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

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This paper analyzes the impact of immigration on different macroeconomic indicators, using production function. We use data on immigrant stock as well as prefecture account from 2009 to 2018. Regression results show that immigrant workers positively affect employment, and do not crowd out native employment. Increase in immigrant workers do not affect any other indicators. However, Geographical Weighted Panel Regression (GWPR) indicates that immigrants' positive impacts on employment, and negative impacts capital-to-output ratio are significant in selective prefectures, which are resulted from an increase in output but not capital. The results show how the average effects capture by OLS may not fully convey the economic impact of immigration. These results are consistent with how Japan has been accepting least-skilled workers in recent years.

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I. Introduction

Immigration's impact on the economy has been studied extensively and produced mixed results. However, most researches have been using Western countries, who 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 even experienced negative growth rates in recent year, immigrant population has been growing steadily, despite restrictive immigration policy. A closer look at the data provided by the Ministry of Health, Labour and Welfare (MHLW), of the 125% increase in foreign workers between 2010 and 2018, "Technical Intern" and "International Student" contribute 36.7% and 25.6%, respectively.

This paper studies the impact of increasing in immigrant population to the economy inputs. Specifically, we try to answer the following questions: (1) the average effects of immigration on production inputs, and (2) whether the impact of immigration are heterogenous across prefectures. The first question can be answered by using the production-method. First, output GDP is decomposed into several input components, then immigration is regressed on each of these components. To approach the latter question, Geographical Weighted Panel Regression (GWPR) is used to produce different estimates for each region. The coefficients can be used to reveal which prefectures are benefited from immigration.

To shed light on the issues, data on production inputs such as capital stock, immigrant and total employment of 47 Japan prefectures from 2009 to 2018 are extracted from government data. Average wage, worked hours, and number of foreign workers can be extracted from MHLW.

Our paper shows a possible crowding-in effects from the base OLS estimation. However, using IV estimation, the links become insignificant, indicating that immigration can be only be concluded to have no negative effects on local labor force. Both methods show no significant relationship between immigration and other economy inputs.

Applying GWPR method produces interesting results on the distinct impacts of immigrant between prefectures. Specifically, immigration negatively affects the capital-to-output ratio in some selected prefectures. Decomposing capital-to-output ratio into capital growth and output growth shows the negative correlations are due to the positive relation between immigration with output growth, but not with capital growth.

While many of the coefficients generated by GWPR method are insignificant, the spread of coefficients carries valuable information on the heterogeneous effects of immigration across prefectures. Further regress these coefficients on immigrants from different education groups confirms several results from previous literatures. Specifically, we found highly-educated immigrants correlated with lower coefficients of total employment and wage-index, suggesting the competition between this group of immigrant and native labors. Student and less educated immigrants are correlated with lower coefficients of capital and TFP, indicating the substitution relationship between less educated workers and capital. The same groups are also correlated with higher total employment and wage-index coefficients. This last result can be explained by the possible complementary effects between immigrant workers and part of the labor force, as found in previous literature immigration in Japan.

Our paper has two contributions to this field. First, we confirm the non-negative effects of immigration of local labor force. Second, economic impacts of immigration are studied on national-level or local-level. This paper contributes to the latter by being the first to apply GWPR method and study the heterogeneous economic impact of immigration.

The rest of this paper is organized as follows. Section II reviews previous studies on immigration and economy growth, as well as on GWPR method. Section III describes the production approach, measure of immigration, GWPR method, and data used. Section IV and V present and discuss the results. Section VI provides concluding remarks.

II. Literature Review

A. Immigrant

Immigrant's impact on domestic market performance has been a hot research topic, especially on labor market outcome. The answer on how native labor reacts 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 native labor market. However, Card and Peri (2016) describes the overall tone of the book towards immigration as "uniformly dismal", saying that it is only "half the story". In many of his work, Peri (2011, 2012) shows that the negative impacts of immigrants on wage or employment level of their native counterparts are nonsignificant. In fact, immigrant workers and native workers are imperfect substitutes of each other, since both possess different skill sets. Thus, native workers will move to another occupation that they have a comparative advantage to immigrant workers (Peri & Sparber, 2009).

Correlation between immigration and capital input has not been a focus of this field. Theoretically, neoclassical growth model predicts that capital-to-output ratio will stay constant in the long-term. Hence, a net positive inflow of immigration, which increases population of the destination countries, should not have any effect on capital-to-output 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 substitute.

Overall, immigrants are found to have a positive correlation with productivity. Using the production function approach, Peri (2012) finds immigrants positively improve total factor productivity of the receiving U.S. states. Gu et al. (2020), using Canadian firm-level data, finds 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 immigrant. One channel through which immigrants can improve productivity is by inducing technological progress, which in turn depends on innovative activities. Using data on H-1B visa program, Kerr and Lincoln (2010) find that cities with higher admission rate of H-1B visa lead to higher patent count from Chinese and Indian.

On the other hand, the number of empirical research on Japan immigration is very limited. Mitani (1993), using Japanese Census, studied the impacts of immigrant workers on Japanese women part-time laborers. The study found immigrants have negative impacts on the number of Japanese women workers only in manufacturing industries, but non-significant in overall. The author also found immigrant workers have a positive impact on wage across industries, but non-significant in manufacturing. Another paper by Ohtake and Ohkusa (1993) found that while immigrant workers are substitute for capital and non-regular workers, the relationship with regular worker changes to complementary. Korekawa (2015) studied the assimilation[1] of Chinese and Brazilian immigrant workers in Japan using 2010 Census. The study found that when compare 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

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

enhanced for those with higher education, and the adverse effects among Brazilian men are alleviated for those that are less educated and married to the Japanese.

B. Geographically Weighted Panel Regression

GWPR is an extension of GWR by allowing data to vary over time. GWR is written in details by Fotheringham et al. (2002). The method allows regression coefficients to vary spatially by running different regression for every region, where the subset of data in each regression is weighted by their proximity 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 & Leung (2002) study the regional industrialization in Jiangsu province and find that the determinants can vary differently in sign and significant levels between northern, southern, and central regions. In regional growth, Partridge et al. (2009) find the determinant factors of employment growth vary differently between U.S. nonmetropolitan. Similarly, Lewandowska-Gwarda (2018) reaches similar conclusion when analyze Poland's regional unemployment data.

GWPR is first proposed in Yu (2010), and is developed further in Yu et al. (2021). The latter finds the developing of high-speed rail system benefits rural regions or areas with low access to high-speed rail system, suggesting a pattern of diminishing effect. 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 vary between states in either direction, which traditional OLS fails to capture.

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

III. Data and Methodology

A. 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

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

where Y_{pt} is the total production, K_{pt} captures aggregate private physical capital, h_{pt} indicate average worked hours per person, A_{pt} measures total factor productivity, α is elasticity of substitution between capital and labor, L_{pt} represents the total number of workers, and finally, ϕ_{pt} is a wage index. Next, define output per worker as $y_{pt} = Y_{pt}/L_{pt}$, and rewrite equation (1) as follows

$$(2) \qquad \mathrm{y}_{\mathrm{pt}} = \frac{Y_{pt}}{L_{pt}} = A_{pt}^{\frac{1}{1-\alpha_{pt}}}\left(\frac{K_{pt}}{Y_{pt}}\right)^{\frac{\alpha_{pt}}{1-\alpha_{pt}}} h_{pt}\phi_{pt}$$

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

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

According to equation (3), total production value for each prefecture increases as a result of an increase in total employment $\hat{L}_{pt}$ and 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 4 parts: total factor productivity $\hat{A}_{pt}$, capital-output-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 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 replaced with total employment $\hat{L}_{pt}$, total factor productivity $\hat{A}_{pt}$, capital-output-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 immigrant workers between two periods.

B. Measure of immigrant workers' change

To capture the change in 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, change of immigrant workers between periods $\hat{\theta}$ in equation (4) can be measured as

(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. Similarly, $\Delta N_{pt} = N_{pt} - N_{pt-1}$ 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, there is a demand shock that leads to a positive correlation between economic indicators and native labor force in a prefecture. Then, equation (5) and (7) indicate that using immigrant to total employment ratio can lead to a negative bias in coefficient β.

To construct a variable that can correctly account for the change of 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 term 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 together,

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

$$\frac{\Delta F_{pt} + \Delta N_{pt}}{L_{pt-1}} \tag{9}$$

the growth rate of labor market size is consisted of the growth rate of immigrant workers and of domestic workers. Thus, $\frac{\Delta F_{pt}}{L_{pt-1}}$ can be used to capture only the impact of immigrant labor force. This term 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 Card and Peri (2016) and Peri (2012).

C. 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 on this method by utilizing panel data. Thus, both methods are similar in theirs estimate procedures. First, we will present the basic of GWR.

$$y_j = x_j \beta_i + \varepsilon_j \tag{10}$$

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 independent variable at each geographic location. In other words, if our sample size is n, GWR will result in n coefficients for each independent variable. In matrix form, coefficients of GWR can be estimated as follow

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

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

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

where $w_n(i)$ is the weights 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 Weighted Least Square method, and the weighting matrix follows equation (12). However, instead of having a constant weight matrix, the weights 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 point that is physically closer to i. Many kernel functions can be used to achieve this result. For this paper, we use bi-square decay function defines as follow

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

where b is the bandwidth.

Equation (13) assigns weight at a decaying rate depends on how far n is from i, and assigns weight equal to zero for any points that are 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, irregular spaced geographical units exist, since some prefectures can be smaller than other. This problem can lead to the extreme case where only one data point is used and, thus, lead to perfect fit. To remedy this problem, adaptive bandwidth is more preferable. Instead of producing a similar optimal bandwidth for all locations, adaptive bandwidth determines the size of dataset to be used at each location. Golden-section search optimization method is used to search for the optimal bandwidth b that minimize the cross-validation score (CV-score)

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

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

(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, equation kernel function (13) can be used to get the weight matrix[3]. CV-score can be estimated by extending equation (14) to

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

[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

Additionally, time fixed effects and individual fixed effects are also included to control for time-variant and time-invariant unobservable. All of 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 & Millo, 2018), and GWmodel (Gollini et al., 2015) packages.

D. Data

We consider the data of 47 prefectures of Japan, between 2009 and 2018. Data on GDP, and number of workers can be taken from the Gross Prefectural Account of Cabinet Office. Similarly, private capital stock is also available from the same department. We also use the capital utilization rate taken from the Ministry of Economy, Trade and Industry. Data on number of foreign workers, as well as average hours worked per person (from Monthly Labor Survey) and wage data (from Basic Survey on Wage Structure) can be extracted from the MHLW.

To construct capital stock for each prefecture, there are two problems need to be resolved: (a) capital utilization rate is only available in national, and (b) the most recent data for capital stock and capital utilization rate is only available until 2017. First, we interpolate the 2018 capital stock by using 2017 capital stock and coefficient obtaining from the following linear regression

$$k_t = \delta k_{t-1} + \epsilon_t \qquad (20)$$

The procedure is done separately for each prefecture.

Next, to construct capital utilization rate for each prefecture, monthly capital utilization rate of manufacturing industry and service industry is average yearly to get the annual rate for both industries. Then, weighted average of both rate is calculated, where the weight of manufacturing (service) industry is the ratio between GDP value of manufacturing (service) industry and the sum of both industries' GDP. Following these steps, capital utilization rate for each prefecture is different depends on the size of theirs manufacturing and service industry. Then, Capital utilization rate for 2018 is interpolated similarly to capital stock. Finally, capital stock is multiplied with capital utilization rate to obtained K_{pt}.

Total factor productivity A_{pt} is not observable. However, it can be calculated by rewriting (1)

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

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 as follows

$$\alpha_{pt} = 1 - \frac{(w_{pt} + t_{pt})}{Y_{pt}} \tag{22}$$

where w_{pt} is the compensation of employees, $t_{pt}$is the taxes on production and imports. Both w_{pt} and t_{pt} are available from Gross Prefecture Product of Cabinet Office.

Finally, wage index for each prefecture is constructed as follow. First, data for ordinary workers and part-time workers in each industry in each prefecture are combined together. Next, for ordinary workers, scheduled hours worked and overtime worked hours are summed up before multiplied by 12 to get the total worked hours annually in each industry. Similarly for part-time workers, total worked hours annually in each industry is calculated by multiplying average worked days per month with average worked hours per day, and with 12. Annual earning (including bonus) is divided by total worked hours to get the average earning per hour separately for ordinary and part-time workers. Afterward, average earning per hour in each industry for each prefecture is calculated using weighted average, where the weights are the ratio between total worked hours of ordinary workers (part-time workers) and total worked hours of both type of workers. Finally, average earning per hour for each prefecture is obtained by once again using weighted average, where the weights now are the ratio between total worked hours of each industry and total worked hours of all industry.

Following the above procedure, wage index ϕ_{pt} can be thought as average earning per hours in each prefecture. Additionally, if marginal productivity for labor input is assumed to equal to wage, then the index also represents productivity of workers 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", reporting that earnings in these sectors fluctuate greatly due to seasons or weather conditions. Nevertheless, the survey still includes valuable information on wage considering that it covers a great part of the economy.

IV. Empirical Result

A. Panel regression result

Before looking the results of GWPR, we first present the baseline result using panel regression. Following the specification of Peri (2012), weighted least square estimator, where each prefecture is weighted by its labor market size, is used. Individual and time fixed effects are included, and standard errors are clustered by prefecture. Table 1 shows the regression results. Each column represents different specifications: column (1) is the basic result, column (2) tests for serial autocorrelation by including lagged dependent variable, column (3) and (4) tests whether the result in sensitive to the periods chosen, column (5) shows the result of 2SLS, and column (6) repeats the weighted OLS with change in immigrant ratio as explanatory variable. Each row is the coefficient for each of the macroeconomic indicators. For brevity, only the coefficients for immigration variable are presented.

In overall, the results in column (1) to (4) indicate a positive impact of immigrant on total employment. Recall that the explanatory variable is the change of total

Table 1. Panel estimate of immigrant's impact on components of gross prefecture product growth

	Dependent variable:					
	Basic OLS	Including lagged dependent variable	2011-2018	2010-2017	2SLS	Change in immigrant ratio as independent variable
	(1)	(2)	(3)	(4)	(5)	(6)
$\hat{L}$	2.288***	1.718***	1.825***	2.305***	1.402	0.014
	(0.590)	(0.713)	(0.622)	(0.582)	(1.355)	(0.010)
$\hat{y}$	-1.317	-2.247	-1.970	-1.034	-3.466	0.031*
	(1.248)	(1.452)	(1.429)	(1.609)	(3.332)	(0.016)
Component of $\hat{y}$						
$\widehat{\frac{K}{Y}}$	-0.554	-1.142	-1.218	-0.566	-4.505	-0.042**
	(1.966)	(2.165)	(2.064)	(2.249)	(5.972)	(0.018)
$\hat{A}$	-0.098	-0.640	-0.257	0.407	2.579	0.028*
	(1.482)	(1.542)	(1.359)	(1.638)	(3.312)	(0.016)
$\hat{h}$	0.585	0.744	0.744	0.080	-2.775	0.009
	(0.747)	(0.851)	(0.756)	(0.722)	(1.863)	(0.009)
$\hat{\phi}$	2.149	0.817	0.931	0.584	6.114	0.085
	(2.813)	(3.289)	(3.360)	(3.485)	(5.706)	(0.066)
F-statistic					33.520	
Observations	423	376	376	376	423	423

Note: The independent variable is change in foreign workers as percentage of ininitial total employment in (1)-(5), and is change in immigrant ratio in (6). Each cell in column (1) to (4) and (6) is the result of diffeerent weighted least squares regression, where each prefecture is weighted by its total employment. Column (5) showss 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

employment that is the result of change in foreign workers. Thus, coefficient around 2 suggests that increasing foreign worker by 1 will enlarge 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 negative and insignificant effect on output per worker. The negative correlation is from the combination of a negative correlation with capital-to-output ratio and total factor productivity, as well as a positive impact on average worked hours, and wage index. Note that the impacts on $\hat{y}$ and its components of are all statistically insignificant.

Immigration and economic indicators can simultaneously affect each other: higher number of immigrant workers can improve the economy of the region, which, in turn, attract more immigrant workers. This demand-driven bias can lead to overestimation of the immigrant coefficients. A common reconciliation approach is to use instrumental variable based on past settlement of immigrants. For this paper, 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 immigrant population in 2006 as our base, year-on-year national growth rate for each group is applied to that group in each prefecture. Finally, immigrants are summed across groups to obtain the imputed immigrant population. Following these steps, our instrumental variable depends only on past settlement that is not included in our regression, and does not depend on the progress of local economy.

The results are presented in column (5). The result of weak instrument diagnostic test using F-statistic indicates that our instrument is appropriate. Comparing to weighted OLS, immigrant shows smaller and insignificant impacts on the total employment. The impacts on $\hat{y}$ and all of its component remain insignificant.

In the previous section, we provided a mathematical proof of using immigrant ratio as explanatory variable may bias the results. Column (6) attempts to prove it empirically. First, the impact of immigrants on 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 immigrant ratio as explanatory variable. Surprisingly, the correlation between immigrant and GDP per capita is positive and significant at 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 coefficients for capital-to-output ratio and total factor productivity are significant at 5% level.

B. Geographical Weighted Panel Regression

Before looking at the estimates of GWPR, we present some diagnostics to justify our method. First, corrected Akaike Information Criterion (AICc) is used to select the optimal kernel functions. Table 3 below show the AICc value of different GWPR model using bi-square, tri-square, and gaussian kernel functions. In overall, bi-square kernel function produces the lowest AICc value. However, the differences seem negligible. For the purpose of this paper, GWPR will be estimated using bi-square kernel function.

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

	Bi-square	Tri-square	Gaussian
$\hat{L}$	-2989	-2982	-2982
$\hat{y}$	-2123	-2122	-2123
$\widehat{K/Y}$	-2034	-2028	-2038
$\hat{A}$	-1707	-1648	-1686
$\hat{h}$	-2621	-2620	-2617
$\hat{\Phi}$	-1235	-1172	-1212

Next, AICc value of the baseline OLS model is calculated and compared with GWPR in Table 3. The results indicate that using GWPR yields lower AICc value in all 5 models. In other words, GWPR is better at fitting the data than OLS.

Table 3. AICc of baseline OLS model and GWPR

	Basic OLS	GWPR
$\hat{L}$	-2756	-2989
$\hat{y}$	-1992	-2123
$\widehat{K/Y}$	-1856	-2034
$\hat{A}$	-1493	-1707
$\hat{h}$	-2497	-2621
$\hat{\phi}$	-1021	-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 shows in Figure 1, Figure 2, Figure 3, Figure 4, Figure 5, respectively.

According to Figure 1, immigrant exerts positive effects on all prefectures, but only significant in some prefectures. Most prefectures from the Tõhoku region to the Chũgoku region are enjoying the benefits of addition immigrant workers. Figure 2, however, while indicating positive effects on output per worker, the effects are insignificant. Coefficients for capital-to-output ratio, through Figure 3, are spread from negative to positive, but none of the positive coefficients are significant, while most of the negative coefficients are significant. Similarly in Figure 4, the impacts on total factor productivity, while insignificant, can be either positive or negative depends on the prefectures. Finally, Figure 5 shows immigrants have positive effects on average worked hours, and Figure shows mostly positive impacts on wage index, however, both are insignificant.

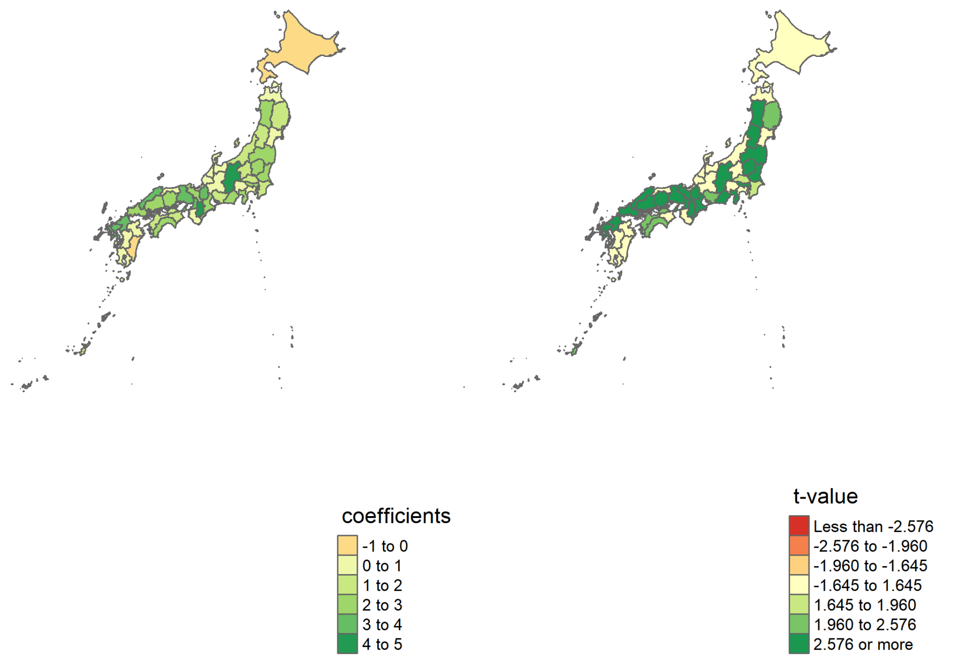

Figure 1. GWPR results of immigrants' effects on total employment

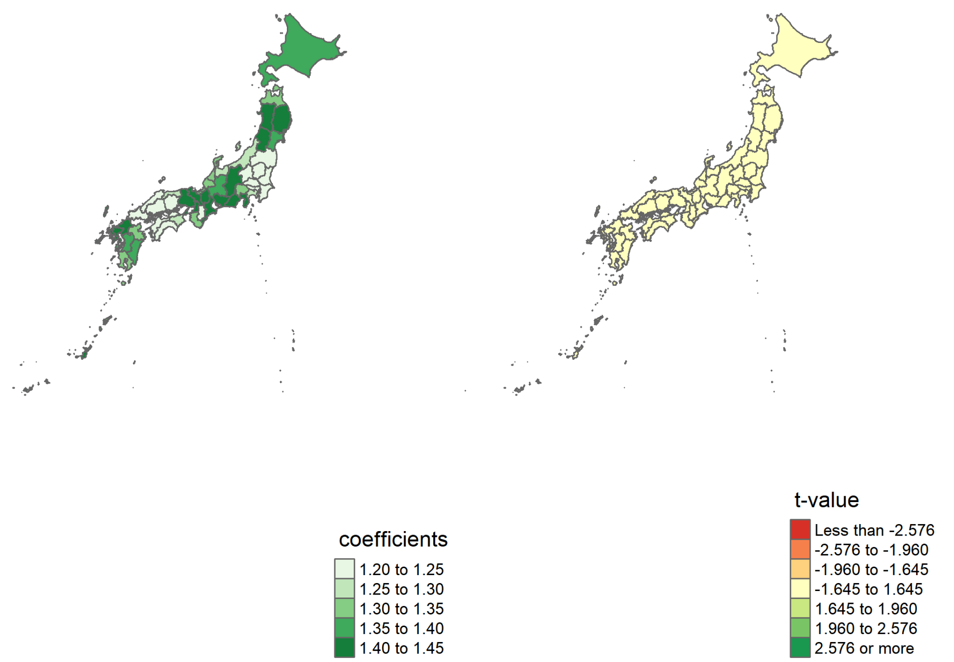

Figure 2. GWPR results of immigrants' effects on output per worker

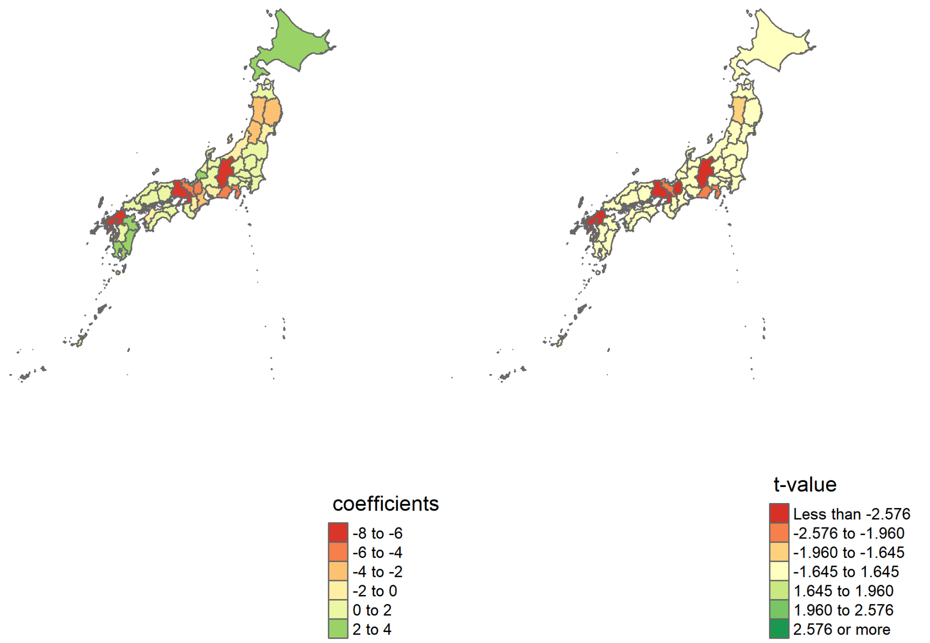

Figure 3. GWPR results of immigrants' effects on capital-to-output ratio

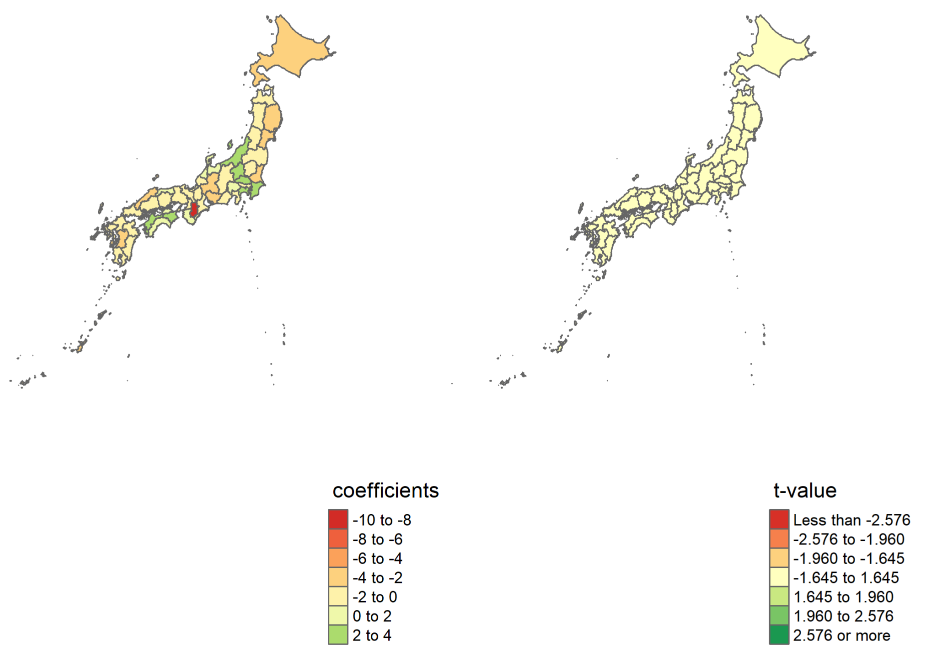

Figure 4. GWPR results of immigrants' effects on total factor productivity

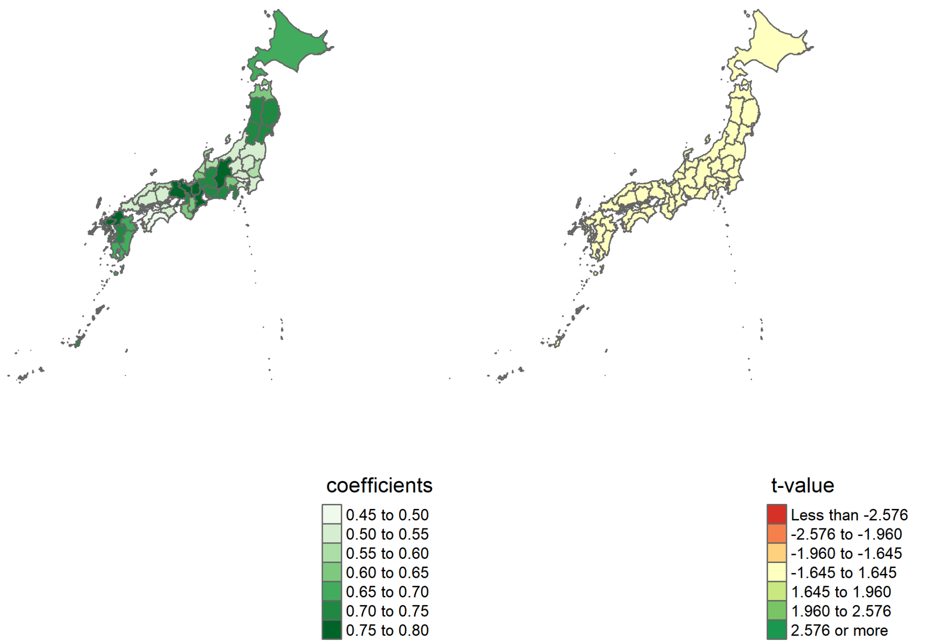

Figure 5. GWPR results of immigrants' effects on average worked hours

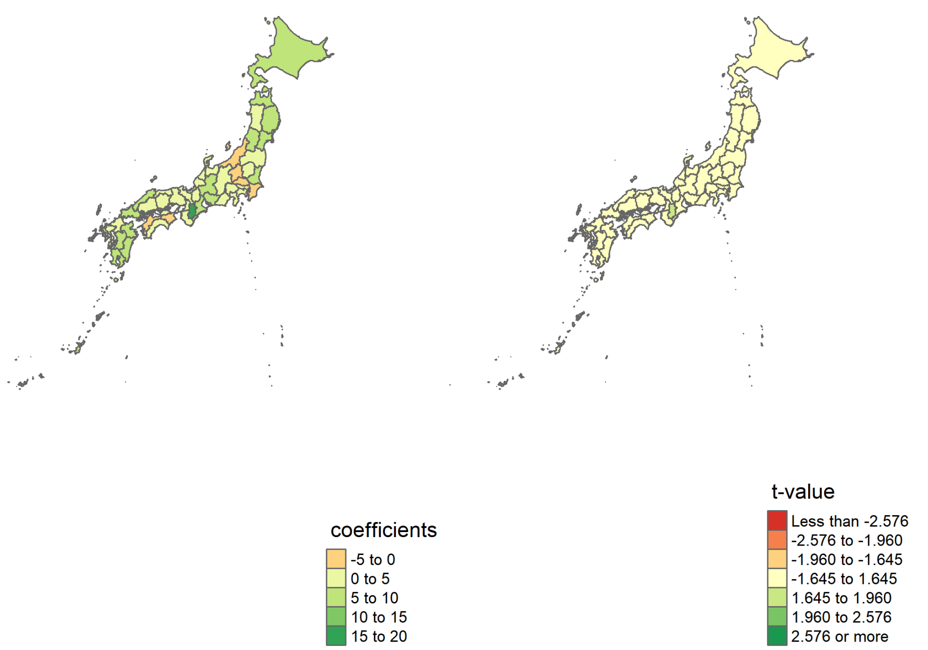

Figure 6. GWPR results of immigrants' effects on wage index

Different from the base OLS above, GWPR indicates immigrants can have some negative effects on capital-to-output ratio. The growth rate of capital-to-output ratio can be further separate into the growth rate of capital minus the growth rate of output, as below

$$\widehat{\frac{K_{pt}}{Y_{pt}}} = \widehat{K_{pt}} - \widehat{Y_{pt}} \tag{23}$$

The decomposition is important in understanding how immigrants influence capital input. According to (15), there are 4 patterns that can lead to a negative capital-to-output 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; (3) the growth rates of both are positive, but GDP grows at a faster rate; and (4) the growth rates of both are negative, but capital declines 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 seem to express both positive and negative effects on capital and output, however, only some selective prefectures experienced significant and positive effects. Focusing on prefectures with a negative effect on capital-to-output ratio, it can be seen that the impacts on growth rate are significant for output, but are insignificant for capital.

The coefficients generated by GWPR method imply that immigrants affect each prefecture differently. We take one step further from previous literature that use GWPR and regress these coefficients on groups of immigrants. Specifically, using publicly available statistics from the 2010 Census, immigrants working population (15-64 years old) are categorized into 3 groups: Highly-educated (those who finish vocational school, have college degree or higher), Less-educated (those with highs school education or less), and Student (those who are attending school). International students are included as a category of its own since they are also an

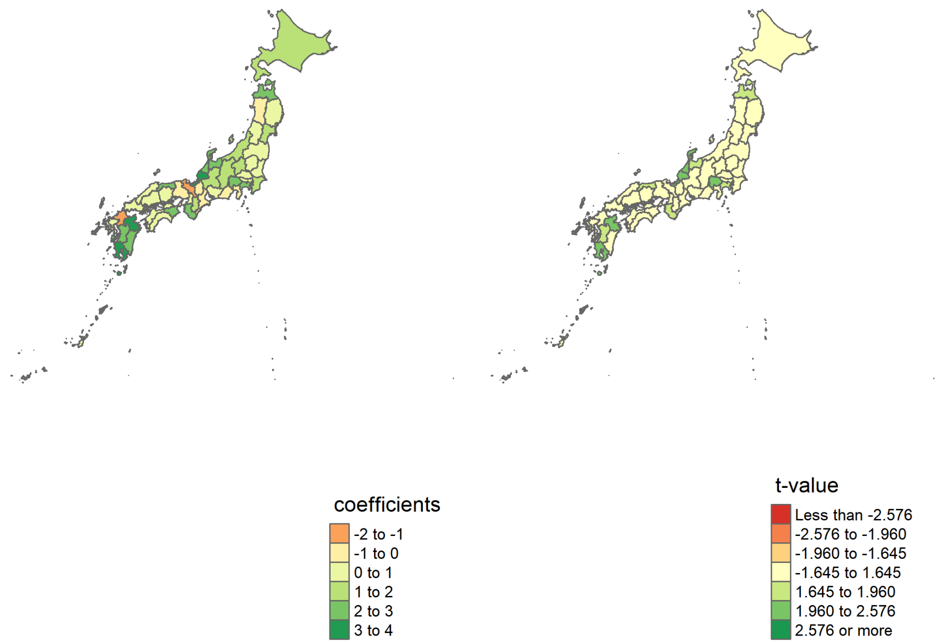

Figure 8. GWPR results of immigrants' effects on capital

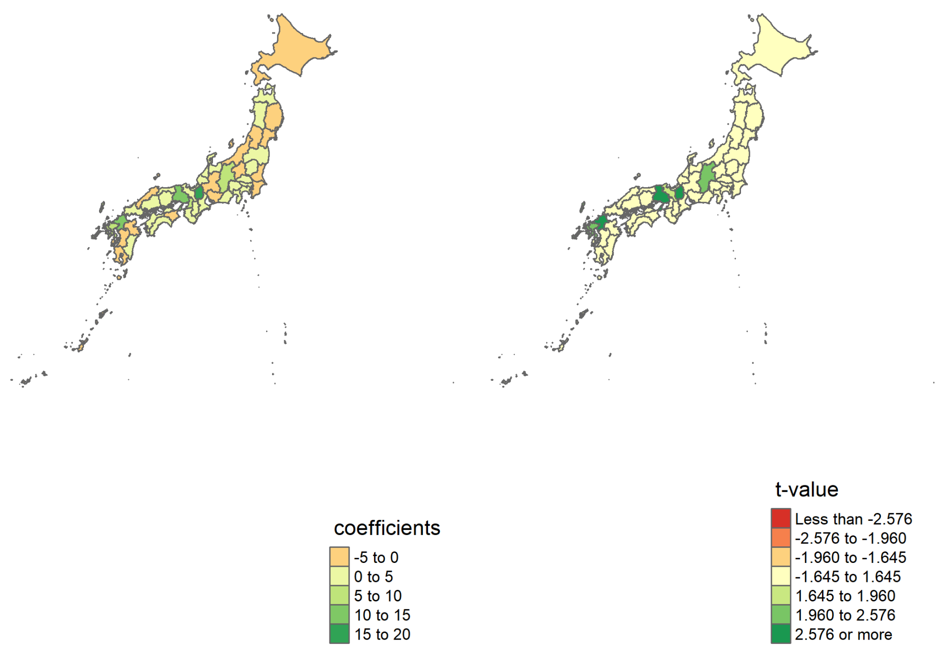

Figure 7. GWPR results of immigrants' effects on output

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

	Dependent variable									
	Total employment		*Capital*		*Output*		*TFP*		*Wage-index*	
	2010	2020	2010	2020	2010	2020	2010	2020	2010	2020
	(7)	(8)	(3)	(4)	(5)	(6)	(1)	(2)	(9)	(10)
Education										
Constant	1.623***	1.850***	1.277***	1.201***	2.094**	2.832***	-0.313	-0.23	3.896***	3.558**
	(0.277)	(0.270)	(0.247)	(0.239)	(1.028)	(1.019)	(0.433)	(0.453)	(0.675)	(0.705)
Highly educated	-0.0001**	-0.0001***	0.0002***	0.0001***	-0.0003	-0.0002	0.0004***	0.0002***	-0.0004***	-0.0002**
	(0.0001)	(0.00003)	(0.0001)	(0.00003)	(0.0002)	(0.0001)	(0.00010)	(0.00010)	(0.0001)	(0.0001)
Less educated	0.00004**	0.00002	-0.00005***	-0.00004***	0.00004	0	-0.0001**	-0.0001***	0.0001	0.0001
	(0.00002)	(0.00001)	(0.00002)	(0.00001)	(0.0001)	(0.0001)	(0.00003)	(0.00002)	(0.00004)	(0.00004)
Student	0.0002**	0.0002***	-0.0003***	-0.0003***	0.001*	0.001*	-0.001***	-0.0005***	0.001***	0.0005**
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0004)	(0.0003)	(0.0001)	(0.00010)	(0.0002)	(0.0002)
Observations	47	47	47	47	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), TFP in (7) and (8), wage-index in (9) and (10). 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*

important labor force[4]. The findings are presented in Table 4. Column (1), (3), and (5) use 2010 Census to construct the 3 immigrant variables, while column (2), (4), and (6) use the 2020 Census[5]. Dependent variables are the coefficients of total employment, capital, output, TFP, and wage-index generated by the GWPR method above. The results suggest show that highly educated immigrants are positively and significantly related with coefficients of TFP, and capital, while negatively and significantly related with coefficients of total employment and wage-index. In contrast, the links seem to reverse for the less educated and student groups: negative and significant for TFP, and capital. Only workers bearing student status are found to be correlated with higher coefficients of output, total employment, and wage-index.

V. Discussion

The base weighted OLS indicate immigrants bring benefit to the local economies by expanding its local workforce, but have insignificant effect on GDP per capita, as well as its component. Using IV and 2SLS method, however, show that while the positive impacts remain, they become insignificant. When explanatory variable is switched to change in immigrant ratio, many of the results are similar to that of weighted OLS, although with a much smaller magnitude. From the Taylor series, the change in immigrant ratio variable is affected by not only the change in number of immigrant workers, but also by the change in number if native workers. This stresses the important of defining the measurement of immigration to correctly identify the link between immigrants and economic outcomes. Using these results,

[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.

one can confirm that immigration does not negatively affect local labor force, such crow-out native labor.

GWPR method reveals the differentiated effects of immigrants on capital-to-output across prefectures. Decompose it into growth rate of capital and growth rate of output shows the negative and significant coefficients in selected prefectures are because immigration increases output but not capital. As a result, immigration leads to higher GDP not through capital, but by increasing the availability of labor force. These results are consistent with the idea that capital needs time to adjust in short term. The coefficients mapped out in Figure 5 do not vary much, and center around the coefficients from the base regression. This suggests that the immigrant impacts on average worked hours are similar across prefectures. Immigrant workers show positive effects on wage-index, but neglectable. This may have been the combined effects of immigrants on different type of workers, as found in previous literatures. However, due to data limitation, we cannot further disentangle the wage effect of immigrants.

These coefficients computed using GWPR, while insignificant in many cases, carry valuable information on how immigrants are differently affecting the regional economy. Utilizing 2010 and 2020 Census, we find that the immigrants characteristics may be correlated with the spread of coefficients. First, highly educated immigrants are linked with higher TFP coefficients, in contrast with that of less educated immigrants and students. It may that immigrants with college degree or more are better at improving TFP by utilizing their professional knowledge. Similar relationships are found between each group of immigrants and capital's coefficients. The negative correlations between less skilled immigrants and capital confirm the substitute relation between the two (Lewis, 2011). Similar reasoning can be used to explain the negative link between capital and international students. While those holding student visas can work, existing restrictions limit them to perform tasks similar to regular workers. As such, they are confined to mostly simple labor.

Next, highly educated immigrants, with possibly higher professional skills and language skills, have to compete with the native for employment, hence, a negative relationship between the group with total employment, and wage-index. On the other hand, less educated immigrants are correlated with higher coefficients of total employment, while students are correlated with higher coefficients of total employment and wage index. While it is not possible to explain the link without high-quality data, previous literatures have shown the possible complementary effects between immigration and labor force in Japan (Mitani, 1993; Ohtake & Ohkusa, 1993).

VI. Conclusion

This paper uses the production function approach and GWPR method to study the relation between immigrant workers and economy inputs of Japanese prefectures. While IV estimation can establish the causal effects between immigration and economic growth, GWPR allows one to explore the possible distinct effects across prefectures.

From the base OLS model, we find higher immigration is related with larger workforce. An estimate of higher than 2 suggests an addition immigrant worker increase labor force by more than 2, implying a crowding-in effects. The effects are still positive, but insignificant in IV estimation. As such, one can only conclude that immigration does not negatively affect the local labor force.

Using GWPR method, we show that immigration exerts distinct effects on some prefectures, which OLS fails to capture. Specifically, while the negative effects of immigration on capital-to-output ratio is neglectable in OLS estimation, GWPR indicates the effects are actually significant in some prefectures. Further analysis finds the negative relationship is because of the positive impact on GDP growth, but none on capital growth.

Regress the coefficients generated by GWPR on immigrants from different education group, using Census data, reveals that the less educated group and student group show some similarity. Highly educated immigrants are positive correlated with higher capital and TFP coefficients, but lower total employment and wage-index coefficients. The latter may due to the possible substitution effects between highly educated immigrant workers and native. Less educated group and student group are negatively correlated with the coefficients of TFP and capital, consistent with the idea that less educated immigrants are substitute of capital. The positive relation between the two groups with total employment may suggest the complementary relationship between immigration and native labor force.

Our paper first confirms the non-negative impact of immigration on local labor workforce. Furthermore, we contribute to the ever expanding study on immigration's impacts on regional economy by applying GWPR method.

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APPENDIX A

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

From

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

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

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

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

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

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

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

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

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

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

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

$$-\frac{F_{pt-1}}{F_{pt-1}+N_{pt-1}}\left(\frac{N_{pt}-N_{pt-1}}{F_{pt-1}+N_{pt-1}}\right)$$

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

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

APPENDIX B

Table B. 1 Number of immigrant workers in all industries and in 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%