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

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Abstract

This paper analyzes the impact of immigration on different macroeconomic indicators, using the production function. We use data on the immigrant stock and prefectures' accounts from 2009 to 2018. Geographically Weighted Panel Regression (GWPR) indicates that immigrants' positive impacts on employment, and negative impacts on capital-to-GDP ratio are significant in selective prefectures, which are resulted from an increase in GDP but not capital. Regressing the coefficients generated by GWPR on immigrant population grouped by education or industry reveal interesting patterns of economic impacts by immigrant workers.

Keywords: immigrant, GWPR, production function, labor, Japan

Highlight:

- Immigration does not crowd out local native workers.
- GWPR reveals the heterogenous economic impact of immigrants between prefectures.
- Immigration leads to a lower capital-GDP ratio in some selected prefectures due to a positive impact on GDP and labor force, but not capital stock.
- The economic impacts of immigrants are different between education and industry groups.

JEL Classification: C32, J15, J61

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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 aging fast and has experienced negative growth rates in recent years, the immigrant population has been growing steadily, despite the restrictive immigration policy. A closer look at the data provided by the Ministry of Health, Labour and Welfare (MHLW) shows that of the 125% increase in foreign workers between 2010 and 2018, “Technical Intern” and “International Student” contributed 36.7% and 25.6%, respectively. Additionally, most papers have been trying to identify the average effects of immigrants across local economies. However, immigrants may have varying economic impacts, depending on the characteristics of the local economy.

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

Data on production inputs such as capital stock, immigrants, 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 foreign workers can be extracted from MHLW.

Applying the GWPR method produces interesting results on the distinct impacts of immigrants between prefectures. Specifically, immigration negatively affects the capital-to-GDP ratio in some selected prefectures. Capital-to-GDP 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 GDP in selected prefectures. However, focusing on prefectures that have their capital-to-GDP ratio negatively affected by immigration, the negative correlations can be explained by the positive link between immigration with GDP growth but not with capital growth. Furthermore, immigrants positively impact total employment and GDP but not capital stock in some selected prefectures. These results suggest that, in Japan, immigration increases GDP by raising the labor input, not capital input. The results also suggest that the marginal productivity of labor is higher in these selected prefectures.

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 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 complementary relationship with the native workers, while the less educated group shows a substitute relationship. 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 paper is organized as follows. Section II reviews previous studies on the link between immigration and economic growth, and the GWPR method. Section III describes the production function approach, measure of immigration, GWPR method, and data used. Sections IV and V present and discuss the results. Section VI provides concluding remarks.

2. Literature Review

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, 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 & 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[1] 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.

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

2.2 Geographically Weighted Panel Regression

GWPR is an extension of 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. (2009) find that the determinant factors of employment growth vary 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. Data and Methodology

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

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

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, α is the elasticity of substitution between capital and labor, L_{pt} represents the total number of workers, and ϕ_{pt} is a wage index. Next, output per worker is defined as $y_{pt} = Y_{pt}/L_{pt}$, and equation (1) is rewritten as follows

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

Finally, we rewrite equation (2) in terms of growth rate by taking the logarithm derivate with respect to time to obtain

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

According to equation (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-GDP ratio $\widehat{\frac{K_{pt}}{Y_{pt}}}$, average hours worked $\hat{h}_{pt}$, and wage index $\hat{\phi}_{pt}$.

Following Peri (2012), equation (4) below is estimated to analyze how immigration affects each term on the right-hand side of equation (3)

(4) $$\hat{\delta}_{pt} = \eta_t + \eta_p + \beta\hat{\theta}_{pt} + \varepsilon_{pt}$$

where $\hat{\delta}_{pt}$ will be replaced with total employment $\hat{L}_{pt}$, total factor productivity $\hat{A}_{pt}$, capital-to-GDP ratio $\widehat{\frac{K_{pt}}{Y_{pt}}}$, average hours worked $\hat{h}_{pt}$, and wage index $\hat{\phi}_{pt}$. η_t, η, and ε_{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.

3.2 Measure of immigrant workers' change

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

(5) $$r_{pt} = \frac{F_{pt}}{N_{pt}+F_{pt}}$$

where F is the number the immigrant workers, and $\hat{N}$ is the number of native workers. Then, the change of immigrant workers between periods $\hat{\theta}$ in equation (4) can be measured as the ratio of immigrant workers between two periods

(6) $$\hat{\theta}_{pt} = r_{pt} - r_{pt-1}$$

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[2]

(7) $$\hat{\theta}_{pt} \approx \left(1 - r_{pt-1}\right)\frac{\Delta F_{pt}}{L_{it-1}} - r_{pt-1}\frac{\Delta N_{pt}}{L_{it-1}}$$

[2] See Appendix A for the full Taylor expansion.

where $L_{it} = F_{it} + N_{it}$ is the sum of immigrant workers and native workers, $\Delta F_{pt} = F_{pt} - F_{pt-1}$ is the change in immigrant workers' number, and $\Delta N_{pt} = N_{pt} - N_{pt-1}$ is the change in native workers' number. Equation (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 (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 (5) and (7) indicate a negative bias in coefficient β.

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

$$\frac{\mathrm{L}_{\mathrm{pt}} - L_{pt-1}}{\mathrm{L}_{\mathrm{pt-1}}} \tag{8}$$

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

$$\frac{(F_{pt} + N_{pt}) - (F_{pt-1} + N_{pt-1})}{\mathrm{L}_{\mathrm{pt-1}}}$$

By grouping immigrant workers and domestic workers variables,

$$\frac{(F_{pt} - F_{pt-1}) - (N_{pt} - N_{pt-1})}{\mathrm{L}_{\mathrm{pt-1}}} = \frac{\Delta F_{pt} + \Delta N_{pt}}{L_{pt-1}} \tag{9}$$

the growth rate of labor market size consists of the growth rate of immigrant and domestic workers. Thus, $\frac{\Delta F_{pt}}{L_{pt-1}}$ can be used to capture only the impact of the immigrant labor force. This is also the first term on the RHS of equation (7) without multiplying the weights. Constructing our explanatory variable this way is also consistent with Peri (2012) and Card and Peri (2016).

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.

(10) $$y_j = x_j \beta_i + \varepsilon_j$$

where $i, j = 1, 2, 3, \ldots, n$ index the geographic location, y_j is the dependent variable, x_j is the independent variable, and ε_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

(11) $$\hat{\beta}_i = [X'W(i)X]^{-1}[X'W(i)Y]$$

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

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

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

Equation (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 (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 paper, we use the bi-square decay function defined as follows

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

where b is the bandwidth.

Equation (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 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)

(14) $$\sum_i^n [y_i - \hat{y}_{\neq i}(b)]^2$$

Finally, we extend to GWPR by simply stacking cross-section data over T periods. Specifically, assuming there are t periods, then (10) becomes

(15) $$y_{jt} = x_{jt}\beta_i + \varepsilon_{jt}$$

The coefficient $\hat{\beta}_i$ can still be estimated using equation (11), where the matrix X and Y will have $(n * t)$-by-1 dimension, and the weight matrix $W(i)$ will have

$(n * t)$-by-$(n * t)$ dimension as follow

(16) $$X = \begin{bmatrix} X_{11} \\ \vdots \\ X_{1t} \\ X_{21} \\ \vdots \\ X_{nt} \end{bmatrix}$$

(17) $$Y = \begin{bmatrix} Y_{11} \\ \vdots \\ Y_{1t} \\ Y_{21} \\ \vdots \\ Y_{nt} \end{bmatrix}$$

(18) $$W(i) = \begin{bmatrix} w_{11}(i) & \dots & 0 & 0 & \dots & 0 \\ \vdots & \ddots & \vdots & \vdots & \ddots & \vdots \\ 0 & \dots & w_{1t}(i) & 0 & \dots & 0 \\ 0 & \dots & 0 & w_{21}(i) & \dots & 0 \\ \vdots & \ddots & \vdots & \vdots & \ddots & \vdots \\ 0 & \dots & 0 & 0 & \dots & w_{nt}(i) \end{bmatrix}$$

Since geographical distances between regions do not change over time, the kernel function (13) can be used to get the weight matrix[3]. CV-score can be estimated by extending equation (14) to

(19) $$\sum_k^t \sum_i^n \left[y_{i,t} - \hat{y}_{\neq i,t}(b)\right]^2$$

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.,

[3] 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.

2020), and modified using lfe (Gaure, 2022), plm (Croissant & Millo, 2018), and GWmodel (Gollini et al., 2015) packages.

3.4 Data

We consider the data from 47 prefectures in Japan between 2009 and 2018. Data on GDP, 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. Data on the number of foreign workers and average hours worked per person (from the Monthly Labor Survey) and wage data (from the Basic Survey on Wage Structure) can be extracted from the MHLW.

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

$$k_t = \delta k_{t-1} + \epsilon_t \tag{20}$$

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 GDP value of the manufacturing (service) industry and the sum of both industries' GDP. 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 (1) to

$$A_{pt} = \frac{Y_{pt}}{K_{pt}^{\alpha}\left(h_{pt}N_{pt}\right)^{1-\alpha}} \tag{21}$$

Thus, A_{pt} is obtainable after we decide on the value of parameter α. Following (Takizawa, n.d.), the elasticity of output to capital α is calculated on the national level as follows

$$\alpha = 1 - \frac{(w+T)}{Y} \tag{22}$$

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. Afterward, 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 ϕ_{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.

4. Empirical Result

Before looking at the estimates of GWPR, 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 1 indicates that we can reject the null hypothesis of no spatial autocorrelation in two out of six models: output per worker and capital-to-GDP ratio. For this paper, 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 1. Moran's I for panel regression

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

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 2 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 paper, GWPR will be estimated using the bi-square kernel function.

Next, the AICc value of the baseline OLS model is calculated and compared with GWPR in Table 3**.** The results indicate that GWPR yields lower AICc values in all five models. In other words, GWPR is better at fitting the data than OLS.

Table 2. Corrected Akaike Information Criterion value of different GWPR models using different kernel functions

	Bi-square	**Tri-square**	**Gaussian**
$\hat{L}$	-2989	-2982	-2982
$\hat{y}$	-2123	-2122	-2123
$(\alpha/1-\alpha)*\widehat{K/Y}$	-2034	-2028	-2038
$(1/1-\alpha)*\hat{A}$	-1582	-1582	-1686
$\hat{h}$	-2621	-2620	-2617
$\hat{\phi}$	-1235	-1172	-1212

Table 3. AICc of baseline OLS model and GWPR

	Basic OLS	**GWPR**
$\hat{L}$	-2483	-2989
$\hat{y}$	-1782	-2123
$(\alpha/1-\alpha) * \widehat{K/Y}$	-1686	-2034
$(1/1-\alpha) * \hat{A}$	-1375	-1582
$\hat{h}$	-2217	-2621
$\hat{\phi}$	-1001	-1235

Finally, GWPR results are presented in the following structure: the left-side map indicates the coefficient β, while the right-side map indicates the t-value. The impact of immigrant workers on $\hat{L}$, $\hat{y}$, $\frac{\hat{K}}{Y}$, $\hat{A}$, $\hat{h}$, $\hat{\phi}$ 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-GDP 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-GDP 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 GDP, as below

(23) $$\left(\frac{\alpha}{1-\alpha}\right)\widehat{\frac{K_{pt}}{Y_{pt}}} = \left(\frac{\alpha}{1-\alpha}\right)\widehat{K}_{pt} - \left(\frac{\alpha}{1-\alpha}\right)\widehat{Y}_{pt}$$

The decomposition is important in understanding how immigrants influence capital input. According to (23), three patterns can lead to a negative capital-to-GDP ratio: (a) the growth rate of capital is negative, while that of GDP remains constant; (2) the growth rate of GDP is positive, while that of capital remains constant; and (3) both growth rates are positive, but GDP grows at a faster rate. The results of re-estimating GWPR separately on the growth rates of capital and GDP are shown in Figure 7 and Figure 8, respectively. Immigrants can positively and significantly affect the capital stock of most prefectures in Chubu and Kansai regions. Furthermore, immigrants have a positive effect on GDP in the northern part of Japan.

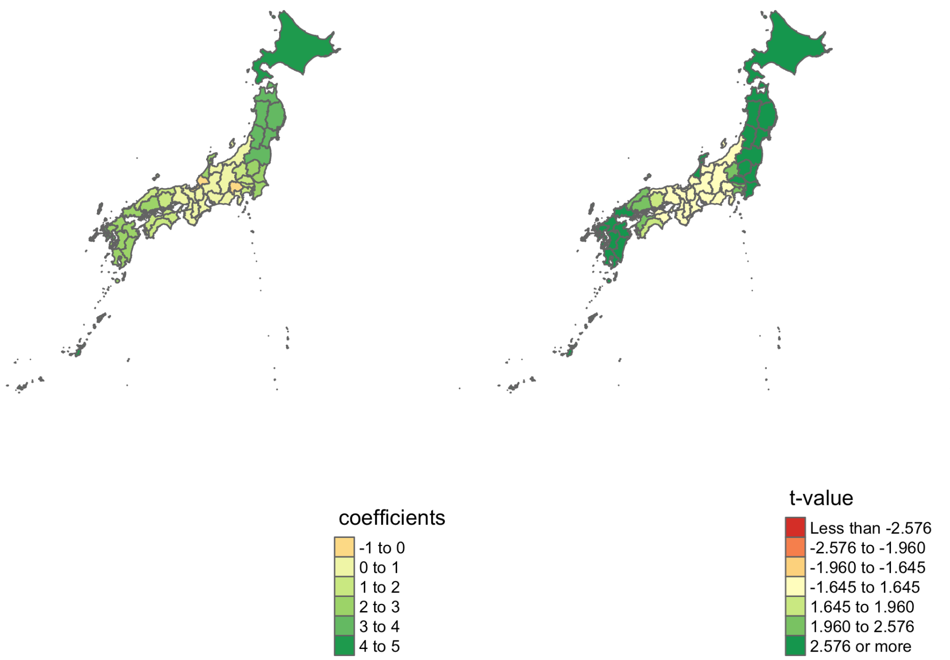

Figure 2. GWPR results of immigrants' effects on total employment

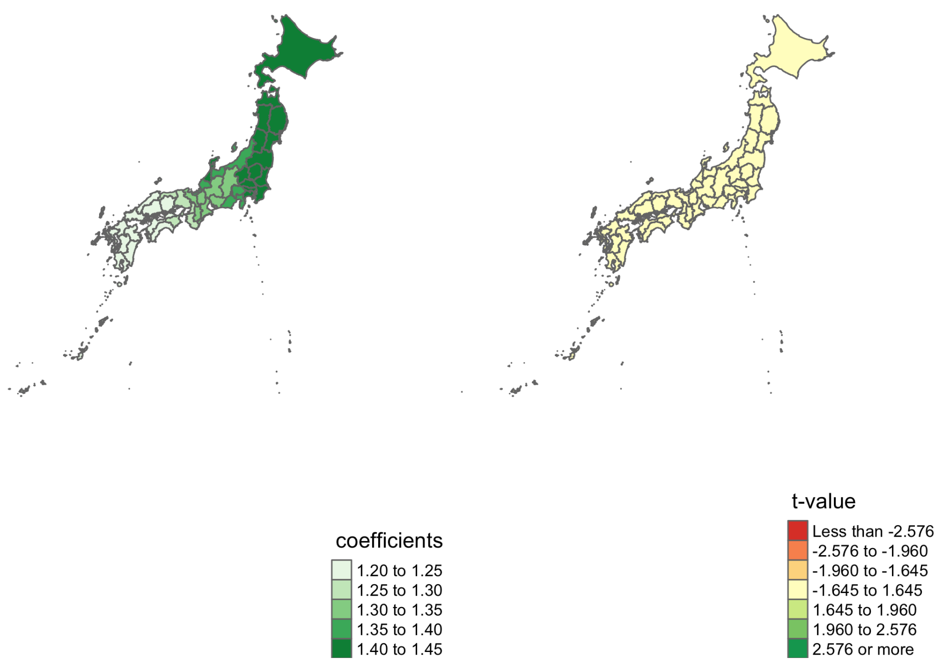

Figure 1. GWPR results of immigrants' effects on output per worker

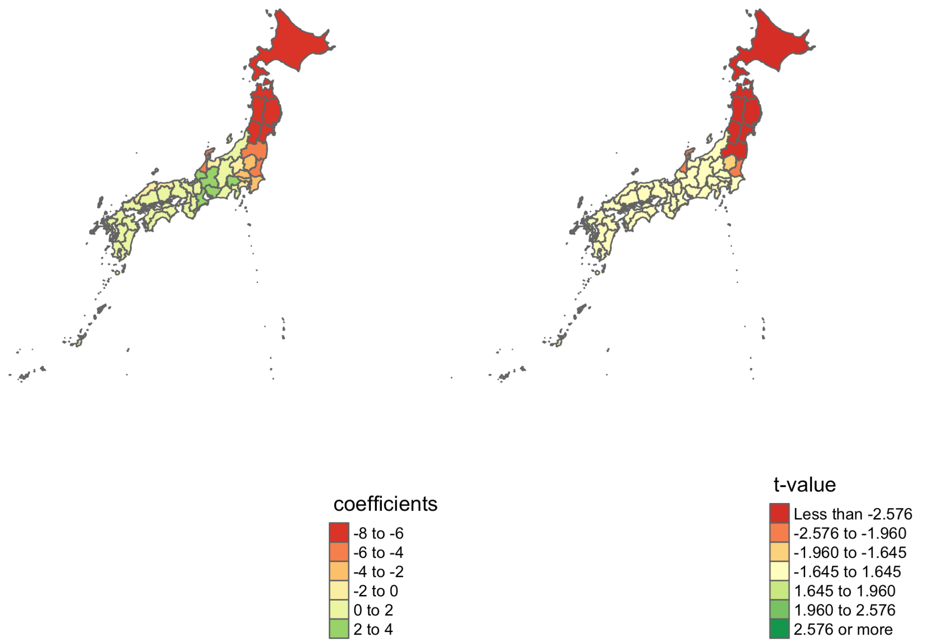

Figure 4. GWPR results of immigrants' effects on capital-to-GDP ratio

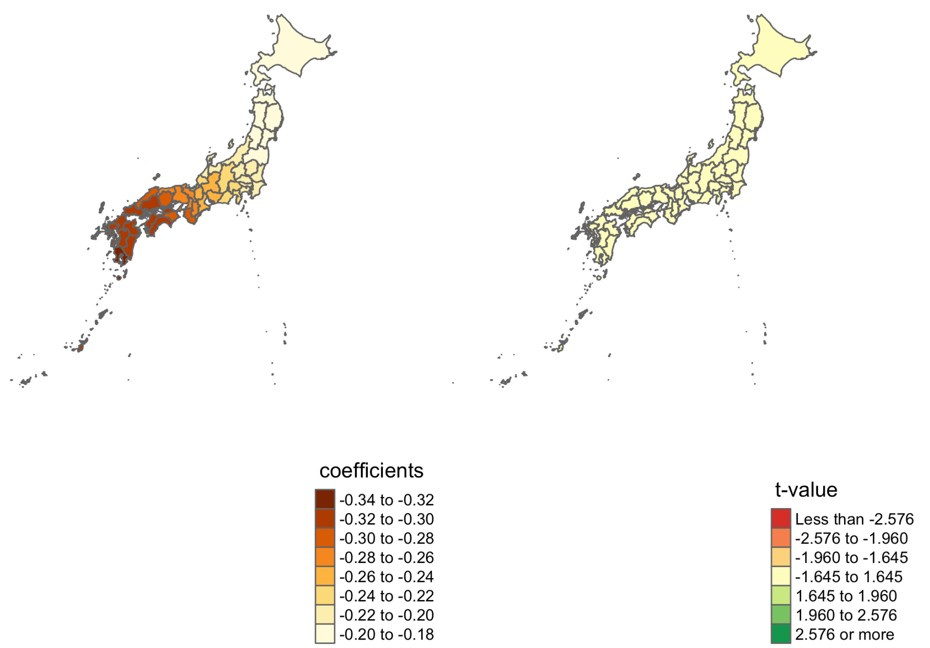

Figure 3. GWPR results of immigrants' effects on total factor productivity

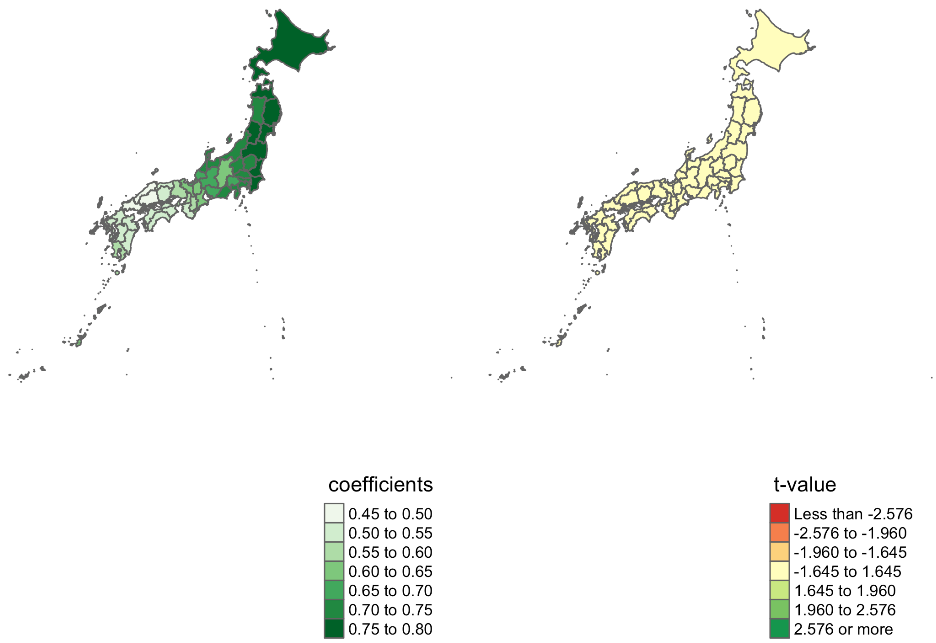

Figure 6. GWPR results of immigrants' effects on average worked hours

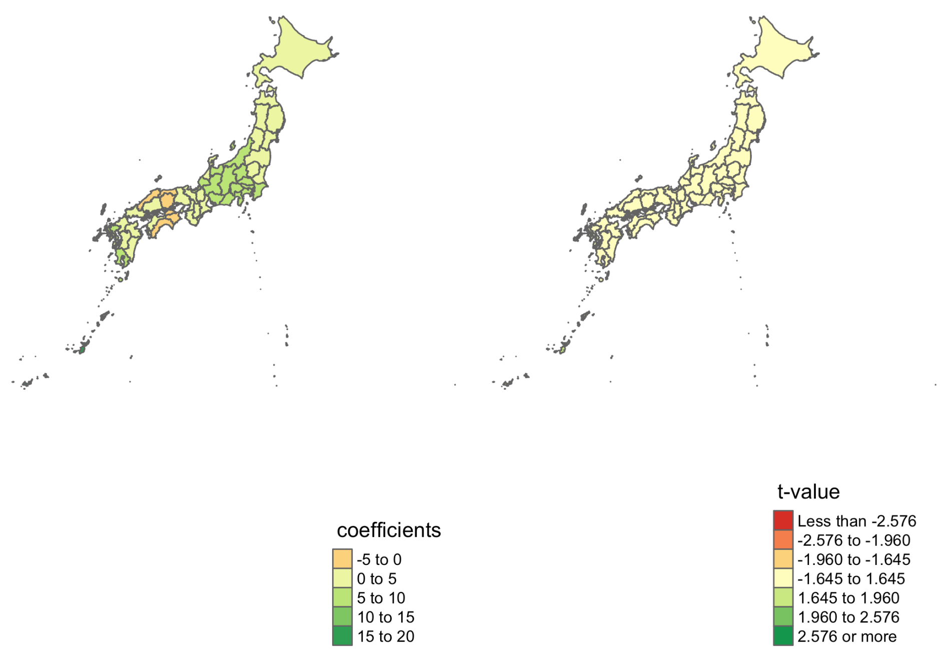

Figure 5. GWPR results of immigrants' effects on wage index

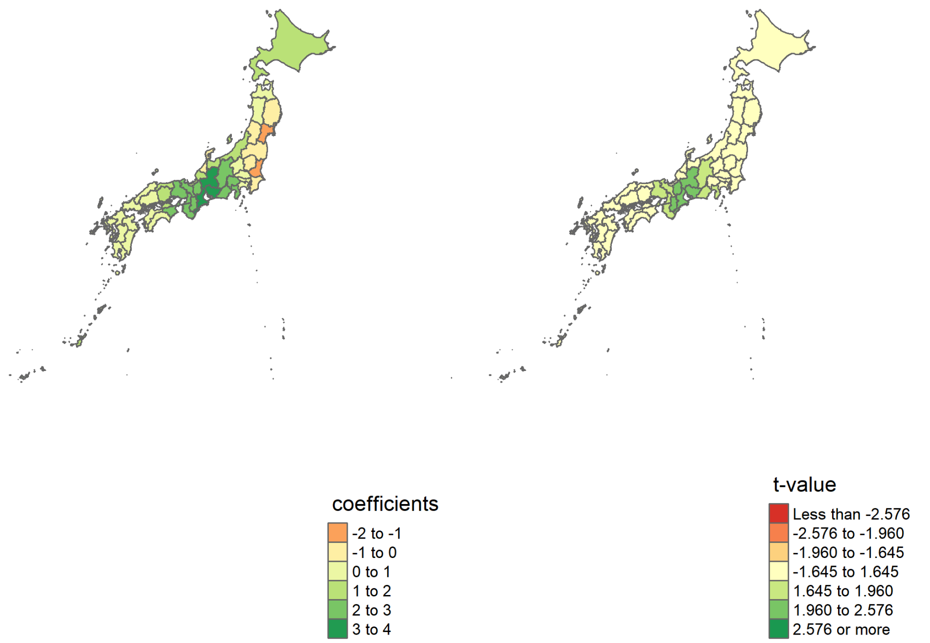

Figure 8. GWPR results of immigrants' effects on capital

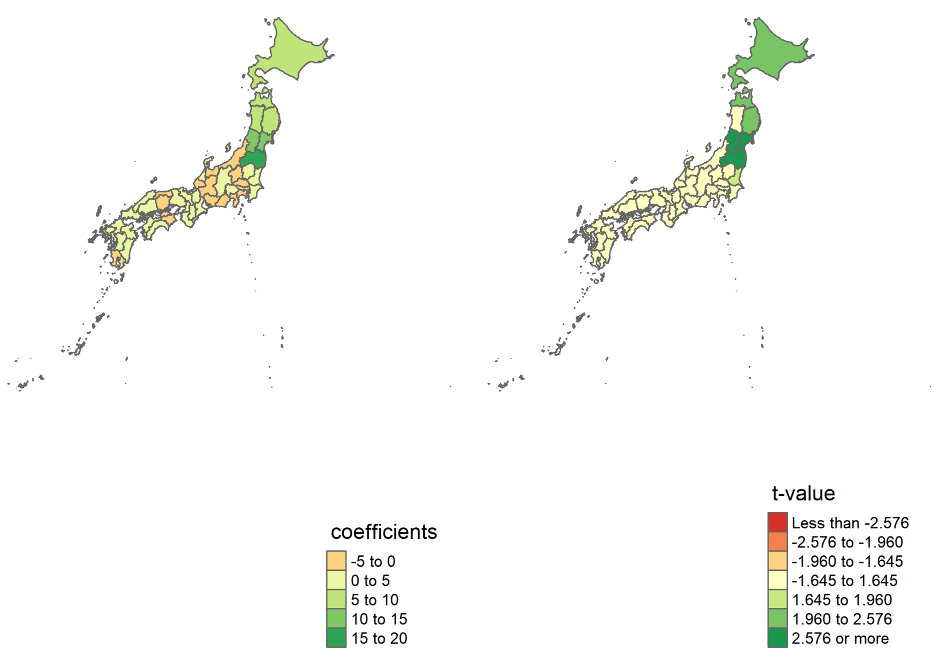

Figure 7. GWPR results of immigrants' effects on GDP

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[4]. 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 4. For brevity, we focus on the coefficients that demonstrate the heterogeneous impacts of immigrants on the local economy, which are the total employment, capital stock, and GDP. 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[5]. The bottom panel categorizes immigrants into three industry groups: primary industry, secondary industry, and tertiary industry[6]. The dependent variables are the coefficients of total employment, capital, and GDP 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

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

[5] 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.

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

Table 4. Regression of immigrant groups on coefficients generated by GWPR

	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***	0.0001***	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 indsutry	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

*Note: 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*

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 GDP, 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 GDP.

5. Discussion

GWPR method reveals the differentiated effects of immigrants on capital-to-GDP across prefectures. Separately estimating the effects on capital and GDP shows the negative and significant coefficients in selected prefectures are because immigration increases GDP 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 B.1 in Appendix B). 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 1, 7, and 8 show two notable trends. First, prefectures that experience higher physical capital stock from immigration do not see higher GDP 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 GDP due to higher immigration. Using the production function, GDP 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 GDP. 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 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 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 substitute 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 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 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 GDP value (Table B.1 in Appendix B). It also has the second largest immigrant worker population, next to Tokyo, but the largest immigrant worker population in the manufacturing industry (Table B.2 in Appendix B).

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 1, 7, and 8: higher immigrant counts in the primary industry lead to higher GDP due to an increase in total employment, not physical capital stock. According to the Prefectural Account published by Cabinet Office (Table B.1), seven prefectures fitting into this trend put greater focus on the primary industry than other prefectures.

6. Conclusion

This paper 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-GDP ratio in northern Japan. Further analysis shows the negative effects are due to the positive relationship between immigration and GDP. In other words, immigration drives GDP growth but not capital growth, thus lowering the capital-to-GDP ratio. Additionally, an increase in immigrants is correlated with higher GDP and total employment, but not 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.

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APPENDIX A

First order Taylor expansion of $\boldsymbol{\hat{\theta}_{pt} = r_{pt} - r_{pt-1}}$

From

(A.1) $$\hat{\theta}_{pt} = \mathrm{r}_{\mathrm{pt}} - r_{pt-1} = \frac{F_{pt}}{F_{pt}+N_{tpt}} - \frac{F_{pt-1}}{F_{pt-1}+N_{pt-1}}$$

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

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

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

Thus, the Taylor series of $\hat{\theta}_{pt}(\mathrm{F}_{\mathrm{pt}}, \mathrm{N}_{\mathrm{pt}})$ around (F_{pt-1}, N_{pt-1}) is

(A.2) $$\hat{\theta}_{pt} \approx \left(\frac{F_{pt-1}}{F_{pt-1}+N_{pt-1}} - \frac{F_{pt-1}}{F_{pt-1}+N_{pt-1}}\right)$$

$$+\left(\frac{1}{\mathrm{F}_{\mathrm{pt-1}}+N_{pt-1}} - \frac{\mathrm{F}_{\mathrm{pt-1}}}{\left(\mathrm{F}_{\mathrm{pt-1}}+\mathrm{N}_{\mathrm{pt-1}}\right)^2}\right)(F_{pt} - F_{pt-1})$$

$$-\frac{\mathrm{F}_{\mathrm{pt-1}}}{\left(\mathrm{F}_{\mathrm{pt-1}}+\mathrm{N}_{\mathrm{pt-1}}\right)^2}(\mathrm{N}_{\mathrm{pt}} - \mathrm{N}_{\mathrm{pt-1}})$$

Hence, (A.2) can be further rewritten as

(A.3) $$\hat{\theta}_{pt} \approx 0$$

$$+\left(1 - \frac{\mathrm{F}_{\mathrm{pt-1}}}{\mathrm{F}_{\mathrm{pt-1}}+\mathrm{N}_{\mathrm{pt-1}}}\right)\left(\frac{F_{pt}-F_{pt-1}}{\mathrm{F}_{\mathrm{pt-1}}+\mathrm{N}_{\mathrm{pt-1}}}\right)$$

$$-\frac{\mathrm{F}_{\mathrm{pt-1}}}{\mathrm{F}_{\mathrm{pt-1}}+\mathrm{N}_{\mathrm{pt-1}}}\left(\frac{\mathrm{N}_{\mathrm{pt}}-\mathrm{N}_{\mathrm{pt-1}}}{\mathrm{F}_{\mathrm{pt-1}}+\mathrm{N}_{\mathrm{pt-1}}}\right)$$

Let $\Delta\mathrm{F} = \mathrm{F}_{\mathrm{pt}} - F_{pt-1}$, and $\Delta\mathrm{N} = \mathrm{N}_{\mathrm{pt}} - N_{pt-1}$. Also, recall that $\mathrm{r}_{\mathrm{pt}} = \frac{F_{pt}}{F_{pt}+N_{pt}}$ and $\mathrm{L}_{\mathrm{pt}} = F_{pt} + N_{Pt}$, then

(A.4) $$\hat{\theta}_{pt} = \left(1 - \mathrm{r}_{\mathrm{pt-1}}\right)\left(\frac{\Delta F}{\mathrm{L}_{\mathrm{pt-1}}}\right) - r_{pt-1}\left(\frac{\Delta\mathrm{N}}{\mathrm{L}_{\mathrm{pt-1}}}\right)$$

APPENDIX B

Table B. 1 Output value of primary, secondary, tertiary industries in 2018

Prefecture	Primary industry (JPY millions)	Secondary industry (JPY millions)	Tertiary industry (JPY millions)	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 of output value of each industry to the total output value in each prefecture.
Source: "Prefectural Account" published by Cabinet Office

Table B. 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%
Hyogo	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%
Kochi	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%
Oita	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