2a. Regular immigrant worker share. Male and female | | 0.012 | | 0.050 | | -0.039 |
| | | (0.214) | | (0.192) | | (0.127) |
| 2b. Temporary immigrant worker share. Male and female | | -0.023 | | 0.154 | | -0.177 |
| | | (0.199) | | (0.185) | | (0.199) |
| II. Small prefectures | | | | | | |
| 3. All immigrant worker share. Male | -0.013 | | -0.042 | | 0.030 | |
| | (0.239) | | (0.235) | | (0.078) | |
| 3a. Regular immigrant worker share. Male | | 0.019 | | 0.005 | | 0.014 |
| | | (0.216) | | (0.246) | | (0.058) |
| 3b. Temporary immigrant worker share. Male | | -0.051 | | -0.100 | | -0.049 |
| | | (0.406) | | (0.348) | | (0.111) |
| 4. All immigrant worker share. Male and female | 0.048 | | -0.060 | | 0.108** | |
| | (0.164) | | (0.172) | | (0.039) | |
| 4a. Regular immigrant worker share. Male and female | | 0.110 | | -0.053 | | 0.163** |
| | | (0.097) | | (0.132) | | (0.065) |
| 4b. Temporary immigrant worker share. Male and female | | -0.020 | | -0.068 | | 0.048 |
| | | (0.301) | | (0.295) | | (0.102) |

Note: Standard errors in parentheses are clustered at the region-skill level. Weighted regression is used, where the weight is the number of native workers in the skill-region-year cell. The dependent variable is the total number of native worker in columns (1) and (2), the number of regular native worker in columns (3) and (4), the number of temporary native worker in columns (5) and (6). Regressions numbered 1, 2, 3, and 4 show the coefficients of the total number of immigrant share. Regressions numbered 1a, 1b, 2a, 2b, 3a, 3b, 4a, and 4b show the coefficients of regression that uses both regular immigrant worker share and temporary immigrant worker share as independent variables. The number of observations is 1,008 for large prefectures group, and 1,953 for small prefectures group See text for details on control variables. For brevity, only immigration's coefficients are showed. *p<0.1; **p<0.05; ***p<0.01

# Chapter 5

# Concluding Remarks

## 5.1 Economic impacts of immigration in Japan

Japan used to permit only high-skilled foreign workers. However, in order to keep its economy competitive and deal with domestic labor shortages, Japan has started to loosen its policy and allowed an increasing number of migrant workers. Each chapter in this dissertation analyzes different economic impacts of immigration in Japan.

Chapter 2 studies the impact of the immigrant population on bilateral trade between Japanese prefectures and foreign countries. The empirical results show that a larger immigrant population is positively linked to larger bilateral trade. Additional estimation indicates that immigrants have a larger impact on the trade of consumer goods, implying the importance of information and knowledge brought by immigrants. Finally, estimating the impacts on the margins of trade reveals that an increase in immigrant count improves trade through both the intensive (defined as the trade of existing goods) and extensive (defined as the number of traded goods) margins, but mainly through the intensive margin.

Chapter 3 shifts the focus to local economic growth. The panel estimation implies that immigrant workers only positively affect the total number of workers. On the other hand, utilizing GWPR shows that several of the economic effects induced by immigrants are masked. First, consistent with the panel estimation, immigrants are found to expand the local labor force of most prefectures. Second, capital-to-output ratio is negatively affected in many prefectures in northern Japan, which is the result of a positive impact on output growth but not on capital growth. Both methods consistently indicate that increasing the number of immigrant workers expands the local labor force without depressing wages. Using simple supply and demand theory, if the demand curve shifts to the right simultaneously when the supply curve shifts to the right due to an increase in immigrant workers, then the wage level will remain unchanged. Finally, estimating the coefficients generated by GWPR on different groups of immigrants indicates that the economic impact of immigration correlates with the industrial structure of each prefecture.

One commonly debated topic when accepting immigrant workers is their impact on the native workers. Chapter 4 tries to answer this question by utilizing the anonymized version of Japanese Population Census microdata. The results indicate a negative effect on the number of native workers at the city-level but not at the prefecture-level, implying that native workers respond to increased competition due to immigration by moving to nearby cities in the same prefecture. To better understand the impact on the natives, workers are further grouped into regular and temporary workers. Interestingly, regular workers are negatively affected by immigration, but not temporary workers. This discrepancy might be due to the characteristics of the employment contract. Since regular workers have better employment protection and possibly higher wage insensitivity, firms can become more profitable by replacing them with immigrant workers, who are more likely to accept lower wages and harsher working conditions. On the other hand, the number and the wage of temporary workers can be easily adjusted. Thus, while an increase in temporary immigrant workers does not affect the employment of their native counterparts, the wages may have been adjusted. Finally, in contrast with previous literature, there is no evidence that immigration negatively affects the inflow of native workers.

## 5.2 Policy proposals

The above results imply that the Japanese economy can benefit from more immigration. In fact, in 2019, a new visa called "Specified Skilled Worker" (SSW) was established to accept low-skilled workers in 12 industries, marking a change in Japan's official stance on only accepting high-skilled foreign workers to also accepting low-skilled workers. Under certain conditions, workers holding SSW can obtain permanent residence, which is a huge difference from the "Technical Intern" visa. In 2023, the Ministry of Land, Infrastructure, Transport, and Tourism proposes allowing transportation industry to accept SSW (Nihon keizai shinbun, 2023). In other words, instead of rotating its stock of low-skilled, Japan is looking to expand the number of low-skilled workers by offering permanent residence. However, simply welcoming more immigrants without a proper assimilation policy can lead to less-than-expected economic effects and future social problems. Thus, this chapter proposes that more focus should be put on assimilating immigrants into Japanese society, specifically

1. Supporting immigrants in acquiring Japanese language skills
2. Ensuring that children of immigrant receive sufficient education

The proposals aim to promote future economic growth by cultivating high-skilled workers and avoid future social problem. They concentrate on two of the four standard measures of immigrant assimilation: language assimilation and socioeconomic status (e.g., education attainment) (Waters and Jiménez, 2005)

### 5.2.1 Supporting immigrants in acquiring Japanese language skills

The "Technical Intern" visa does not have a clear Japanese language skill requirement (except those working in nursing care). SSW requires the applicants to have at least N4 in the Japanese Language Proficiency Test (JLPT) (Ministry of Foreign Affairs of Japan, n.d.). However, achieving N4 proves one can understand basic Japanese in classroom settings, not everyday life or workplace settings (JLPT, n.d.). While the low requirement lessens the cost of acquiring the visa, it creates other problems, such as the inability to communicate or find information after coming to Japan, especially when facing harassment or conflicts. Furthermore, improving language skills can help alleviate the "downgrading" effects, which prevent immigrants from utilizing their potential. Therefore, it is necessary to raise the language skill standards of immigrants by raising the language requirement before coming to Japan (Saito, 2023), or requiring workers to reach a certain language skill level after arrival.

### 5.2.2 Ensuring that children of immigrant receive sufficient education

Tables 5.1 and 5.2 below provide some statistics about the education of foreign-national children in Japan. Table 5.1 indicates that thousands of foreign-national children do not receive elementary education. According to Ministry of Education, Culture, Sports, Science and Technology (n.d.) (MEXT), foreign national children are not required to complete compulsory education. However, one can ask for compulsory education at public schools on human rights grounds. Thus, foreign-national children may not be able to receive the education they need and start working or helping with housework. Even when attending school, they may face expulsion (for long-term absence), which does not happen to their Japanese counterpart (Kinoshita, 2019). Table 5.2 highlights another problem of insufficient Japanese language education, which will amply the lack of education problem and may create a group of less-educated foreign immigrants in the future.

[**Table 5.1**]

[**Table 5.2**]

The principle of Japan's immigration policy has been about welcoming high-skilled workers. However, Japan has turned to low-skilled immigrant workers to support its domestic economy. Warabi and Kawaguchi (2023) writes about the specific case of Kurdish asylum-seekers. While some local economies have depended heavily on them, thousands are left in limbo: They cannot work legally and are often detained for overstaying. Their children are also rejected by schools either because the children are not fluent enough in Japanese, or because their parents do not hold a valid visa.

The above proposals aim to better integrate immigrants into the society, which will alleviate the impact of "downgrading effect" and cultivate future high-skilled workers.

## 5.3 Future research

This section highlights another important outcome of immigration: the fiscal impact. Immigrants can enrich the public coffers by raising tax revenue, or put pressure on the budget by raising social expenditure. Table 5.3 summarizes some research that explores the fiscal impact of immigration. At first glance, most of these papers report a positive fiscal impact of immigration. However, the results vary depending on the immigrants' characteristics, or the aspect that is being studied.

There are various methods to empirically measure the fiscal impacts of immigrants: regression, simulation, and numerically calculating the net contribution using various datasets.

[**Table 5.3**]

Storesletten (2000) simulates the fiscal effects of immigration using computable general equilibrium (CGE) features overlapping generation (OLG) model. Natives are assumed to leave nonnegative bequests, due to budget constraints and longevity uncertainty (i.e., natives will leave positive bequests to the next generation). On the other hand, immigrants are assumed to enter the country without any wealth, but there is a certain chance that they will leave the country and bring with them their current wealth. Immigrants are further distinguished into legal and illegal groups. The migration rate of the former group is affected by government policy, while the latter is not. Natives and legal immigrants will face the same tax rate. Illegal immigrants neither contribute to the public budget nor are eligible for government transfers, but share similar public goods consumption rates with their legal counterparts. Based on these assumptions, medium- and high-skilled immigrants during the working age are net contributors. However, return migration can reduce the tax revenue potential contribution of immigrants.

Schou (2006) employs a similar simulation method but with different grouping conditions. Immigrants are separated into four groups: immigrants from developed and undeveloped countries, and descendants of immigrants from developed and underdeveloped countries. Natives and four groups of immigrants share similar or different population parameters (e.g., fertility rates), employment rates (lower for immigrants), public transfers (larger employment-related benefits, but lower pensions for immigrants), and individual public consumption (natives consume at a higher rate later in life). The author finds that while immigration might increase the fiscal cost faster than revenue, economic integration of immigrants can turn the net fiscal impact positive.

Shimasawa and Oguro (2010) employ a dynamic CGE with OLG feature to evaluate immigration policy as a tool to cope with the aging population in Japan. Additionally, the model incorporates both immigrant-receiving and immigrant-sending countries into the model. Different scenarios of immigration policies are evaluated based on whether they focus on permanent or temporary immigrants, on a large- or small-scale, or roll out at a sooner or later date. The authors find that the fiscal performance of Japan benefits the most from an immigration policy that welcomes a large inflow of permanent immigrants at an earlier period. One caveat is that the authors assume that immigrants are homogenous to natives once they enter the countries. In other words, there is a perfect integration of immigrants into the society.

Dustmann and Frattini (2014) examine the fiscal impact of immigration using two methods. First, using a probit model, the authors regress the probability of receiving state benefits or tax credits and social housing on immigrant status. Next, they utilize household consumption data, government revenue and expenditures to numerically calculate each group's contribution and burden on public coffers. To summarize the results, in the probit model, immigrants, especially intra-EU immigrants, are less likely to receive benefits than natives. Comparing the accumulated contributions between 1995-2011, regardless of the arrival date of immigrants, intra-EU immigrants contribute the most (+£4 billion), followed by extra-EU immigrants (-£118 billion), and natives (-£591 billion). When the attention is shifted to recent immigrants (who arrived after the year 2000), intra-EU immigrants contribute the most (+£19 billion), followed by extra-EU immigrants (+£5 billion), and natives (-£61 billion). In other words, immigrants, regardless of their origins, are net contributors.

Martinsen and Pons Rotger (2017) approach the topic with a unique dataset. They utilized a dataset that contains 100% of the EU citizens in Denmark from 2002 to 2013. Several other administrative datasets are also combined to obtain the contributed tax amount, as well as welfare services expenditures such as healthcare, education, and criminal costs. The cost of public goods is calculated on the average cost basis. Net fiscal contribution is defined as the difference between tax contributions and the costs of welfare services and public goods. The authors find evidence that intra-EU immigrants contribute positively and significantly to the Danish welfare state. So far, the positive and significant fiscal impact of intra-EU immigrants is probably due to the fact that EU citizens can integrate easily into the society if they move between EU countries and, thus, are less likely to face the penalty from the ”downgrading” effect.

d'Albis et al. (2019) estimate a structural vector autoregression (VAR) model with fixed effects using a panel of 19 OECD countries from 1980 to 2015. The endogenous variables are chosen to describe the fiscal, economic, and demographic conditions. GDP per capita responds positively to a migration shock, which results from an increase in the share of working-age population and employment rates. Decomposing the positive effect on net taxes per capita reveals an increase in tax revenue per capita and a decrease in transfer per capita. The local labor market also responds positively to the migration shock. The external shock leads to a decrease in unemployment rate and unemployment spending, but an increase in active labor market spending. Thus, immigrants benefit the most from job search support programs and, hence, lead to lower unemployment rates. While the aggregate impacts seem ambiguous, the response functions indicate that public spending on labor market programs decreases after the shock. Finally, the authors develop an OLG model to theoretically explain the empirical results above.

Fiorio et al. (2022) employ the tax-benefit microsimulation model EUROMOD and the microdata EU statistics on income and living conditions (EU-SILC) and other administrative data to calculate individual tax contributions and public costs across EU14. Specifically, they manage to decompose contributions into income tax, social insurance and social security contributions, and value-added tax (VAT). On the other hand, public spending is decomposed into cash transfers, and in-kind benefits such as education, healthcare, and social housing. The average net contribution of natives is €32 annually, compared to €1,510 for immigrants. When looking at specific countries, natives can become higher contributors than immigrants in some cases. When the authors control for demographic characteristics, the contribution gap between the two groups becomes insignificant, implying that immigrants are selected to have a higher probability of becoming net contributors. Christl et al. (2022) extend the work by including 27 EU countries, and develop an indicator for the long-term fiscal impact. They show that both immigrants and natives are burdens on the public budget. Specifically, the order of the current fiscal impact, from the least burden to the most burden, is extra-EU immigrants, intra-EU immigrants, and natives. However, when lifecycle approach is considered to take into account the lifetime contributions, they find that natives are the least burden, followed by intra-EU immigrants, and extra-EU immigrants last.

Römer (2023) criticizes the social expenditures to GDP ratio as an indicator for the fiscal effect of immigration, stating that it should be disaggregated into sub-policy indicators. Specifically, the author focuses on social welfare expenditures to GDP, social generosity, and unemployment generosity. Additionally, since the fiscal impact of immigration may occur at a lag or evolve over time, General Error Correction Model is used to estimate the temporal dynamics of the relationship. The dependent and independent variables enter the equation in first-difference form. Furthermore, 1-year-lag of the dependent and independent variables also enter the right-hand side of the equation. The results indicate a positive association between net migration and unemployment and pension generosity, rejecting the hypothesis that immigrants are a fiscal burden.

So far, most papers focus on the direct fiscal impact of immigration: whether they pay more in tax or receive more benefits. Colas and Sachs (forthcoming) argue that the indirect effect that immigrants have on their native counterparts should also be considered. For example, Peri and Sparber (2009) finds that as low-skilled immigrants enter the workforce, instead of losing jobs, low-skilled natives move to tasks that require more managerial skills and, hence, increase their pay. As a result, in addition to the direct tax contribution of immigrants, natives also contribute more in income tax, hence the indirect fiscal impact of immigration. The authors first develop a theoretical model that explicitly account for the indirect fiscal impact of low-skilled immigrants in the form of the native's tax contribution and employment. Then, in addition to combining the American Community Survey (ACS) and other administrative datasets, they calibrate the model with parameters from previous research to numerically compute the value. As a result, the authors find evidence that immigration can be a net contributor after subtracting the costs estimated by several studies.

As aging population continues, Japan may turn to immigration as a way to increase tax revenue and, in turn, improve fiscal performance. However, as previous literature has shown, the fiscal impact of immigrants can vary depending on their characteristics and, thus, requires more research to acquire the correct estimation in Japan.

## Tables and Figures

**Table 5.1:** Foreign-national children who are not under compulsory education in 2021

| | **Lower estimate** | **Upper estimate** |
|---|---|---|
| Elementary student | 6,700 (7.2%) | 8,944 (9.7%) |
| Junior high school student | 3,346 (8.4%) | 4,296 (10.8%) |
| Average | 10,046 (7.5%) | 13,240 (9.9%) |

*Note:* Lower estimate is the sum of foreign-national children who are 1) not enrolled . in school, 2) with unknown school enrollment, plus the 3) difference from the number of children registered in the Basic Resident Registration. Upper estimate is the a) lower estimate, plus b) the number of foreign-national who relocated domestically or internationally (including planned)
*Source:* Survey on foreign-national children's schooling (MEXT, 2022a)

**Table 5.2:** The number of foreign-national children require Japanese language guidance in public school

| Year | **Japanese national** | **Foreign national** |
|---|---|---|
| 2008 | 4,895 | 28,575 |
| 2010 | 5,496 | 28,511 |
| 2012 | 6,171 | 27,013 |
| 2014 | 7,897 | 29,198 |
| 2016 | 9,612 | 34,355 |
| 2018 | 10,371 | 40,755 |
| 2021 | 10,677 | 47,619 |

*Source:* Survey on the admission of students requiring Japanese language guidance (MEXT, 2022b)

**Table 5.3:** Literature on the fiscal impact of immigration

| Research | Country | Method | Result |
|---|---|---|---|
| Storesletten (2000) | US | Simulation | (+) Working-age immigrants with high- and medium-skilled are net contributors<br>(-) Return migration can decrease the contribution amount. |
| Schou (2006) | Denmark | Simulation | (-) Immigration leads to relatively higher increase in fiscal cost than revenue.<br>(+) Economic integration can turn the net fiscal impact of immigration positive |
| Rowthorn (2008) | EU, US | Literature survey | (*) The overall fiscal benefits of immigration is small |
| Shimasawa and Oguro (2010) | 16 developed and developing countries | Simulation | (+): Improve the Japanese economy and welfare of current and future generations |
| Dustmann and Frattini (2014) | UK | Numerical estimation | (+): Immigrants arriving after 2000, especially those from the European Economic Area, have positive net fiscal contributions. |
| Martinsen and Pons Rotger (2017) | Denmark | Numerical estimation | (+): EU citizen has a positive net contribution |
| d'Albis et al. (2019) | 19 OECD countries | Panel VAR, theoretical model | (+): Increase GDP/capita and working age ratio. Improves fiscal balance by reducing per capita transfer by gov. and per capital old-age public spending |
| Christl et al. (2022) | EU 27 | Numerical estimation | (+): The current immigrants are less of a burden on the public budget than natives.<br>(-): However, accounting for demographic composition using life cycle approach shows that natives are less of a burden than immigrants. |
| Fiorio et al. (2022) | EU 14 | Numerical estimation | (+): Overall, migrants make larger net fiscal contribution than natives However, accounting for age composition and employment statues show that immigrants are selected on characteristics that make them positive net contributors. |
| Römer (2023) | 21 OECD countries | General Error Correction model | (+): Reject the hypothesis that migrant is a burden on the welfare state |
| Colas and Sachs (forthcoming) | US | Numerical estimation | (+): The indirect impact of low-skilled immigrants is in the range of \$770 to \$2100 annually, which outweights the negative direct fiscal impacts in some cases. |

# Appendix

## A.1 First Taylor expansion of $\hat{\theta}_{pt} = r_{pt} - r_{p,t-1}$

From

$$\hat{\theta}_{pt} = r_{pt} - r_{p,t-1} = \frac{F_{pt}}{F_{pt} + N_{pt}} - \frac{F_{p,t-1}}{F_{p,t-1} + N_{p,t-1}} \tag{A.1}$$

The first-order derivative of $\hat{\theta}_{pt}$ is

$$\frac{\partial \hat{\theta}_{pt}(F_{pt}, N_{pt})}{\partial F_{pt}} = \frac{1}{F_{pt} + N_{pt}} - \frac{F_{pt}}{(F_{pt} + N_{pt})^2} \frac{\partial \hat{\theta}_{pt}(F_{pt}, N_{pt})}{\partial N_{pt}} = -\frac{F_{pt}}{(F_{pt} + N_{pt})^2}$$

Thus, the Taylor series of $\hat{\theta}_{pt}(F_{pt}, N_t)$ around $(F_{p,t-1}, N_{p,t-1})$ is

$$\begin{aligned} \hat{\theta}_{pt} \approx & \left( \frac{F_{p,t-1}}{F_{p,t-1} + N_{p,t-1}} - \frac{F_{p,t-1}}{F_{p,t-1} + N_{p,t-1}} \right) \\ & + \left[ \frac{1}{F_{p,t-1} + N_{p,t-1}} - \frac{F_{p,t-1}}{(F_{p,t-1} + N_{p,t-1})^2} \right] (F_{pt} - F_{p,t-1}) \\ & - \frac{F_{p,t-1}}{(F_{p,t-1} + N_{p,t-1})^2} (N_{pt} - N_{p,t-1}) \end{aligned} \tag{A.2}$$

Hence, equation A.2 can be further rewritten as

$$\begin{aligned} \hat{\theta}_{pt} & \approx 0 \\ & + \left[ 1 - \frac{F_{p,t-1}}{F_{p,t-1} + N_{p,t-1}} \right] \left( \frac{F_{pt} - F_{p,t-1}}{F_{p,t-1} + N_{p,t-1}} \right) \\ & - \frac{F_{p,t-1}}{F_{p,t-1} + N_{p,t-1}} \left( \frac{N_{pt} - N_{p,t-1}}{F_{p,t-1} + N_{p,t-1}} \right) \end{aligned} \tag{A.3}$$

Let $\Delta F = F_{pt} - F_{p,t-1}$, and $\Delta N = N_{pt} - N_{p,t-1}$. Also, recall that $r_{pt} = \frac{F_{pt}}{F_{pt} + N_{pt}}$ and $L_{pt} = F_{pt} + L_{pt}$, then

$$\hat{\theta}_{pt} = (1 - r_{p,t-1}) \left( \frac{\Delta F}{L_{p,t-1}} \right) - r_{p,t-1} \left( \frac{\Delta N}{L_{p,t-1}} \right) \tag{A.4}$$

## A.2 Supplementary data of chapter 3

**Table A.1:** Output value of primary, secondary, tertiary industries in 2018

| | (JPY millions) | | | (%) | | |
|---|---|---|---|---|---|---|
| **Prefecture** | **Primary industry** | **Secondary industry** | **Tertiary industry** | **Primary industry** | **Secondary industry** | **Tertiary industry** |
| Hokkaido | 807,709 | 3,568,708 | 15,942,170 | 4.0 | 17.6 | 78.5 |
| Aomori | 206,594 | 915,345 | 3,399,709 | 4.6 | 20.2 | 75.2 |
| Iwate | 146,332 | 1,398,785 | 3,342,965 | 3.0 | 28.6 | 68.4 |
| Miyagi | 139,496 | 2,532,873 | 7,359,968 | 1.4 | 25.2 | 73.4 |
| Akita | 110,177 | 806,520 | 2,665,312 | 3.1 | 22.5 | 74.4 |
| Yamagata | 121,077 | 1,362,292 | 2,827,141 | 2.8 | 31.6 | 65.6 |
| Fukushima | 120,506 | 2,671,817 | 5,266,273 | 1.5 | 33.2 | 65.3 |
| Ibaraki | 283,151 | 5,633,366 | 8,384,131 | 2.0 | 39.4 | 58.6 |
| Tochigi | 165,796 | 4,251,072 | 4,972,858 | 1.8 | 45.3 | 53.0 |
| Gunma | 111,272 | 3,783,491 | 5,357,842 | 1.2 | 40.9 | 57.9 |
| Saitama | 98,119 | 6,107,900 | 17,370,424 | 0.4 | 25.9 | 73.7 |
| Chiba | 204,502 | 5,207,103 | 16,022,623 | 1.0 | 24.3 | 74.8 |
| Tokyo | 52,549 | 13,515,327 | 101,970,849 | 0.0 | 11.7 | 88.3 |
| Kanagawa | 42,322 | 8,575,381 | 26,686,075 | 0.1 | 24.3 | 75.6 |
| Niigata | 163,397 | 2,780,404 | 6,360,734 | 1.8 | 29.9 | 68.4 |
| Toyama | 46,410 | 1,840,566 | 3,034,380 | 0.9 | 37.4 | 61.7 |
| Ishikawa | 43,403 | 1,469,861 | 3,381,758 | 0.9 | 30.0 | 69.1 |
| Fukui | 31,236 | 1,178,561 | 2,462,886 | 0.9 | 32.1 | 67.1 |
| Yamanashi | 55,779 | 1,348,539 | 2,189,999 | 1.6 | 37.5 | 60.9 |
| Nagano | 153,411 | 2,986,227 | 5,449,688 | 1.8 | 34.8 | 63.4 |
| Gifu | 61,416 | 2,754,231 | 5,164,096 | 0.8 | 34.5 | 64.7 |
| Shizuoka | 132,793 | 7,746,819 | 10,169,480 | 0.7 | 42.9 | 56.3 |
| Aichi | 167,145 | 17,246,486 | 24,752,379 | 0.4 | 40.9 | 58.7 |
| Mie | 80,544 | 3,869,690 | 4,613,732 | 0.9 | 45.2 | 53.9 |
| Shiga | 37,813 | 3,339,314 | 3,527,959 | 0.5 | 48.4 | 51.1 |
| Kyoto | 37,195 | 3,414,128 | 7,264,726 | 0.3 | 31.9 | 67.8 |
| Osaka | 20,330 | 8,569,385 | 32,336,642 | 0.0 | 20.9 | 79.0 |
| Hyogo | 100,602 | 6,835,141 | 15,062,048 | 0.5 | 31.1 | 68.5 |
| Nara | 21,385 | 910,390 | 2,980,067 | 0.5 | 23.3 | 76.2 |
| Wakayama | 74,670 | 1,272,666 | 2,361,467 | 2.0 | 34.3 | 63.7 |
| Tottori | 49,855 | 400,914 | 1,455,378 | 2.6 | 21.0 | 76.4 |
| Shimane | 48,022 | 651,733 | 1,936,609 | 1.8 | 24.7 | 73.5 |
| Okayama | 73,992 | 2,710,348 | 5,120,166 | 0.9 | 34.3 | 64.8 |
| Hiroshima | 69,578 | 3,810,989 | 8,337,469 | 0.6 | 31.2 | 68.2 |
| Yamaguchi | 36,760 | 2,658,355 | 3,766,620 | 0.6 | 41.1 | 58.3 |
| Tokushima | 58,584 | 1,091,997 | 2,063,987 | 1.8 | 34.0 | 64.2 |
| Kagawa | 56,539 | 1,062,841 | 2,818,636 | 1.4 | 27.0 | 71.6 |
| Ehime | 104,552 | 1,497,876 | 3,518,690 | 2.0 | 29.2 | 68.7 |
| Kochi | 94,421 | 407,334 | 1,953,978 | 3.8 | 16.6 | 79.6 |
| Fukuoka | 161,143 | 4,046,671 | 15,722,748 | 0.8 | 20.3 | 78.9 |
| Saga | 81,466 | 951,274 | 2,187,478 | 2.5 | 29.5 | 67.9 |
| Nagasaki | 123,663 | 1,153,586 | 3,514,007 | 2.6 | 24.1 | 73.3 |

| | | | | | | |
|---|---|---|---|---|---|---|
| Kumamoto | 190,416 | 1,644,903 | 4,416,771 | 3.0 | 26.3 | 70.6 |
| Oita | 90,332 | 1,421,658 | 3,093,606 | 2.0 | 30.9 | 67.2 |
| Miyazaki | 170,312 | 921,367 | 2,665,235 | 4.5 | 24.5 | 70.9 |
| Kagoshima | 261,060 | 1,223,094 | 4,243,853 | 4.6 | 21.4 | 74.1 |
| Okinawa | 60,060 | 798,639 | 3,737,329 | 1.3 | 17.4 | 81.3 |
| **Total** | 5,567,886 | 154,345,967 | 423,232,941 | | | |

Note: Output value of primary, secondary, and tertiary industries are shown in JPY million in the second to fourth columns. The last three columns show the ratio output value of each industry to the total output value in each prefecture.
Source: "Prefectural Account" published by Cabinet Office

**Table A.2:** Number of immigrant workers in all industries and in the manufacturing industry in 2009 and 2018

| | All industries | | | Manufacturing industry | | |
|---|---|---|---|---|---|---|
| **Prefecture** | **2009** | **2018** | **Growth rate** | **2009** | **2018** | **Growth rate** |
| Hokkaido | 6,125 | 21,026 | 243% | 2,395 | 5,781 | 141% |
| Aomori | 1,126 | 3,137 | 179% | 673 | 1,569 | 133% |
| Iwate | 1,948 | 4,509 | 131% | 1,443 | 2,687 | 86% |
| Miyagi | 3,689 | 11,001 | 198% | 1,501 | 4,155 | 177% |
| Akita | 1,550 | 1,953 | 26% | 1,139 | 987 | -13% |
| Yamagata | 1,856 | 3,754 | 102% | 1,346 | 2,143 | 59% |
| Fukushima | 3,448 | 8,130 | 136% | 2,076 | 3,382 | 63% |
| Ibaraki | 14,161 | 35,062 | 148% | 7,092 | 15,215 | 115% |
| Tochigi | 10,342 | 24,016 | 132% | 3,996 | 10,579 | 165% |
| Gunma | 12,349 | 34,526 | 180% | 6,384 | 14,432 | 126% |
| Saitama | 23,298 | 65,290 | 180% | 11,855 | 25,827 | 118% |
| Chiba | 18,201 | 54,492 | 199% | 6,437 | 14,320 | 122% |
| Tokyo | 138,907 | 438,775 | 216% | 11,162 | 26,302 | 136% |
| Kanagawa | 31,700 | 79,223 | 150% | 12,891 | 24,600 | 91% |
| Niigata | 3,936 | 8,918 | 127% | 2,213 | 4,080 | 84% |
| Toyama | 4,842 | 10,334 | 113% | 2,681 | 5,217 | 95% |
| Ishikawa | 4,224 | 9,795 | 132% | 2,561 | 5,214 | 104% |
| Fukui | 4,057 | 8,651 | 113% | 3,056 | 3,873 | 27% |
| Yamanashi | 4,266 | 6,910 | 62% | 2,860 | 2,780 | -3% |
| Nagano | 10,226 | 17,923 | 75% | 6,329 | 9,215 | 46% |
| Gifu | 18,621 | 31,279 | 68% | 10,836 | 18,099 | 67% |
| Shizuoka | 34,618 | 57,353 | 66% | 18,823 | 24,936 | 32% |
| Aichi | 67,728 | 151,669 | 124% | 34,831 | 68,776 | 97% |
| Mie | 15,195 | 27,464 | 81% | 9,571 | 14,228 | 49% |
| Shiga | 9,235 | 17,238 | 87% | 5,665 | 10,164 | 79% |
| Kyoto | 6,624 | 17,436 | 163% | 1,978 | 5,075 | 157% |
| Osaka | 29,545 | 90,072 | 205% | 9,281 | 23,395 | 152% |

| | | | | | | |
|---|---|---|---|---|---|---|
| Hyōgo | 12,985 | 34,516 | 166% | 5,824 | 14,804 | 154% |
| Nara | 2,233 | 4,116 | 84% | 1,266 | 1,950 | 54% |
| Wakayama | 973 | 2,395 | 146% | 551 | 1,002 | 82% |
| Tottori | 1,352 | 2,755 | 104% | 897 | 1,495 | 67% |
| Shimane | 1,864 | 4,297 | 131% | 1,047 | 1,742 | 66% |
| Okayama | 7,154 | 16,297 | 128% | 3,772 | 7,702 | 104% |
| Hiroshima | 14,493 | 31,851 | 120% | 7,828 | 16,887 | 116% |
| Yamaguchi | 2,727 | 7,723 | 183% | 1,275 | 3,285 | 158% |
| Tokushima | 2,511 | 4,389 | 75% | 1,606 | 2,056 | 28% |
| Kagawa | 2,823 | 8,703 | 208% | 2,062 | 4,860 | 136% |
| Ehime | 4,156 | 8,376 | 102% | 2,991 | 5,649 | 89% |
| Kōchi | 982 | 2,592 | 164% | 248 | 730 | 194% |
| Fukuoka | 11,745 | 46,273 | 294% | 2,668 | 9,779 | 267% |
| Saga | 1,624 | 5,258 | 224% | 1,020 | 2,565 | 151% |
| Nagasaki | 2,513 | 5,433 | 116% | 1,170 | 1,933 | 65% |
| Kumamoto | 3,038 | 10,155 | 234% | 1,150 | 2,878 | 150% |
| Ōita | 3,017 | 6,254 | 107% | 874 | 2,169 | 148% |
| Miyazaki | 1,273 | 4,144 | 226% | 562 | 1,882 | 235% |
| Kagoshima | 1,839 | 6,862 | 273% | 859 | 3,040 | 254% |
| Okinawa | 1,699 | 8,138 | 379% | 155 | 903 | 483% |
| **Total** | 562,818 | 1,460,463 | 159% | 218,900 | 434,342 | 98% |

Source: "Foreigner Employment Status" published by MHLW

## A.3 Derivation of theoretical and empirical models of Chapter 4

Consider that workers belong to skill group $i$ in region $j$ at time $t$ have the following labor demand function

$$w_{ijt} = X_i L_{ijt}^{\gamma} \tag{A.5}$$

where $w_{ijt}$ represents the wage in a $(i, j, t)$ cell, $L_{ijt}$ is the sum of native and immigrant workers, $\gamma < 0$ is the factor price elasticity, and $X_i$ is the demand shifter that is only different between skill group. Furthermore, the number of native workers at national level is fixed at $\bar{N}_i$.

Immigrant is assumed to start at $t = 0$, and the inflow is assumed to stay constant every period. Let $M$ represents the inflow of immigrant, then $M_{ij}$ is the annual inflow of immigrant to a $(i, j)$ cell. On the other hand, suppose $N_{ij,-1}$ is the number of native workers in cell $(i, j)$ at $t = -1$ (before immigration), and that the distribution of native worker does not represent the long-run equilibrium, then native workers will resort themselves to balance the wage difference.

Additionally, immigrant workers are assumed to not migrate between prefectures after entering region $j$, while native workers are assumed to make migration decision every period. Let $\Delta N_{ijt}$ denotes the net migration of native workers, equation A.5 can be written as

$$\ln w_{ijt} = \ln X_i + \gamma \ln[N_{ij,-1} + (t+1)M_{ij} + \Delta N_{ij0} + \Delta N_{ij1} + ... + \Delta N_{ijt}] \qquad \text{(A.6)}$$

At $t = -1$, equation A.6 becomes $\ln w_{ij,-1} = \ln X_i + \gamma \ln N_{ij,-1}$. Substitute this into equation (A.6) and approximate using $\ln(1+x) \approx x$, then equation A.6 can be simplified into

$$\ln w_{ijt} \approx \ln w_{ij,-1} + \gamma[(t+1)m_{ij} + g_{ij0} + ... + g_{ijt}], fort \geq 0 \qquad \text{(A.7)}$$

where $m_{ij} = \frac{M_{ij}}{N_{ij,-1}}$ and $g_{ijt} = \frac{\Delta N_{ijt}}{N_{ij,-1}}$

Native workers in skill group $i$ make migration decision by comparing the wage in region $j$ to the average national wage. Additionally, native workers can only migrate in the next period. The lags represent the cost of changing locations. Equation A.8 below describes the net migration rate in $(i, j, t)$

$$g_{ijt} = \sigma(\ln w_{ij,t-1} - \ln \bar{w}_{i,t-1}) \qquad \text{(A.8)}$$

where $\sigma$ is the supply elasticity, $\ln \bar{w}_{i,t-1}$ is the long-run equilibrium wage for skill group $i$ after natives respond to immigrant inflow up to period $t-1$.

In the next part, we will show how equation A.8 can be rewritten to express net migration rate in terms of inflow of immigrant. First, the equilibrium before immigration happens (at $t = -1$) is:

$$\ln \bar{w}_{i,-1} = \ln X_i + \gamma \ln N_i^* \qquad \text{(A.9)}$$

where $N_i^*$ denotes the long-run equilibrium of the distribution of native workers in skill group $i$. Equation (A.10) below can be obtained by substituting equation A.9

into equation A.8, evaluating at $t = 0$

$$g_{ij0} = \sigma(\ln w_{ij,-1} - \ln \bar{w}_{i,-1}) = \gamma\sigma\theta_{ij} \tag{A.10}$$

where $\theta_{ij} = \ln\left(\frac{N_{ij,-1}}{N_i^*}\right)$

For simple mathematical derivations, we first solve the model assume there is only one wave of immigration at $t = 0$. Next, assume that region $j$ has a share $p_{ij}$ of native worker belongs to skill group $i$, and receives a share $q_{ij}$ of immigrant inflow from the same skill group, then immigrant ratio at $t = 0$ can be written as

$$m_{ij0} = \frac{M_{ij0}}{N_{ij0}} = \frac{p_{ij}M_i}{q_{ij}N_i} = k_{ij}m_i \tag{A.11}$$

where $k_ij = \frac{p_{ij}}{q_ij}$.

Net migration rate can be solved recursively to obtain

$$g_{ijt} = \gamma\sigma(1+\gamma\sigma)^t\theta_{ij} + \gamma\sigma(1+\gamma\sigma)^{t-1}(1-k_{ij})m_i, 0 < (1+\gamma\sigma) < 1 \tag{A.12}$$

In equation A.12, net migration rate depends on the migration of native workers (the first term), and the inflow of immigrant workers (the second term). The cumulative net migration rate of natives at period t can be obtained by aggregating equation (A.12)

$$G_{ijt} = \sum_{\Phi=0}^{t} g_{ijt} = [(1+\gamma\sigma)^{t+1} - 1]\theta_{ij} + [1-(1+\gamma\sigma)^t](1-r_{ij})m_i \tag{A.13}$$

Equation A.13 describes the cumulative net migration rate of natives assuming there is only one wave of immigration. This one-time increase in immigrant supply is represented by the second term. Thus, an annual inflow of immigration can be obtained by aggregating this term over time. Let $\Omega_{ijt} = [1-(1+\gamma\sigma)^t](1-r_{ij})m_i$, then the net migration rate caused by an increase in immigrant supply at year 0 is $\Omega_{ijt}$. Similarly, the net migration rate caused by immigrant supply at year $t-1$ is $\Omega_ij1$. Hence, the cumulative net migration rate in year $t$ induced by an increase in immigrant supply from year 0 to year $t-1$ is:

$$
\begin{aligned}
G^*_{ijt} &= [(1+\gamma\sigma)^{t+1}-1]\theta_{ij} + \sum_{\Phi=1}^{t}[1-(1+\gamma\sigma)^{\Phi}](1-r_{ij})m_i \\
&= [(1+\gamma\sigma)^{t+1}-1]\theta_{ij} + \left\{t + \frac{1+\gamma\sigma}{\gamma\sigma}[1-(1+\gamma\sigma)^t]\right\}(1-k_ij)m_i
\end{aligned}
\tag{A.14}
$$

Therefore, without the restricted assumption that there is only one wave of immigration at the beginning, net migration rate of native can be expressed in terms of native internal migration and immigrant inflow as

$$
g_{ijt} = G^*_{ijt} - G^*_{ij,t-1} = \gamma\sigma(1+\gamma\sigma)^t\theta_{ij} + [1-(1+\gamma\sigma)^t](1-k_{ij})m_i \tag{A.15}
$$

where $m_i = \frac{M_i}{N_i}$, where $M_i$ is the immigration inflow to skill group $i$ (at national level).

Next, the total number of native workers in $(i,j,t)$ cell is given the initial stock $N_{ij,-1}$ and the net migration flow defined in A.15, specifically

$$
\begin{aligned}
G^*_{ijt} &= \ln N_{ij,-1} + \sum_{\Phi=0}^{t} g_{ij\Phi} \\
&= \ln N_{ij,-1} + [(1+\gamma\sigma)^{t+1}-1]\theta_{ij} \\
&+ \left\{\frac{t}{t+1} + \frac{1+\gamma\sigma}{\gamma\sigma}\frac{[1-(1+\gamma\sigma)^t]}{t+1}\right\}\tilde{m}_{it} \\
&- \left\{\frac{t}{t+1} + \frac{1+\gamma\sigma}{\gamma\sigma}\frac{[1-(1+\gamma\sigma)^t]}{t+1}\right\}\tilde{m}_{itt}
\end{aligned}
\tag{A.16}
$$

where $\tilde{m}_{it} = (t+1)m_i$, and $\tilde{m}_{ijt} = (t+1)m_{ij}$.

The wage of native workers in $(i,j,t)$ cell can be obtained by substituting the net migration rate defined by equation A.15 into the wage function A.7:

$$
\begin{aligned}
\ln w_{ijt} &= \ln w_{ij,-1} + \gamma[(1+\gamma\sigma)^{t+1}-1]\theta_{ij} \\
&+ \left\{\frac{t}{t+1} + \frac{1+\gamma\sigma}{\gamma\sigma}\frac{[1-(1+\gamma\sigma)^t]}{t+1}\right\}\tilde{m}_{it} \\
&+ \left\{\frac{1}{t+1} - \frac{1+\gamma\sigma}{\gamma\sigma}\frac{[1-(1+\gamma\sigma)^t]}{t+1}\right\}\tilde{m}_{itt}
\end{aligned}
\tag{A.17}
$$

Finally, the empirical model of equations A.16 and A.17 can be obtained by applying two approximation methods a) $(1+x)^t \approx (1+xt)$, b) $\frac{t}{t+1} \approx 1$ and $\frac{1}{t+1} \approx 0$ if $t$ is relatively large

$$\ln N_{ijt} = \ln N_{ij,-1} + \gamma\sigma\theta_{ij} + \gamma\sigma(t\theta_{ij}) - \gamma\sigma\tilde{m}_{it} + \gamma\sigma\tilde{m}_{ijt} \tag{A.18}$$

$$\ln w_{ijt} = \ln w_{ij,-1} + \gamma^2\sigma\theta_{ij} + \gamma^2\sigma(t\theta_{ij}) - \gamma^2\sigma\tilde{m}_{it} + \gamma(1+\gamma\sigma)\tilde{m}_{ijt} \tag{A.19}$$

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