KEO Discussion Paper No. 174

Immigration, imports, and (im)mutable Japanese labor markets

Akira Sasahara, Yumin Sui, and Emily Taguchi

February 2023

KEO Discussion Paper No. 174

Immigration, imports, and (im)mutable Japanese labor markets*

Akira Sasahara† *Keio University*
Yumin Sui‡ *Keio University*
Emily Taguchi§ *University of Cologne*

February 2023

Abstract

This paper investigates the effects of globalization–measured by an increase in immigration and in imports from China–on labor market outcomes in Japan. We attempt to identify the causal links using a shift-share instrument based on previous settlement patterns of migrants for immigration shocks, and the one based on previous spatial allocation of sectoral employment for import shocks. The results suggest limited impact of these variables on wages, however, significant effects are found in the late 1990s, suggesting their interactions with Japan's Lost Decade.

Key Words: immigration, China trade shock, wages, Japan
JEL codes: F16, F22, F66

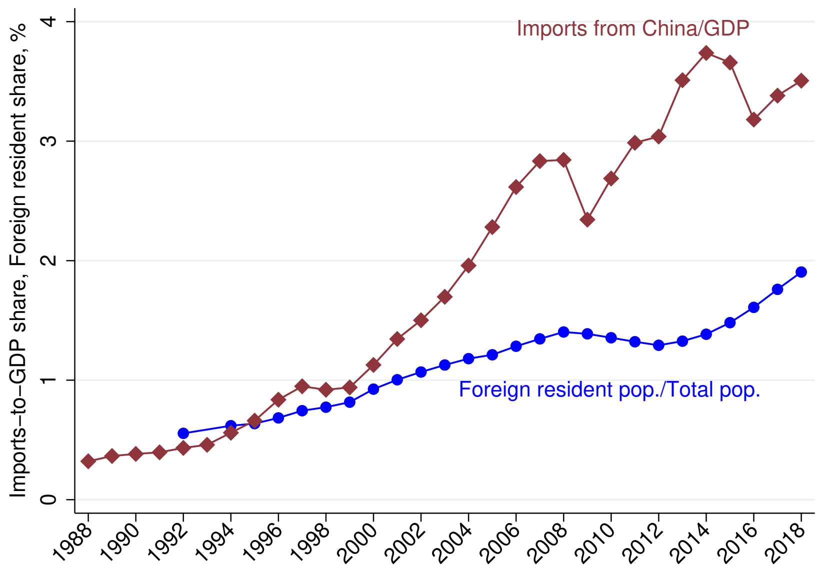
*The authors would like to thank Jaerim Choi, Masahiro Endoh, Jongkwan Lee, Lester Lusher, and Vasil Yasenov for helpful comments and insightful discussions. They are also grateful to feedback from advisors and fellow classmates at the Professional Career Program of Keio University. Akira Sasahara acknowledges financial support from the Japan Society of Promotion of Science KAKENHI under grant numbers 21H00713, 21K1329, and 22H00063. The authors acknowledge paid English language editing services by a private firm. All errors are the authors' responsibility.

†(Corresponding author) Faculty of Economics, Keio University. E-mail: sasahara@keio.jp
‡Faculty of Economics, Keio University. E-mail: suiyumin0617@keio.jp
§Department of Economics, University of Cologne. E-mail: etaguchi@smail.uni-koeln.de

1 Introduction

Globalization takes various forms, including an increase in the international flow of people and goods and services. Increasing globalization often leads to public concern. For example, a recent article shows that Japanese citizens hold greater opposition to refugees' settlements (Horiuchi and Ono, 2018), potentially reflecting their apprehensions about depressing wages and deteriorating public safety.[1] Previous studies have shown adverse labor market effects of imports from China (e.g., Autor et al., 2013). Japan is also exposed to these globalization shocks, as it experienced a 1.4 percentage points (hereafter pp) increase in foreign resident share and a 3.2 pp increase in imports from China as a share of GDP between the early 1990s and the late 2010s, as shown in Figure 1.

FIGURE 1: Foreign nationals living in Japan and imports from China



Note: The data on foreign nationals living in Japan come from the *Statistics on Foreign Residents* (*Zairyū Gaikokujin Tōkei*), the Ministry of Justice and the population data come from the Statistics Bureau of Japan. We exclude Permanent Special Residents (*Tokubetsu Eijūsha*) from the category of "foreign nationals." The import data come from UN Comtrade and the GDP data come from the *World Development Indicators*.

The goal of this study is to investigate the labor market effects of these changes using Japanese data and examine whether these public concerns are valid. To do so, we construct a panel dataset spanning nearly 30 years from 1989 to 2018, consisting of five stacked cross-sections. We then regress the wage growth rates on two globalization variables: (1) immigration and (2) imports from China, and a rich

[1] Nishikido (2019) shows that individuals in prefectures with higher unemployment rates tend to oppose immigration, suggesting that their concerns come from their perceptions that immigration may deteriorate local economic conditions. Okubo (2021) also notes that immigration is often seen as a source of downward pressure on wages, which may cause conflicts and crimes.

set of control variables. Further, we carefully deal with potential endogeneity by employing shift-share instruments, utilizing lagged spatial allocation of immigrants of each ethnic group to identify the effects of immigration shocks, and lagged spatial allocation of sectoral employment to identify the effects of import shocks.

We estimate a number of regressions to examine the effects of these shocks on wages by firm size, age group, sector, and period. We find that the effects are mostly statistically insignificant. However, statistically significant and negative effects on wages are indeed found in the 1995–2000 period, suggesting that globalization shocks adversely impacted the Japanese economy, which experienced lower productivity growth during what is known as Japan's Lost Decade (see, for example, Hayashi and Prescott, 2002).

There are several reasons for the insignificant effect. First, as documented by Genda et al. (2010), Japan has had rigid wages for institutional reasons, making these less sensitive to globalization shocks.[2] Second, the increase in the number of immigrants in Japan is still smaller than that in other developed countries. For example, according to the *World Development Indicators*, foreign population as a share of the total population increased by more than 10 pp between 1985 and 2015 in Singapore, Switzerland, Norway, and Spain. By contrast, the increase was only 0.9 pp in Japan in the same period. This suggests that the recent increase in immigrant inflow in Japan may not have been large enough to trigger noticeable labor market effects.

Third, the limited effects of immigration may be a product of its multiple offsetting effects. While an expansion of labor supply due to immigration leads to downward pressure on wages, it also increases consumer demand, which works to increase labor demand and in turn wages (e.g., Bodvarsson et al., 2008).[3] In addition, immigrants may not be a perfect substitute for Japanese natives and may have complementary and productivity-enhancing effects, as documented in the US context (e.g., Ottaviano and Peri, 2012; Peri, 2012) and the South Korean context (Kim et al., 2022).

Regarding the limited labor market effects of imports from China, existing studies document that while imported final goods from China have a negative effect on manufacturing employment in Japan, imported inputs from China have a positive effect (see Taniguchi, 2019; Kiyota et al., 2021; Kainuma and Saito, 2022; Choi et al., 2023). While we do not estimate the effects of final goods and inputs separately, we assume that the estimated null effects of imports from China are a combination of the two opposing effects.

[2] Genda et al. (2010) note that "the starting salaries for Japanese new graduates (conditional on educational background) have been downwardly rigid in Japan since the 1980s."

[3] For example, Bodvarsson et al. (2008) find a limited effect of immigration on wages in the Miami labor market in the 1980s. They argue that the limited effect is explained by an increase in consumer demand for services generated by immigrants.

Our paper contributes to two strands of literature. First, it contributes to the literature on the effects of immigration on wages. Some existing studies find negative effects (Borjas, 2003, the US; Dustmann et al., 2013, the UK; Edo, 2020, France; Malchow-Møller et al., 2012, Denmark) and others find null effects (Gandal et al., 2004, Israel; Bodvarsson et al., 2008, and Peri and Yasenov, 2019, the US) and positive effects (Kim et al., 2022, South Korea). In the context of the Japanese economy, Nakamura (2010) finds that workers in regions with more immigrants tend to receive higher wages using individual-level data.[4] Our paper differs from his because we use prefecture-level data and employ a shift-share instrument to identify causal effects. In addition, we find that immigration effects on wages are mostly null.

Second, we contribute to the literature on the effects of the China trade shock. In the US context, imports from China reduced manufacturing wages (Autor et al., 2013), but no such effect was observed in Germany (Dauth et al., 2014). Endoh (2018) finds, using establishment-level data on large firms in Japan, that import competition did not reduce the wages of low-skilled workers but increased the wages of college graduates. Endoh (2021) extends his analysis to cover smaller firms, with similar results. Our study differs from his because we use prefecture-level data, allowing for the inter-sectoral effects of import competition on non-manufacturing sectors within each local labor market.

The remainder of this paper is organized as follows. Section 2 outlines our regression model and identification strategy. Section 3 summarizes the data sources and provides an overview of key variables. Section 4 presents the regression results. Section 5 concludes. The Appendix presents additional analyses and details.

2 Empirical approach

2.1 Baseline regression model

We estimate regressions following the literature, including Edo (2020) and Autor et al. (2013). The baseline model is as follows:

$$\Delta \ln(wage_{i,t}) = \beta_t + \beta_1 \Delta mig_{i,t} + \beta_2 \Delta ipw_{i,t}^{CHN} + \mathbf{X}_{it}\boldsymbol{\beta}_3 + u_{i,t}, \tag{1}$$

where $\ln(wage_{i,t}) = 100 \times [\ln(wage_{i,t+5}) - \ln(wage_{i,t})]$, log changes in prefecture i's average hourly wage from year t to year $t{+}5$. The variable $wage_{i,t}$ is computed as the total annual payments (12×monthly payments + bonuses) divided by the total hours worked per year (12×monthly planned hours worked +

[4] Nakamura (2010) finds that immigration had a positive effect on wages of native workers through reallocation of native workers and capital across regions.

$12\times$monthly overtime hours worked).[5] Nominal hourly wages are deflated to the 2020 price level using prefectural CPIs.

This equation includes two key explanatory variables. First, $\Delta mig_{i,t}$ measures the size of immigration shocks and is defined as follows:

$$\Delta mig_{i,t} = \frac{MIG_{i,t+5} - MIG_{i,t}}{Pop_{i,t}/1000}, \tag{2}$$

where $MIG_{i,t}$ indicates the stock of foreign residents in Japan; and $Pop_{i,t}$ denotes the working age population (ages 15–65), including Japanese and foreign residents, measuring the size of each local labor market. The population variable is divided by 1,000. Thus, Δmig represents the change in migrant stock per 1,000 working age individuals from year t to year $t+5$.[6]

Our definition of "immigrants" is foreign nationals living in Japan, excluding diplomats and short-term visitors such as tourists and conference attendees. The original dataset considers Special Permanent Residents (*Tokubetsu Eijū Sha*, hereafter SPRs), individuals who were born in Japan and maintain their ancestry nationalities for historical reasons, as foreign residents. However, we exclude the SPR population when constructing our immigration variables because we attempt to capture *inflows* of immigrants during that period.[7] Although the denominator is the working age population, as we are interested in the overall effects of immigration including the channels through the goods market (e.g., an increase in demand for goods and services), foreign residents who are in education or training or dependents are also included in Δmig.[8] Another reason why the "immigrants who are not in the labor force" is included in the numerator is that only the overall number of immigrants–but not the number of "immigrants who are in the labor force"–is available at the prefecture-level for each ethnicity. As a result, we are unable to construct an appropriate shift-share instrument for an immigration variable using immigrants in the labor force only.

Second, $\Delta ipw^{CHN}_{i,t}$ measures the degree of import penetration from China, and it is defined as fol-

[5]These variables are obtained from the *Basic Survey of Wage Structure* by the Ministry of Health, Labour and Welfare of Japan. According to its website, each year, each firm reports the June monthly wage of the year and bonuses from last year. Therefore, the data on bonuses are taken from the next year's survey. The database covers firms with 10 or employees.

[6]The database does not provide us with migration data for 1989. Therefore, we use the migration data for 1988 and construct the variable as follows: $\Delta mig_{i,1989} = \left[MIG_{i,1994} - MIG_{i,1988} \times \frac{5}{6}\right] / \left[Pop_{i,1989}/1000\right]$. We take the same approach for one of the control variables, $\Delta \ln(Pop^{Native})$.

[7]The start year of the SPR data is 1992 because the Special Act on Immigration Control was enacted in 1991. We use the 1992 SPR population data to construct the 1989 immigration variables. In addition, there are two groups of Korean SPR population, the Republic of Korea (*Kankoku*) and Korea (*Chōsen*). The end year of the *Chōsen* SPR data is 2014 for an unknown reason. Therefore, we impute the number of total Korean SPRs in 2018 using the 2014 share of the two groups of SPRs, *Chōsen*/(*Kankoku*+*Chōsen*)$= 0.10$.

[8]Appendix H reruns regressions using different migration variables: (1) the one excluding migrants who are not in the labor force, and (2) the one using the total population in the denominator.

lows:

$$\Delta ipw_{i,t}^{CHN} = \sum_{s \in S} \frac{L_{i,s,t} \times \Delta im_{s,t}^{CHN \rightarrow JPN}}{\sum_{s' \in S} L_{i,s',t}} \text{ with } \Delta im_{s,t}^{CHN \rightarrow JPN} = \frac{\Delta IM_{s,t}^{CHN \rightarrow JPN}}{\sum_{i'} L_{i',s,t}}. \quad (3)$$

The variable $\Delta IM_{s,t}^{CHN \rightarrow JPN} = IM_{s,t+5}^{CHN \rightarrow JPN} - IM_{s,t}^{CHN \rightarrow JPN}$ denotes five-year changes in Japanese imports from China's sector s. The variable $L_{i,s,t}$ is the number of employees in sector s of prefecture i in year t. Thus, $\Delta im_{s,t}^{CHN \rightarrow JPN}$ represents Japanese imports from China per sector s's employee. Sectoral import penetration $\Delta im_{s,t}^{CHN \rightarrow JPN}$ is used to find the weighted average of sectoral import shocks where the weight is the sectoral employment $L_{i,s,t}$.[9] The set of sectors is indicated by S, which includes 63 manufacturing sectors, and non-manufacturing sectors.[10]

The period fixed effects are denoted by $\boldsymbol{\beta}_t$. Vector $\mathbf{X}_{it}$ includes two sets of control variables: (1) labor market controls, variables from the same group of workers as the dependent variable, and (2) macroeconomic variables. The labor market controls include (1) the log of beginning-of-the-period annual income, (2) the log of beginning-of-the-period average tenure, (3) the log of beginning-of-the-period average age, and (4) the beginning-of-the-period female share of that worker group. The macroeconomic controls include (1) log changes in native population, (2) beginning-of-the-period log of population density, (3) beginning-of-the-period male share, (4) beginning-of-the-period unemployment rate, (5) beginning-of-the-period urban population share, (6) beginning-of-the-period share of the 60+ age population, (7) beginning-of-the-period share of workers in labor unions, and (8) sectoral value-added shares.[11] The error term is indicated by $u_{i,t}$. All regressions are estimated using the initial populations as weights.

2.2 Instrumental variables for endogenous variables

The regression model suffers from endogeneity because immigrants' settlement patterns and imports from China are affected by local economic conditions, which may in turn affect the dependent variable, wages. To deal with the endogeneity of immigration, following previous studies (e.g., Card, 2009; Bianchi et al., 2012; and Peri, Shih, et al., 2015), we construct an instrument based on previous

[9]As sectoral employment data are not available from every year, the gap between the survey year of the employment data and year t differs across periods. When constructing the explanatory variable in equation (3), the sectoral employment data from 1991 is used for the 1989–1994 period, 1996 for the 1995–2000 period, 2001 for the 2001–2006 period, 2006 for the 2007-2012 period, and 2012 for the 2013–2018 period.

[10]See Appendix A for a list of 63 manufacturing sectors. We include non-manufacturing sectors in set G because we also analyze the effects on non-manufacturing wages.

[11]It includes 10 sectoral value-added shares from (1) agriculture, (2) mining, (3) manufacturing, (4) construction, (5) utility, (6) wholesale/retail, (7) finance, (8) real estate, (9) transportation, and (10) public sector. It excludes hospitality, information and telecommunication, education, healthcare and medical, and other unclassified service sectors.

immigrants' settlement patterns. Specifically, we use the following shift-share instrument:

$$\Delta mig_{i,t}^{Bartik} = \frac{\Delta \widehat{MIG}_{i,t}}{Pop_{i,t}/1000}, \tag{4}$$

where

$$\Delta \widehat{MIG}_{i,t} = \sum_{g \in G} \frac{MIG_{g,i,t-1}}{\sum_i MIG_{g,i,t-1}} \times (MIG_{g,t+5} - MIG_{g,t}),$$

indicates the number of immigrants predicted by (1) the share of ethnic group g's immigrants in prefecture i in a year before year t, $MIG_{g,i,t-1}/\sum_i MIG_{g,i,t-1}$,[12] and (2) the overall change in the number of ethnic group g's immigrants throughout Japan, $MIG_{g,t+5} - MIG_{g,t}$.[13] The set of origin economies is indicated by G, which includes 172 economies consistently available throughout the sample period.[14] We exclude all Korean SPRs when constructing $\Delta mig_{i,t}^{Bartik}$.[15]

To address the endogeneity of the import variable, following Autor et al. (2013), we use the instrument:

$$\Delta ipw_{i,t}^{OTH} = \sum_{s \in S} \frac{L_{i,s,t-5} \times \Delta im_{s,t}^{CHN \to OTH}}{\sum_{s' \in S} L_{i,s',t-5}} \quad \text{with} \quad \Delta im_{s,t}^{CHN \to OTH} = \frac{\Delta IM_{s,t}^{CHN \to OTH}}{\sum_{i'} L_{i',s,t}}, \tag{5}$$

where $\Delta IM_{s,t}^{CHN \to OTH}$ denotes the five-year changes in Chinese exports to eight developed countries: Australia, Canada, Switzerland, Denmark, Germany, Spain, Finland, and New Zealand.[16] The variable $\Delta IM_{s,t}^{CHN \to OTH}$ is meant to capture China's supply shocks, increasing Chinese exports to Japan. The weighted average of $\Delta im_{s,t}^{CHN \to OTH}$ is found using each prefecture's sectoral employment five years ago as the weight.[17]

The validity of shift-share instruments has been discussed in several studies (e.g., Adão et al., 2019; Goldsmith-Pinkham et al., 2020; Borusyak et al., 2022). According to them, for an estimate to be

[12] Most existing studies fix the year for the share part at a lagged year. For example, Edo (2020) uses share data from 1954 to analyze the effects in 1962–1976. Malchow-Møller et al. (2012) use share data from 1987 for the 1993–2004 period. Peri, Shih, et al. (2015) use share data from 1980 for the 1990–2010 period. These studies use share data from a 5-to-10 fixed lagged year when constructing their instruments. However, in this study, fixing the share data at the initial level (or using the share from every five years back) leads to low first-stage F-statistics probably because immigration to Japan is less strongly affected by previous settlement patterns relative to other countries. Therefore, our shift-share instrument for immigration shocks uses the share data from the previous year for each, following Bianchi et al. (2012).

[13] We use the migration data from 1988 to impute the five-year change for the 1989–1994 period, $(MIG_{g,1994} - MIG_{g,1988}) \times 5/6$, because the migration data from the year 1989 are not available.

[14] See Appendix B for a list of 172 origin economies.

[15] In the sample period, almost all SPRs, 99%, are of Korean descent. The SPR population data for other ethnic groups are not available consistently throughout the sample period. See Appendix C for the details about Korean SPRs.

[16] Autor et al. (2013) use Chinese exports to the United States, instead of Canada. However, UN Comtrade does not provide us with HS 92 data on Chinese exports to the US for 1989. Therefore, we replace the US with Canada when constructing the instrument shown in equation (5).

[17] As sectoral employment data are not available for every year, the number of lags slightly differ across periods. When constructing the instrument in equation (5), the sectoral employment data from 1986 is used for the 1989–1994 period, from 1991 for 1995–2000 period, 1996 for 2001–2006, 2001 for 2007–2012, and 2006 for 2013–2018.

consistent, one of the following two conditions must be satisfied: (1) the shares are uncorrelated with the error term controlling for covariates or, (2) the macroeconomic changes are uncorrelated with the error term controlling for covariates.[18] We believe that both the conditions are satisfied for several reasons. First, we introduce many control variables explaining the initial spatial distributions of immigrants and sectoral employment, which help reduce the correlation between each of the two globalization variables and the error term. Second, Chinese exports to eight *other* developed countries must be considered exogenous for Japan by construction. Third, national changes in the number of immigrants in each ethnic group must also be seen as exogenous because, for example, national immigration policies are absorbed by period dummies. Therefore, after the inclusion of all controls, both the shares and changes must be exogenous from each prefecture's viewpoint.

3 Data

3.1 Data sources and details

Our dataset comprised data from various sources. The data on the prefecture-level and origin-country-level numbers of foreign residents are obtained from the *Statistics on Foreign Residents in Japan* (*Zairyū Gaikokujin Tōkei*) of the Ministry of Justice, Japan. The import shock variables are constructed using trade data from the UN Comtrade database. The unit of trade value is the nominal USD. Therefore, we convert them into the JPY 2020 prices using the exchange rate from the Penn World Table 10.0 (Feenstra et al., 2015) and the CPI from the Statistics Bureau of Japan. We obtain employment data from the *Establishment and Enterprise Census of Japan* (*Jigyōsho Kigyō Tōkei Chōsa*) and the *Economic Census for Business Activity of Japan* (*Keizai Sensasu Katsudō Chōsa*).

The data on wages, work hours, and the number of employees come from the *Basic Survey on Wage Structure* (*Chingin Kozo Kihon Chōsa*) by the Ministry of Health, Labour, and Welfare. We obtain prefecture-level total population, population of the age 60+ group, urban population share, and population in the urban area with more than 4,000 people per square kilometer from the Japanese Census.[19] The population density is determined by dividing the total population by habitable area, which is obtained from the Geospatial Information Authority of Japan, Ministry of Land, Infrastructure, Transport, and Tourism. The prefecture-level unemployment rates come from the Japanese Census and the Labor Force Survey of the Statistical Bureau of Japan.[20] Data on the number of workers joining labor unions

[18] This summary comes from Lu et al. (2020).

[19] As the urban population share data are available every five years, the urban population data from 1985, 1990, 1995, 2000, 2005, and 2010 are used for the initial years of each sub-period, 1988, 1995, 2001, 2007, and 2013, respectively.

[20] Neither of the two sources singly provides us with the data for the entire period of 1989-2018. Therefore, we use the

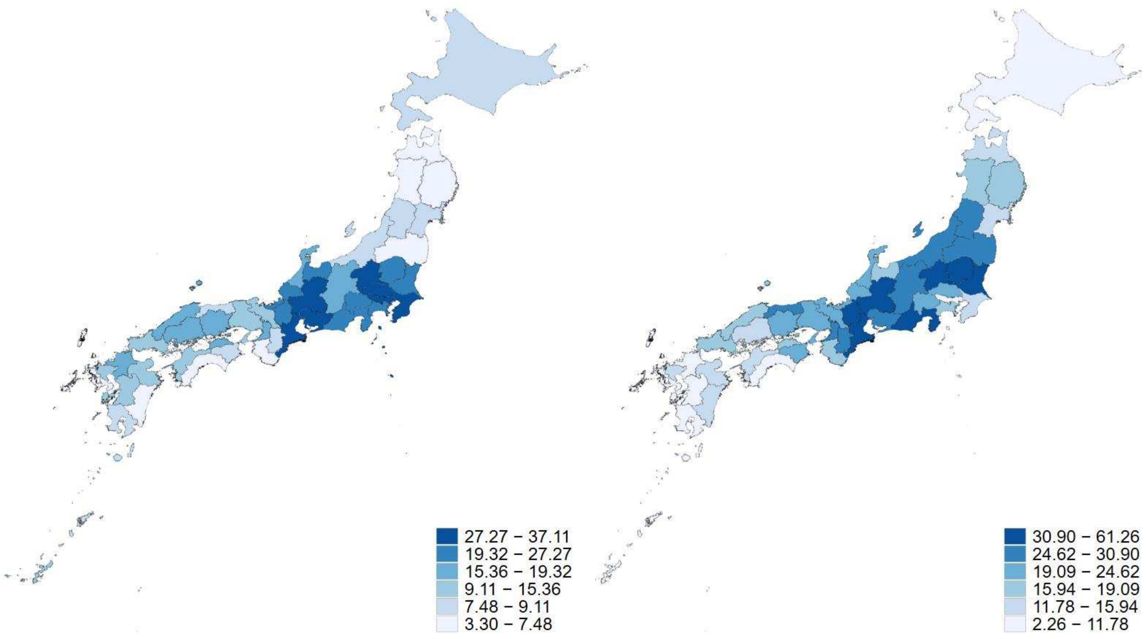
are obtained from the General Survey on Working Conditions. The prefecture-sector level value-added data are obtained from the Cabinet Office of Japan.

3.2 Descriptions of the data

This section describes the key variables. Panel A of Figure 2 displays the geographical distribution of migration shocks during the long-run period, 1989–2018. The displayed variable is $\sum_{t \in T} \Delta mig_{i,t}$ where $T = \{1989, 1995, 2001, 2007, 2013\}$ and $\Delta mig_{i,t}$ comes from equation (2). This shows that urban prefectures in the Kanto and Chubu areas are exposed to greater migration shocks, whereas rural prefectures are less exposed to such shocks. Panel B of Figure 2 shows the geographical distribution of $\sum_{t \in T} \Delta ipw_{i,t}^{CHN}$ during 1989–2018. The result indicates that the distribution differs from the one for the immigration variable. The correlation coefficient of the two variables, $Corr(\sum_{t \in T} \Delta mig_{i,t}, \sum_{t \in T} \Delta ipw_{i,t}^{CHN})$, is 0.46.[21] Table 1 summarizes the top five, median, and bottom five prefectures in terms of the size of $\sum_{t \in T} \Delta mig_{i,t}$ and $\sum_{t \in T} \Delta ipw_{i,t}^{CHN}$.

FIGURE 2: Japanese prefectures with immigration shocks and import shocks

Panel A: Immigration Panel B: Imports from China



Note: Panel A shows the sum of the migration shocks during 1989-2018, $\sum_{t \in T} \Delta mig_{i,t}$, where $T = \{1989, 1995, 2001, 2007, 2013\}$ and the unit is the change in the number of migrants per 1,000 population. Panel B shows the import penetration variables during 1989–2018, $\sum_{t \in T} \Delta ipw_{i,t}^{CHN}$, where the unit is 10,000 JPY.

Census unemployment rates for the years 1989, 1994, 2001, and 2006 and use the unemployment rates from the latter source for the years, 2007, 2012, 2013, and 2018. As a result, the unemployment rates from 1990, 1995, 2000, and 2005 are used for the years 1989, 1994, 2001, and 2006, respectively.

[21] See Table D2 in Appendix D for the correlation between the two variables in each period.

TABLE 1: Summary of immigration shocks and import shocks

	Migration shocks $\sum_{t \in T} \Delta mig_{i,t}$		Import shocks $\sum_{t \in T} \Delta ipw^{CHN}_{i,t}$	
1	Tokyo	37.1	Shiga	61.26
2	Aichi	36.4	Gunma	45.61
3	Gunma	34.0	Tochigi	35.30
4	Mie	31.8	Ibaraki	34.88
5	Gifu	30.1	Shizuoka	32.33
23	Kagawa	15.4	Okayama	19.49
24	Kyoto	15.4	Toyama	19.09
43	Kochi	6.7	Kochi	10.35
44	Iwate	5.8	Nagasaki	10.21
45	Wakayama	5.0	Kagoshima	9.90
46	Aomori	4.2	Hokkaido	5.59
47	Akita	3.3	Okinawa	2.26

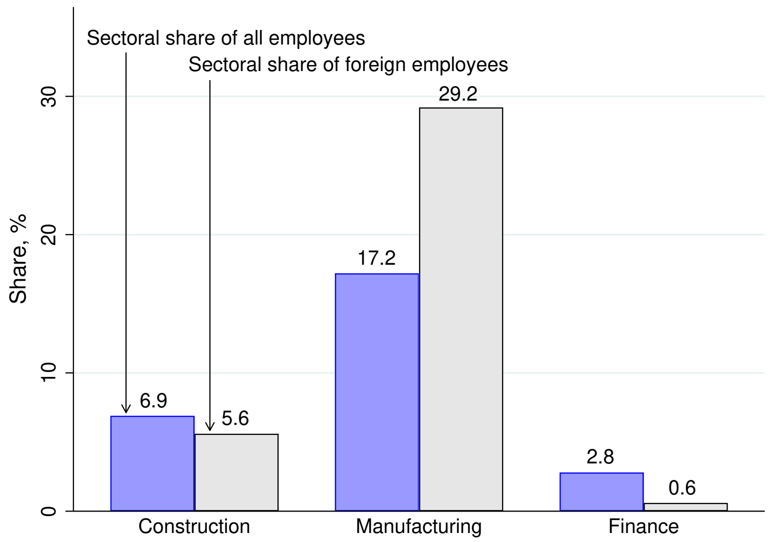
Note: The table shows (1) the sum of the migration shock variables during 1989–2018, $\sum_{t \in T} \Delta mig_{i,t}$; the unit is the change in the number of immigrants per 1,000 population, and (2) the import penetration shocks during 1989-2018, $\sum_{t \in T} \Delta ipw^{CHN}_{i,t}$; the unit is 10,000 JPY, for the top five prefectures, median prefectures, and bottom five prefectures, respectively.

The aggregate sectoral and cohort immigration patterns are described in Figure 3 and 4. The former shows the sectoral distribution of employees in the construction, manufacturing, and financial sectors. This shows a greater concentration and a smaller concentration of foreign employees than all employees in the manufacturing and finance sectors. It shows a greater concentration and a smaller concentration of foreign employees than all employees in the manufacturing and finance sectors, respectively. Figure 4 displays $Pop^{Immigrant}_{g,t}/Pop^{Total}_{g,t} \times 100$ where $Pop^{Immigrant}_{g,t}$ denotes the number of immigrants (stock) of age cohort g in year t, and $Pop^{Total}_{g,t}$ denotes the total population. This shows that the immigrant shares in younger cohorts increased more rapidly than in other cohorts, with a 5 pp increase in the 20–24 year cohort and a 4.2 pp increase in the 25–29 year cohort. A simple supply-demand analysis would imply a greater depressing effect on wages in younger cohorts in the manufacturing sector.

The average hourly manufacturing wages of all prefectures and the top five and bottom five prefectures in terms of each shock, listed in Table 1, are shown in Figure 5. [22] Part I is caused by migration shocks and Part II, by import shocks. Panels A and C show that manufacturing firms in prefectures with greater exposure to immigration and import shocks pay higher wages than those with lower exposure. However, Panels B and D show that prefectures with greater exposure to these shocks experienced slightly lower wage growth paths in the late 1990s, the early 2000s, and then after 2010. This suggests that immigration and imports from China exerted a slight downward pressure on wages. We take an

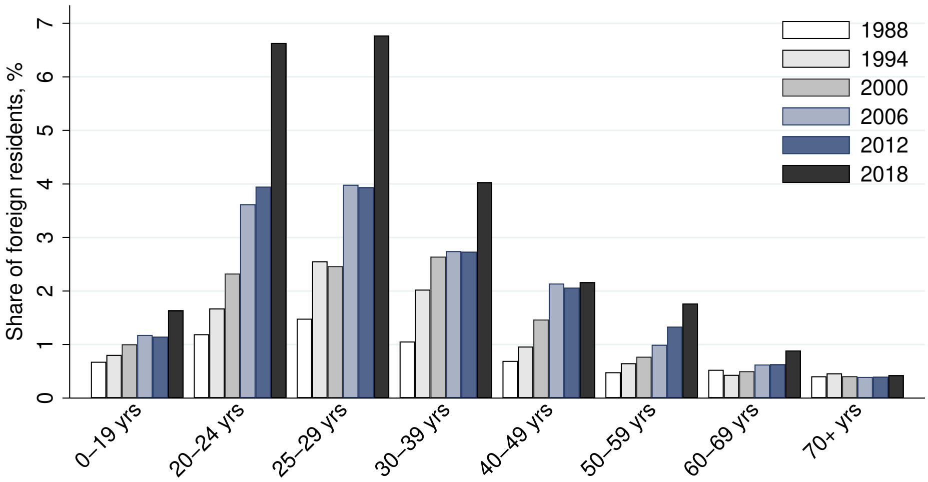
[22] We focus on manufacturing wages because (1) there is greater concentration of migrant workers in the manufacturing sector as shown in Figure 5, and (2) most imports from China are manufacturing goods.

FIGURE 3: Sectoral employment shares



Note: The data are from Figure II-2 of Japan Institute for Labour Policy and Training (2020), Chapter 2, p. 7.

FIGURE 4: Share of immigrant population by age cohort

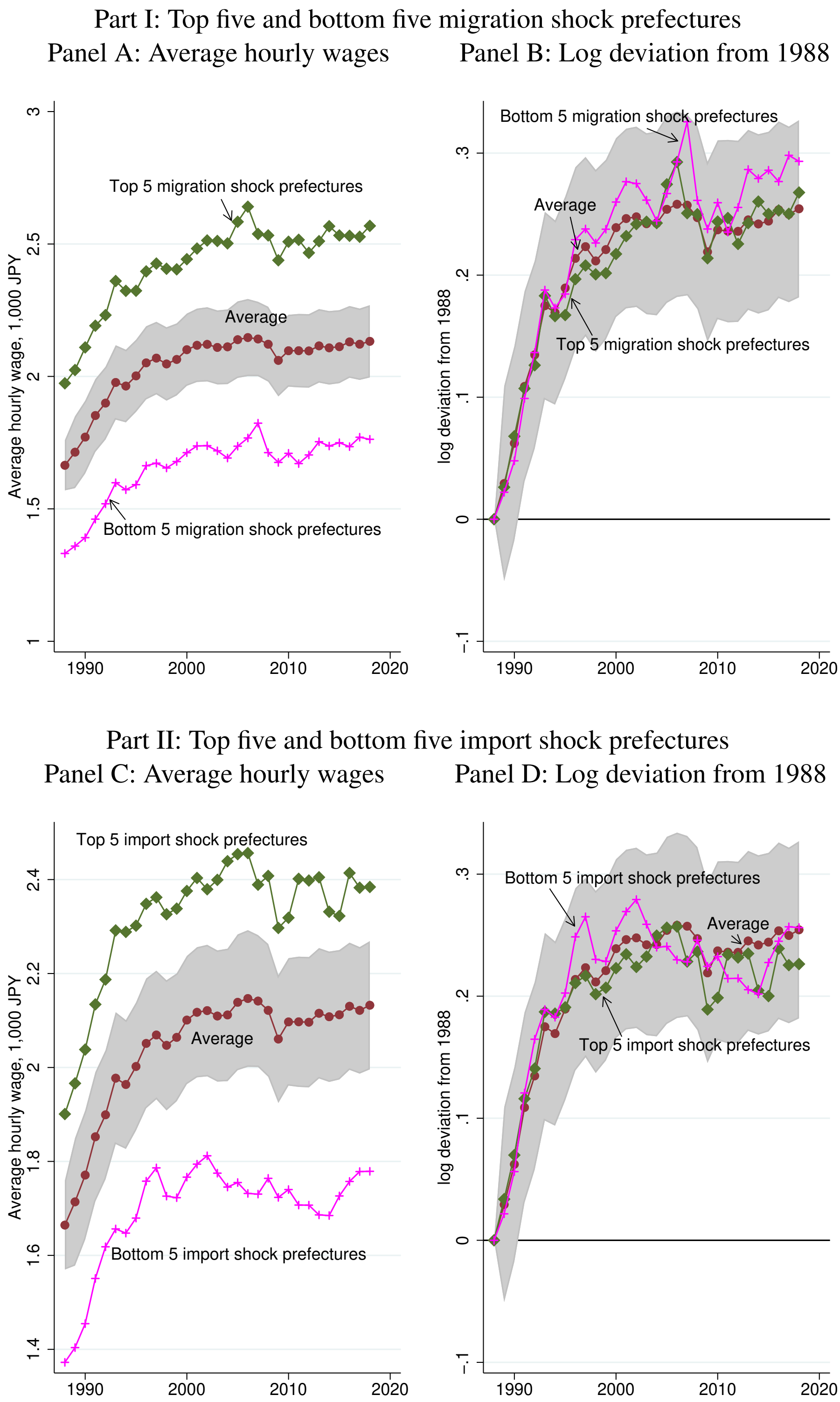


Note: Foreign resident population data come from *Statistics on Foreign Residents* (*Zairyū Gaikokujin Tōkei*) of the Ministry of Justice. Native Japanese population data are obtained from the Statistics Bureau of Japan.

econometric approach to examine whether these differences are statistically significantly different from zero.

The dataset is a stacked cross-section of 47 prefectures for five periods, 1989–1994, 1995–2000, 2001–2006, 2007–2012, and 2013–2018. Therefore, the baseline regressions include $47 \times 5 = 235$ observations. Table 2 presents summary statistics of the variables used in the baseline regressions. Appendix D presents additional details.

FIGURE 5: Average hourly manufacturing wages



Note: Panels A and C plot the coefficients from regressing the average hourly manufacturing wages (1,000 JPY in 2020 prices) on year dummies. Panels B and D use log of wages as the dependent variable. The bands indicate 95% confidence intervals. Each regression is based on (2018–1988+1)×47 = 1457 observations.

TABLE 2: Summary statistics of variables

	Mean	Std. dev.	Min	Max
Dependent variable				
Δ ln(annual wage) $\times$100	0.6	2.6	-6.5	6.9
Endogenous variable				
Δmig	3.2	4.0	-9.6	18.5
Δipw^{CHN}	4.2	4.7	-7.5	20.8
Instruments				
Δmig^{Bartik}	3.1	3.7	-8.1	22.1
Δipw^{OTH}	9.3	7.9	0.3	39.4
Labor market controls				
ln(initial annual income)	8.4	0.1	8.1	8.8
ln(initial tenure)	2.4	0.1	2.0	2.6
ln(initial age)	3.7	0.0	3.6	3.8
Initial female labor share	34.1	4.5	24.4	45.8
Macroeconomic controls				
Δ ln(native population) $\times$100	-0.8	2.2	-6.8	6.2
Initial ln(population)	14.5	0.7	13.3	16.4
Initial ln(population density)	2.3	0.7	0.9	4.6
Initial unemployment rate	3.8	1.1	1.7	10.3
Initial urban population share	49.9	18.6	23.4	98.2
Initial share of age 60+ population	26.3	6.2	12.1	40.7
Initial share of labor union workers	11.8	3.1	6.3	27.7
Initial value-added share, agriculture	2.5	1.9	0.0	9.9
Initial value-added share, mining	0.2	0.2	0.0	1.1
Initial value-added share, manufacturing	24.3	8.9	4.8	50.0
Initial value-added share, construction	7.9	2.8	3.5	15.1
Initial value-added share, utility	3.8	2.0	1.2	15.7
Initial value-added share, wholesale retail	11.8	3.3	5.3	21.8
Initial value-added share, finance	4.5	1.3	2.7	13.6
Initial value-added share, real estate	11.0	2.1	6.7	17.5
Initial value-added share, transportation	6.9	1.5	3.8	14.7
Initial value-added share, public	5.9	2.0	2.6	12.0

Note: The sample size is 235. The unit of Δmig and its instrument is the number of immigrants per 1,000. The unit of Δipw^{CHN} is 1,000 JPY (in 2020 prices) per employee and the unit of its instrument is 100 USD (in current prices) per employee. See the main text for the data sources.

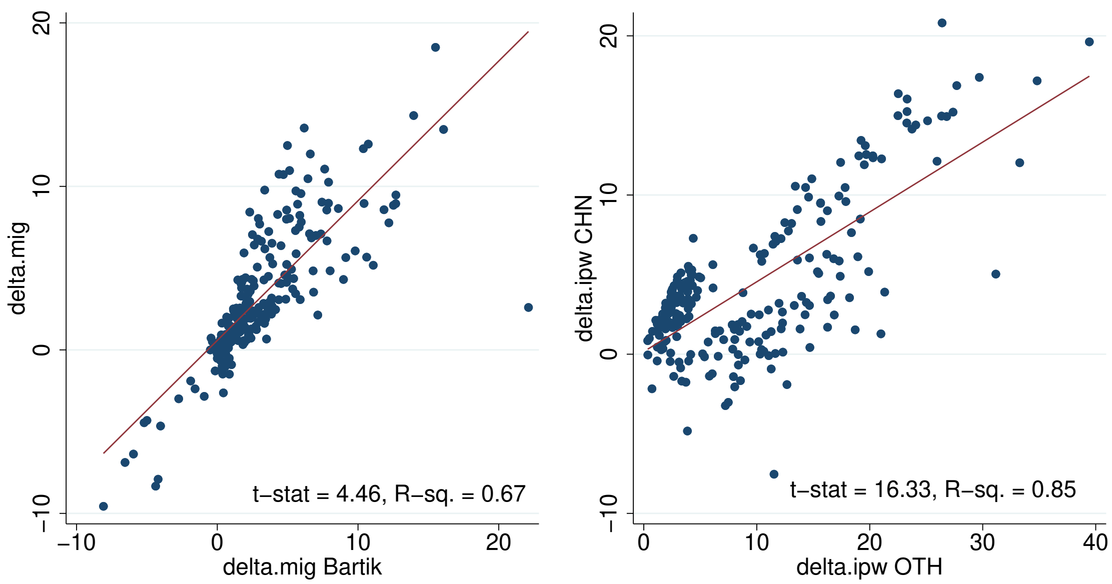
3.3 First-stage results

We confirm the validity of our instruments for identifying the causal effects of migration and import shocks. Figure 6 indicates that each of the two globalization variables is strongly correlated with the instrument. As our baseline regression model includes the two endogenous variables simultaneously and the control variables listed in Table 2, we run regressions with all explanatory variables.

Columns (1) and (3) of Table 3 separately regress each of the two endogenous variables on the corresponding instrument, leading to large first-stage F-statistics of 47.09 and 147.79 for Δmig and Δipw^{CHN}, respectively, well higher than the commonly used cutoff value of 10 (Staiger and Stock, 1997). Column (2) regresses Δmig on Δmig^{Bartik} and Δipw^{OTH}, showing that the majority of the variation in Δmig is explained by Δmig^{Bartik} rather than Δipw^{OTH} because the statistical significance of Δipw^{CHN} is weaker than that of Δmig^{Bartik} and the coefficient is negative. We observe a similar pattern in column (4) while regressing Δipw^{CHN} on Δmig^{Bartik} and Δipw^{OTH}: the statistical significance of Δmig^{Bartik} is weaker and the coefficient of that variable is negative.[23]

FIGURE 6: First-stage fits

Panel A: Immigration Panel B: Imports from China



Note: The sample size is 235 for each panel. The t-statistics and R-squared in the figure are based on regressions with period dummies and standard errors clustered by prefecture. One outlier is dropped from Panel A for illustrative purposes.

TABLE 3: First-stage regression results

	Δmig		Δipw^{CHN}	
	(1)	(2)	(3)	(4)
Δmig^{Bartik}	0.78***	0.81***		-0.16*
	(0.11)	(0.12)		(0.08)
Δipw^{OTH}		-0.09*	0.43***	0.45***
		(0.04)	(0.04)	(0.03)
R-squared	0.84	0.84	0.89	0.90
F-statistic for excluded instruments	47.09	24.26	147.79	110.07
p-value of F-statistic	0.000	0.000	0.000	0.000

Note: The sample size is 235 for each regression. All regressions include labor market controls and macroeconomic controls as regressors. All regressions are estimated using initial populations as weights. ***, **, and * indicate the statistical significance at the 1%, 5%, and 10% level, respectively. Standard errors clustered by prefecture are in parentheses.

[23]The negative coefficient of Δipw^{OTH} in column (2) is presumably because immigrants had expected the arrival of China trade shocks and chose locations less exposed to import shocks. The negative coefficient of Δmig^{Bartik} in column (4) is presumably because prefectures with greater share of immigrants tend to be service-oriented and less exposed to import shocks.

4 Estimation results

4.1 Baseline results

Panel A of Table 4 presents baseline results for the full sample.[24] The OLS results are presented in columns (1)–(3), indicating that neither migration shocks nor import shocks have a significant effect on wages, regardless of the set of control variables. To address the endogeneity of Δmig and Δipw^{CHN}, columns (4)–(6) employ the instrumental variable approach. These columns report the Cragg-Donald Wald F-statistics and Kleibergen-Paap rk Wald F-statistics testing for weak IVs. All columns in Panel A report sufficiently high F-statistics, indicating essentially no concern for weak IVs.

In column (4), the coefficient of Δmig is 0.12 and statistically significant at the 5% level. A comparison of (1) and (4) suggests that the OLS estimates have downward bias. If there is an omitted variable x with a positive coefficient β_x with $Corr(\Delta mig, x) < 0$, there will be a downward bias. One candidate for such omitted variables is, for example, regional growth policies targeting rural prefectures with fewer immigrants. The downward bias could also be caused by the omission of variable x with a negative coefficient β_x with $Corr(\Delta mig, x) > 0$. A candidate variable is, for example, faster growth of firms in urban prefectures, strengthening the market power of firms in the labor market and reducing the labor share in the same prefectures.

The effects of import shocks are insignificant in all columns in Panel A. A comparison of each set of OLS and IV estimates ((1) and (4), (2) and (5), and (3) and (6)) suggests that there is a slight upward bias with OLS. A possible cause is reverse causality: prefectures with higher wage growth increased their purchasing power and increased imports from China. This generates a positive correlation between $\Delta \ln(wage)$ and Δipw^{CHN}, leading to upward bias.

While the first-stage F-statistics in Panel A suggest that IVs are working properly, a critique may arise because the immigrant population decreased during the 2007–2012 period due to the 2008–09 Financial Crisis as shown in Figure 1. Jaeger et al. (2018) note that a shift-share instrument exploits the pull factors of immigration caused by previous settlements. Consequently, variations in the immigrant population may not be suitable for constructing a shift-share instrument when immigrants are pushed out of the country due to dire economic conditions. Therefore, Panel B of Table 4 reports the results after excluding the 2007–2012 period, which decreases the estimated coefficient velues. Nevertheless, our central result reported in column (6), using the IV approach with the greatest number of controls, indicates that neither immigration nor imports from China have a significant effect on wages.

[24] Appendix G reruns the same sets of regressions using the wage growth rates based on different definitions of wages. However, the results are essentially the same as the baseline results.

TABLE 4: Effects on the average hourly wage

Dep. var. = 100 × $[\ln(wage_{i,t+5}) - \ln(wage_{i,t})]$

	OLS			IV		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Full sample (235 obs.)						
Δmig	0.07	0.04	-0.02	0.12*	0.10	0.01
	(0.05)	(0.05)	(0.05)	(0.07)	(0.10)	(0.08)
Δipw^{CHN}	-0.02	0.02	0.01	-0.07	-0.01	-0.04
	(0.05)	(0.04)	(0.05)	(0.06)	(0.07)	(0.08)
R-squared	0.54	0.56	0.66	0.53	0.55	0.65
C.-D. Wald F-statistic				107.69	60.14	63.02
K.-P. rk Wald F-statistic				44.61	23.29	33.56
Panel B: Dropping the 2007-2012 period (188 obs.)						
Δmig	0.11**	0.07	-0.11**	0.20***	0.14	-0.14
	(0.06)	(0.05)	(0.04)	(0.07)	(0.11)	(0.20)
Δipw^{CHN}	-0.12*	-0.04	-0.12**	-0.16**	-0.07	-0.13
	(0.06)	(0.06)	(0.06)	(0.07)	(0.08)	(0.09)
R-squared	0.55	0.58	0.71	0.54	0.57	0.71
C.-D. Wald F-statistic				74.45	27.53	10.99
K.-P. rk Wald F-statistic				41.13	10.92	6.06
Period dummies	✓	✓	✓	✓	✓	✓
Labor market controls		✓	✓		✓	✓
Macroeconomic controls			✓			✓

Note: The sample size is 235 for each regression. See the note for Table 3 for numbers in parentheses and significance symbols. Standard errors are clustered by prefecture.

We find at least three reasons for the null wage effects of immigration. First, as Genda et al. (2010) suggest, wages are rigid in Japanese labor markets for institutional reasons. Second, the increase in the share of immigrants share in the total population is smaller in Japan compared with other developed countries. The immigrant share increased by 0.9 pp in Japan between 1985 and 2015, when there were several countries with over 10 pp increase. This may explain the limited effects of immigration on wages. Third, while an immigrant supply shock generates downward pressure on wages, it also increases consumer demand, leads to technology adoption, and has complementary effects on native workers, which work to increase wages (e.g., Peri and Yasenov, 2019; Bodvarsson et al., 2008). The combination of these conflicting wage effects may explain the null wage effects of immigration.

The null wage effects of imports from China are presumably caused by a combination of the negative effects of imported final goods and the positive effects of imported inputs documented in the context of imports from China on Japanese manufacturing employment (e.g., Taniguchi, 2019, and Choi et al., 2023). Endoh (2018) and Endoh (2021) also suggest worker-level heterogeneous wage reactions within each firm, which may be canceled out within each prefecture in our analysis.

4.2 Results by firm size, age cohort, and sector

The dependent variable used in the previous section is the average wage of all workers, ignoring the effects of endogenous changes in firm, sectoral characteristics, and worker characteristics. To take these aspects into consideration, this section estimates the regressions by firm size, age group, and sector. Previous studies have shown that import shocks affect wages differently, depending on firm size (e.g., Endoh, 2018 and Endoh, 2021). Therefore, we estimate the effects on wages by firm size: (1) small firms, with 10–99 employees, (2) medium-sized firms, with 100–999 employees, and (3) large firms, with 1000+ employees. In addition, three sectors are consistently available throughout the sample period: (1) construction, (2) manufacturing, and (3) finance and real estate (hereafter finance).[25]

Figure 7 reports the results. Circled dots on the left indicate coefficients estimated using the specification in column (6) of Table 4, with 235 observations, and diamond-shaped dots on the right indicate coefficients estimated by dropping the 2007–2012 period, with 188 observations. Bars in the figure illustrates first-stage Cragg-Donald Wald F-statistics, and show that our instruments are strong enough for all regressions. The results indicate that, in either sample, none of the immigration and import effects on wages are statistically significant.

Another important determinant of wages is workers' age (see Kawaguchi and Mori, 2019, for the Japanese context), and we run separate regressions by age cohort. The sample size for the group of employees aged 60+ in the finance sector is not large enough to run an IV model, and we are thus unable to estimate the coefficients.

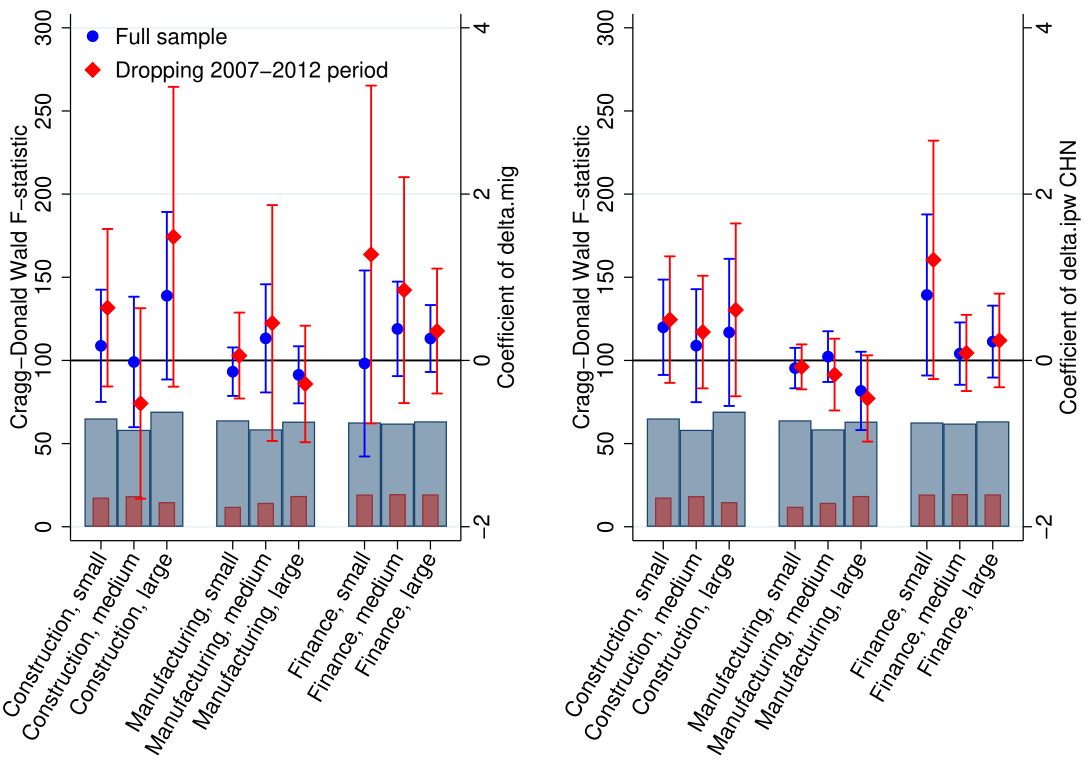
Panel A of Figure 8 summarizes the effects of immigration shocks, with circled dots and thicker bars indicating results with the full sample, and diamond-shaped dots and thinner bars indicating results without the 2007–2012 period. In the full sample, Δmig has no statistically significant effect on wages. The exclusion of the 2007–2012 period slightly increases the coefficients of Δmig, and the effects on the wages of the three groups–(1) the group of 40s in the manufacturing sector, (2) the group in their 20s in the finance sector, and (3) in their 30s in the finance sector–turn out to be positive and significant at least at the 10% level. These results are consistent with the sectoral allocation of foreign workers, as shown in Figure 3. As there is a smaller share of foreign workers in the finance sector, we expect a smaller downward pressure on wages in that sector. As a result, positive effects on wages through the goods market and complementary effects dominate the negative effects of labor supply expansion.

Panel B of Figure 8 shows coefficients of Δipw^{CHN} and the relevant statistics. There are no sizable differences between with and without the 2007–2012 period. Import shocks have no impact on wages

[25] The data from other sectors are not available for earlier years of our sample period, 1989–2018.

FIGURE 7: Results by sector and by firm size

Panel A: Immigration Panel B: Imports from China



Note: The figure shows coefficients of Δmig and Δipw^{CHN} in Panels A and B, respectively, where the dependent variable is $100 \times [\ln(wage_{i,t+5}) - \ln(wage_{i,t})]$. All the regressions employ the specification in column (6) of Table 4. The sample size is 235 for all point estimates. The dots represent point estimates. Bands represent 95 percent confidence intervals. The bars indicate the first-stage Cragg-Donald Wald F-statistic. The thicker bars come from the full sample regressions and the thinner bars come from the those without the 2007–2012 period.

in the construction sector. There are slight positive effects on wages of the group of the 40s in the manufacturing sector and the 20s in the finance sector. We assume that the positive effects of imported inputs are appear for these two groups of workers.

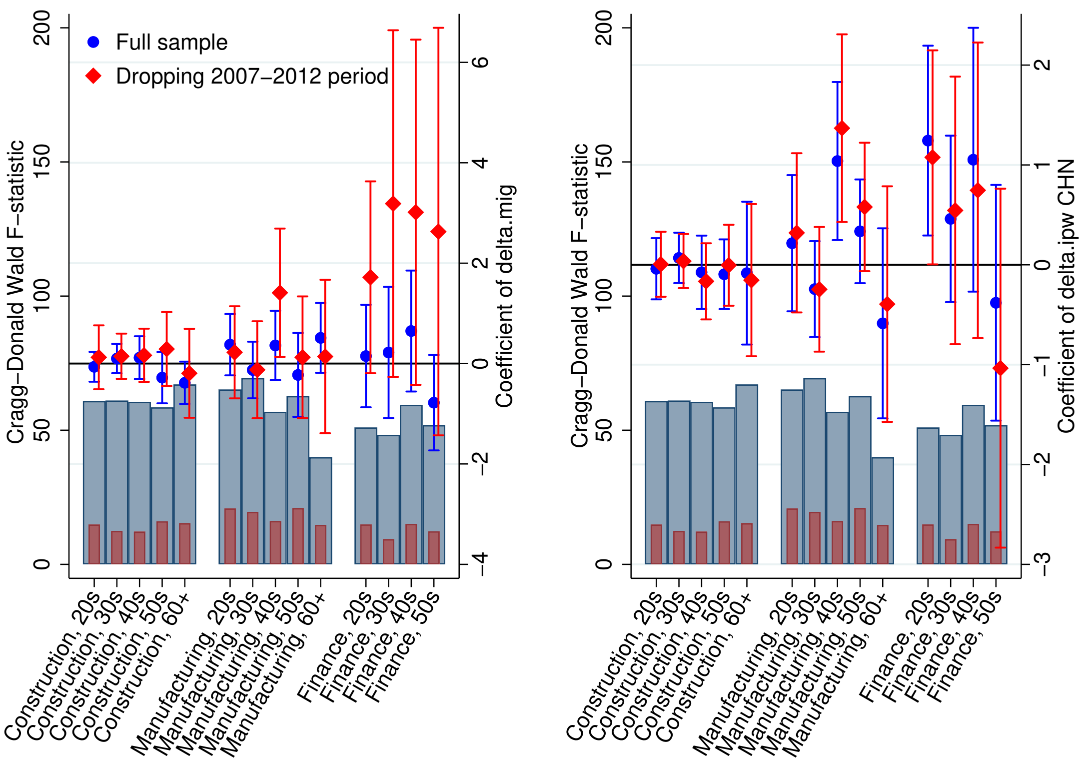
Figures E1 and E2 in Appendix E show the results for medium and large firms, respectively. Regarding the effects of immigration, statistically significant and negative effects are found in the "medium-sized firms in the manufacturing sector, age 60+ group" and significant positive effects are found from the "large firms in the manufacturing sector, age 30s group." Regarding the effects of imports from China, statistically significant and negative effects are found from the "medium-sized firms in the construction sector, age 60+ group" and "large firms in the construction sector, 40s."

As in the last analysis of this section, we run regressions period-by-period because there are potentially different effects of globalization shocks across periods. As there are three sectors, five age

FIGURE 8: Results by sector and by age cohort, small firms

Panel A: Immigration

Panel B: Imports from China



Note: The figure shows the results for small firms, defined as those with 10–99 employees. See the note in Figure 7.

categories, three firm sizes, and five periods, 225 combinations exist. Among the 225 samples, 194 include sufficiently large observations to run the IV model. Of the 194 coefficients of Δmig, 95 coefficients are negative. Since the validity of these coefficients relies on the p-value of the coefficient and the first-stage F-statistic, Panel A of Figure 9 plots the negative coefficients, taking the p-value on the vertical axis and the first-stage F-statistic on the horizontal axis.[26] As our shift-share instrument for Δmig with the 2007–2012 period is less likely to be valid, the results from that period are indicated by diamond-shaped dots. This shows that only 16 coefficients are in the range where the p-value is less than 0.05, and the first-stage F-statistic is greater than 10.[27] Panel B presents an enlarged view of this range. Out of the 16 coefficients in the panel, nine are from the 2007–2012 period, meaning that only seven negative coefficients are valid.

Table 5 lists the coefficients and other important statistics of the effects of Δmig shown in Panel B of Figure 9. All the coefficients come from the 1995–2000 period. The largest negative effect comes

[26] Figure E3 in Appendix E shows that same figure for positive coefficients of Δmig.

[27] Appendix F shows firs-stage regression results with different sets of controls to understand which control variables are related with lower first-stage F-statistics.

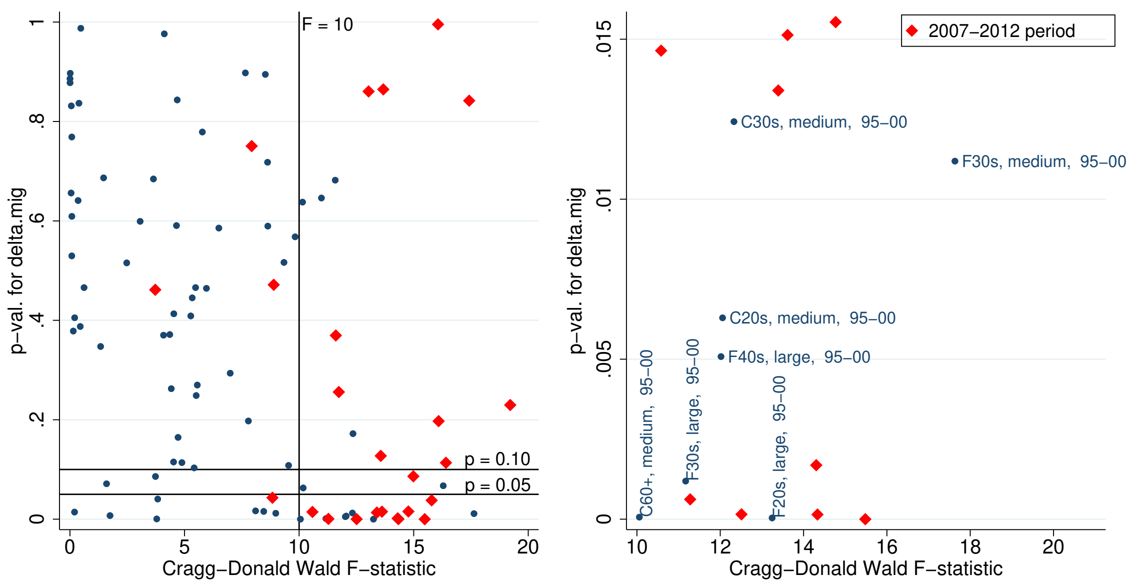
from the 60+ age category of medium-sized firms in the construction sector. An increase in the share of foreign employees by one per 1,000 population reduces the wage growth rate by 4.13 pp. According to the cross-sectional distribution of Δmig during the 1995–2000 period, moving from the 25th percentile prefecture to the 75th percentile prefecture raises the value of Δmig by 4.[28] Therefore, a move from the 25th to 75th leads to $4 \times 4.13 = 16.52$ pp increase in the wage growth rate, which is about three quarters of the 25th-to-75th percentile move of the wage growth rate of the same group of observations, 23.6.[29]

According to Table 5, the negative coefficients come from either the construction or the finance sector, and either medium-sized or large firms. We assume that these results are related to the recession during the 1990s, when productivity growth stagnated as documented by Hayashi and Prescott (2002). Additionally, Shimpo (2005) shows that output prices in the finance sector decreased and stagnant productivity growth contributed to the decline during the 1990s. Griffin and Odaki (2009) find that TFP growth rates were smaller for larger firms than for smaller firms during the 1988–1996 period. These findings suggest greater adverse shocks to larger firms in these sectors. These are probably why immigration's downward pressure on wages appears to be visible in these groups of observations.

FIGURE 9: Effects on hourly wages, negative coefficients of Δmig

Panel A: All coefficients

Panel B: p-value < 0.05 and F-stat. > 10



Note: The figure shows p-values and first-stage F-statistics from 194 regressions, three sectors (construction, manufacturing, and construction), five age categories (20s, 30s, 40s, 50s, and 60+), three firm sizes (small, medium, and large), and five periods (89–94, 95–00, 01–06, 07–12, and 13–18), with some missing coefficients due to insufficient observations.

[28] See Panel A of Table D1 in Appendix D.

[29] See Panel A of Table D3 in Appendix D.

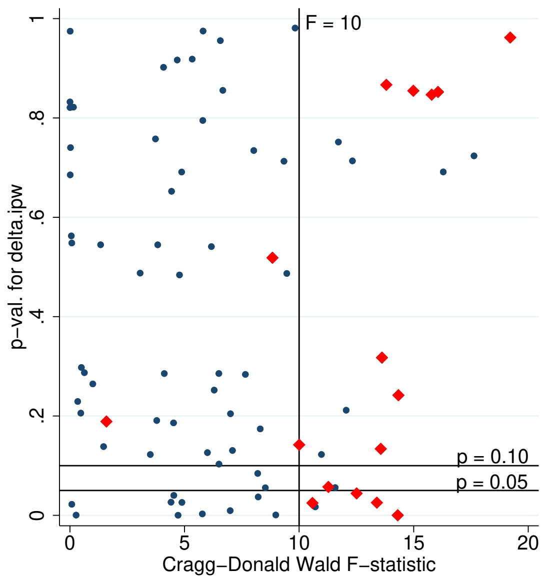
TABLE 5: Negative immigration effects on wages

Sector, age, firm size, period	Coef.	Std. err.	p-value	C.D. F-stat.	K.-P. F-stat.	Sample size
C60+, medium, 95-00	-4.13	1.03	0.000	10.06	14.06	41
F30s, large, 95-00	-1.96	0.60	0.001	11.17	14.34	47
F20s, large, 95-00	-1.20	0.29	0.000	13.25	15.59	47
F40s, large, 95-00	-0.90	0.32	0.005	12.02	10.24	47
C30s, medium, 95-00	-0.70	0.28	0.012	12.33	7.21	46
C20s, medium, 95-00	-0.63	0.23	0.006	12.06	15.24	46
F30s, medium, 95-00	-0.58	0.23	0.011	17.63	36.26	47

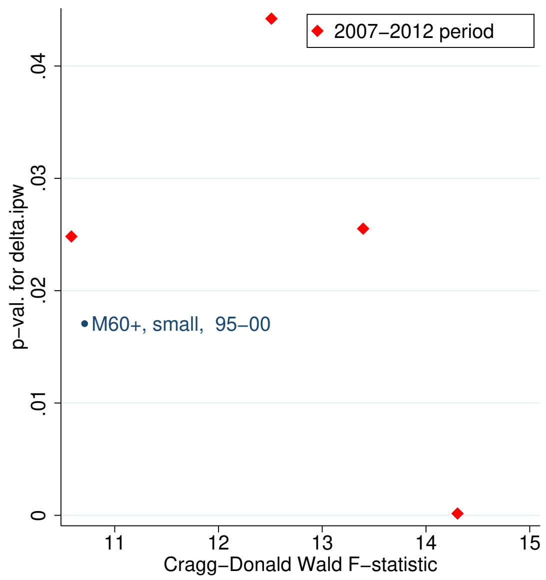
Note: The table summarizes the coefficients, standard errors, p-values, Cragg-Donald Wald F-statistics, and Kleibergen-Paap rk Wald F-statistics, shown in Panel B of Figure 9 with circled dots. C and F indicate the "construction" and "finance," respectively.

FIGURE 10: Effects on hourly wages, negative coefficients of Δipw^{CHN}

Panel A: All coefficients



Panel B: p-value < 0.05 and F-stat. > 10



Note: See the note for Figure 9.

Regarding the effects of import shocks, of the 194 coefficients of Δipw^{CHN}, 81 are negative. Figure 10 plots the 81 negative coefficients by taking the p-value and the first-stage F-statistic on the two axes.[30] It shows that, out of the 81 negative coefficients, only five are in the valid range. Out of the five, four are from the 2007–2012 period. As a result, only the estimate from the group of 60+ employees working in small firms in the manufacturing sector in the 1995–2000 period is estimated with a sufficiently high first-stage F-statistic and statistical significance. The coefficient of this group is -6.77, meaning that a one unit increase in Δipw^{CHN}; in other words, a 10,000 JPY increase in the exposure to imports from

[30]Figure E4 in Appendix E shows that same figure for positive coefficients of Δipw^{CHN}. Table E1 lists all the valid positive coefficients.

China, reduces the wage growth rate by 6.77 pp.

A move from the 25th percentile to the 75th percentile prefecture in the 1995-2000 period results in an increase in Δipw^{CHN} by 21,000 JPY, which reduces the wage growth rate by 14.22 pp.[31] This change in the wage growth rate is greater than the 25th-to-75th move in the wage growth rate of the same group of observations, 10.5.[32] The negative effect on older workers in the manufacturing sector is consistent with Autor et al. (2013)'s findings from the US.

TABLE 6: Effects on starting salaries

Dep. var. = $100 \times [\ln(salary_{i,t+5}) - \ln(salary_{i,t})]$

	Male high school (1)	Female high school (2)	Male college (3)	Female junior college (4)
Panel A: Full sample (235 obs.)				
Δmig	0.05	-0.06	0.07	0.21
	(0.07)	(0.10)	(0.07)	(0.14)
Δipw^{CHN}	0.02	0.03	0.16*	0.21
	(0.09)	(0.14)	(0.08)	(0.15)
R-squared	0.49	0.43	0.49	0.46
C.-D. Wald F-statistic	57.77	58.79	61.92	64.04
K.-P. rk Wald F-statistic	30.50	34.46	29.84	32.40
Panel B: Dropping the 2007-2012 period (188 obs.)				
Δmig	-0.11	-0.11	0.16	0.42
	(0.13)	(0.24)	(0.19)	(0.27)
Δipw^{CHN}	0.01	-0.05	0.11	0.25
	(0.11)	(0.16)	(0.10)	(0.17)
R-squared	0.52	0.48	0.54	0.50
C.-D. Wald F-statistic	16.68	17.16	17.67	18.02
K.-P. rk Wald F-statistic	6.81	6.92	7.07	7.35

Note: The sample size is 235 for each regression. All regressions include macroeconomic variables and year dummies as controls. In addition, the share of female workers for the 20–24 age cohort is added as controls. All regressions are estimated using initial populations as weights. Standard errors clustered by prefecture are in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively.

4.3 Effects on starting salaries

We acknowledge that the individuals used to compute the average wages may differ across periods. To fix the characteristics of workers in each period, we use the data on average starting monthly salaries of (1) male high school graduates, (2) female high school graduates, (3) male college graduates, and (4) female junior college graduates, in all sectors.[33] These groups may compete more directly with new immigrants. Our regressions here include macroeconomic control variables, year dummies, and the share

[31] See Panel B of Table D1 in Appendix D.

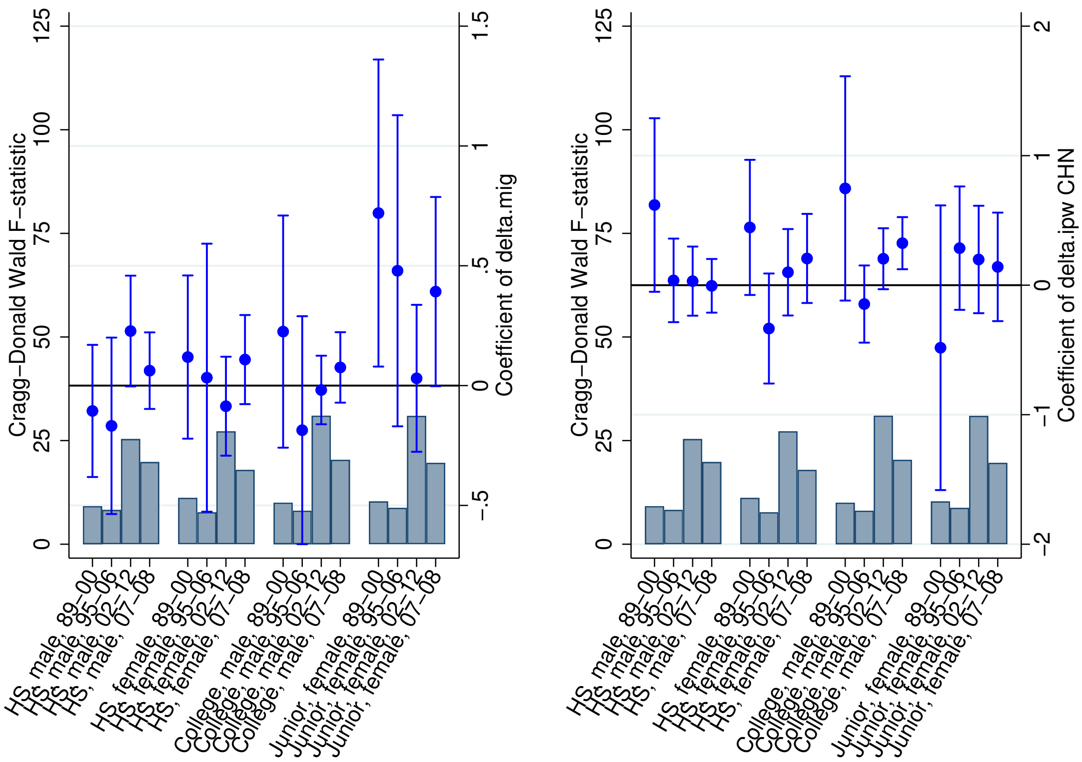
[32] See Panel B of Table D3 in Appendix D.

[33] The data on starting salaries of female college graduates are not available for the entire period of 1989–2018. The 'junior college' category includes 'junior college (tanki daigaku)' and 'higher engineering school (koto senmon gakko).'

of female workers in the 20–24 age cohort as controls to closely match the specification in the previous section.

FIGURE 11: Effects on starting salaries by period, 94 obs. each

Panel A: Immigration Panel B: Imports from China



Note: The dependent variable is $100 \times [\ln(salary_{i,t+5}) - \ln(salary_{i,t})]$. All regressions include marcroeconomic controls, year dummies, and the share of female workers in the age 20–24 cohort. The sample size for each regression is 94 unless there are some missing observations. See the note in Figure 7 also.

Panel A of Table 6 reports the results for the full sample, showing that immigration shocks have no significant effects on the starting salaries of all four education groups. However, import shocks have a significant positive effect on wages of male college graduates. A one unit increase in Δipw^{CHN}–i.e., a 10,000 JPY increase in exposure to import shocks–raises the wage growth rate of that category by 0.16 pp. The median value of Δipw^{CHN} is 2.49, which would lead to an increase in the wage growth rate by 0.42 pp, or three times higher than the median wage growth of male college graduates, 0.14. The positive effects on male college graduates are consistent with Endoh (2018), who reports that import competition raised wages for college graduates using individual-level data. Panel B shows the results without the 2007-2012 period, which indicate that neither immigration shocks nor import shocks have a significant effect on wages.

Figure 11 reports results from each of the two stacked cross-sections, with the effects of immigration shocks in Panel A and those of import shocks in Panel B. We use two stacked cross-sections because regressions with one cross-section in each period lead to low first-stage F-statistics.[34] It shows that negative coefficients are entirely statistically significant. Further, greater coefficients (in absolute value) tend to be associated with lower first-stage F-statistics, making the confidence intervals wider. Overall, it is difficult to conclude that immigration and imports affected average starting salaries.

5 Concluding remarks

We have analyzed the labor market effects of globalization–(1) immigration and (2) imports from China–in the context of the Japanese economy using data from 1989 to 2018 in an attempt to estimate the causal effects of these shocks by using shift-share instruments. Our results suggest that neither immigration nor import shocks are the primary determinants of wage growth paths for most worker groups. We find statistically significant and negative effects on wages for only a limited number of groups, and these negative effects are found entirely during the 1995–2000 period, that is, during Japan's Lost Decade.

The limited labor market effects of globalization may be because the Japanese economy has rigid labor markets, making wage structures less flexible, and immigration shocks have been relatively small compared with other developed countries. In addition, globalization has multiple channels through which it affects labor markets. While immigration exerts downward pressure on wages through an expanded labor supply, it also increases consumption demands and stimulates the economy. Although imported final goods have a pro-competitive effect, imported inputs have a complementary effect on production. The identification of the effects of each channel is left to future research. Nevertheless, we hope that our analysis provides us with important insights and helps us understand the interactions between labor markets and globalization.

References

Adão, Rodrigo, Michal Kolesàr, and Eduardo Morales (2019). "Shift-share designs: theory and inference". In: *Quarterly Journal of Economics* 134.4, pp. 1949–2010.

[34] Figure E5 in Appendix E reports results from each one of the stacked cross-sections, each of which consists of 47 observations; the result is one of the following: (1) the effects on starting salaries are essentially zero or (2) first-stage F-statistics are low.

Autor, David H., David Dorn, and Gordon H. Hanson (2013). “The China syndrome: local labor market effects of import competition in the United States”. In: *American Economic Review* 103.6, pp. 2121–2168.

Bianchi, Milo, Paolo Buonanno, and Paolo Pinotti (2012). “Do immigrants cause crime?” In: *Journal of the European Economic Association* 10.6, pp. 1318–1347.

Bodvarsson, Örn B., Hendrik F. Van den Berg, and Joshua J. Lewer (2008). “Measuring immigration’s effects on labor demand: a reexamination of the Mariel Boatlift”. In: *Labour Economics* 15.4, pp. 560–574.

Borjas, George J. (2003). “The labor demand curve is downward sloping: reexamining the impact of immigration on the labor market”. In: *Quarterly Journal of Economics* 118.4, pp. 1335–1374.

Borusyak, Kirill, Peter Hull, and Xavier Jaravel (2022). “Quasi-experimental shift-share research designs”. In: *Review of Economic Studies* 89.1, pp. 181–213.

Card, David (2009). “Immigration and inequality”. In: *American Economic Review Papers and Proceedings* 99.2, pp. 1–21.

Choi, Jaerim, Masahiro Endoh, and Akira Sasahara (2023). “The China shock and supply chains: when rising imports raise exports”. Unpublished manuscript, University of Hawai‘i at Manoa and Keio University.

Dauth, Wolfgang, Sebastian Findeisen, and Jens Suedekum (2014). “The rise of the East and the Far East: German labor markets and trade integration”. In: *Journal of the European Economic Association* 12.6, pp. 1643–1675.

Dustmann, Christian, Tommaso Frattini, and Ian P. Preston (2013). “The effect of immigration along the distribution of wages”. In: *Review of Economic Studies* 80.1, pp. 145–173.

Edo, Anthony (2020). “The impact of immigration on wage dynamics: evidence from the Algerian independence war”. In: *Journal of the European Economic Association* 18.6, pp. 3210–3260.

Endoh, Masahiro (2018). “The effect of import competition on wages in the Japanese manufacturing sector”. In: *Asian Economic Papers* 17.1, pp. 46–67.

— (2021). “The effect of import competition on labor income inequality through firm and worker heterogeneity in the Japanese manufacturing sector”. In: *Japan and the World Economy* 59.September, p. 101076.

Feenstra, Robert C., Robert Inklaar, and Marcel P. Timmer (2015). “The next generation of the Penn World Table”. In: *American Economic Review* 105.10, pp. 3150–3182.

Gandal, Neil, Gordon H. Hanson, and Matthew J. Slaughter (2004). “Technology, trade, and adjustment to immigration in Israel”. In: *European Economic Review* 48.2, pp. 403–428.

Genda, Yuji, Ayako Kondo, and Souichi Ohta (2010). “Long-term effects of a recession at labor market entry in Japan and the United States”. In: *Journal of Human Resources* 45.1, pp. 157–196.

Goldsmith-Pinkham, Paul, Isaac Sorkin, and Henry Swift (2020). “Bartik instruments: what, when, why, and how”. In: *American Economic Review* 110.8, pp. 2586–2624.

Griffin, Naomi N. and Kazuhiko Odaki (2009). “Reallocation and productivity growth in Japan: revisiting the lost decade of the 1990s”. In: *Journal of Productivity Analysis* 31, pp. 125–136.

Hayashi, Fumio and Edward C. Prescott (2002). “The 1990s in Japan: a lost decade”. In: *Review of Economic Dynamics* 5.1, pp. 206–235.

Horiuchi, Yusaku and Yoshikuni Ono (2018). “Public opposition to refugee resettlement: the case of Japan”. RIETI Discussion Paper Series 18-E-050.

Jaeger, David A., Joakim Ruist, and Jan Stuhler (2018). “Shift-share instruments and the impact of immigration”. NBER Working Paper No. 24285.

Japan Institute for Labour Policy and Training (2020). “An analysis on the employment situation of foreign workers (Gaikoku jin rōdō sha no koyō jyōkyō ni kansuru bunseki)”. JILPT Shiryō Series, No. 235, December 2022. Available at https://www.jil.go.jp/institute/siryo/2020/documents/235.pdf.

Kainuma, Shuhei and Yukiko U. Saito (2022). “China’s impact on regional employment: propagation through supply chains and co-agglomeration patterns”. In: *The World Economy* 45.11, pp. 3559–3601.

Kawaguchi, Daiji and Hiroaki Mori (2019). “The labor market in Japan, 2000–2018”. In: *IZA World of Labor* 385v2.

Kim, Hyejin, Jongkwan Lee, and Giovanni Peri (2022). “Do low-skilled immigrants improve native productivity but worsen local amenities? learning from the South Korean experience”. NBER Working Paper No. 30464.

Kiyota, Kozo, Sawako Maruyama, and Mina Taniguchi (2021). “The China syndrome: a cross-country evidence”. In: *The World Economy* 44.9, pp. 2758–2792.

Lu, Yi, Yoichi Sugita, and Lianming Zhu (2020). “Wage markdowns and FDI liberalization”. Unpublished manuscript, Tsinghua University, Hitotsubashi University, and Osaka University.

Malchow-Møller, Nikolaj, Jakob R. Munch, and Jan Rose Skaksen (2012). “Do immigrants affect firm-specific wages?” In: *Scandinavian Journal of Economics* 114.4, pp. 1267–1295.

Nakamura, Jiro (2010). “Impacts of international migration on the labor market in Japan”. In: *Japan Labor Review* 7.3, pp. 68–85.

Nishikido, Momoko (2019). “Welcoming change? an individual- and prefecture-level analysis of public opinion towards immigration in Japan”. Master’s Programme in Economic Growth, Population, and Development, Lund University.

Okubo, Toshihiro (2021). “Public preferences on immigration in Japan”. In: *Japan and the World Economy* 58.1, p. 101073.

Ottaviano, I. P. Gianmarco and Giovanni Peri (2012). “Rethinking the effect of immigration on wages”. In: *Journal of European Economic Association* 10.1, pp. 152–197.

Peri, Giovanni (2012). “The effect of immigration on productivity: evidence from U.S. states”. In: *Review of Economics and Statistics* 94.1, pp. 348–358.

Peri, Giovanni, Kevin Shih, and Chad Sparber (2015). “STEM workers, H-1B visas, and productivity in US cities”. In: *Journal of Labor Economics* 33.S1 Part 2, S225–S255.

Peri, Giovanni and Vasil I. Yasenov (2019). “The labor market effects of a refugee wave: synthetic control method meets the Mariel boatlift”. In: *Journal of Human Resources* 54.2, pp. 267–309.

Shimpo, Kazushige (2005). “Interindustry effects of productivity growth in Japan: 1960–2000”. In: *Journal of the Japanese and International Economies* 19.4, pp. 568–585.

Staiger, Douglas and James H. Stock (1997). “Instrumental variables regression with weak instruments”. In: *Econometrica* 65.3, pp. 557–586.

Taniguchi, Mina (2019). “The effect of an increase in imports from China on local labor markets in Japan”. In: *Journal of the Japanese and International Economies* 51.March, pp. 1–18.

Appendix

A List of manufacturing sectors

TABLE A1: Sectors used when constructing import shock variables

No.	Description	No.	Description
1	Live stock food products	33	Nonferrous metals
2	Seafood products	34	Tin, aluminium, and other metals
3	Vegetable, fruits, agricultural products	35	Hardware
4	Beverages (non alcoholic)	36	Air conditioning apparatus
5	Alcoholic drinks	37	Architectural metal products
6	Teas and coffees	38	Bolts, nuts, and rivets
7	Fertilizers	39	Engines and turbines motors
8	Tobaccos	40	Industrial machine
9	Textiles	41	Agricultural machinery
10	Wooden products and construction materials	42	Construction and mining machinery
11	Paper and pulp	43	Textile machinery
12	Chemical fertilizers	44	Office machinery
13	Inorganic chemicals	45	Electrical measuring instrument
14	Organic chemicals	46	Medical apparatus and instruments
15	Fats and oils processed products	47	Optical instruments
16	Medical products	48	Communication equipment
17	Other chemical products	49	Industrial electrical machinery
18	Refined oils and coke	50	Consumer electrical machinery
19	Paving material	51	Electric lighting fixtures
20	Plastic products	52	Autos and their related products
21	Tires and robber products	53	Rail cars and their related products
22	Leather and fur	54	Vessels and their related products
23	Bags	55	Aircrafts and their related products
24	Glass	56	Other transportation equipment
25	Cement	57	Ornaments
26	Clay for construction	58	Watches and clocks
27	Ceramics	59	Musical instruments and records
28	Refractories	60	Toys and sporting goods
29	Carbon and graphite	61	Office supplies and equipment
30	Abrasive	62	Weapons
31	Masonry materials	63	Miscellaneous
32	Steel		

B List of 172 origin economies for the migration variables

Afghanistan, Albania, Algeria, Andorra, Angola, Antigua and Barbuda, Argentina, Australia, Austria, Bahamas, Bahrain, Bangladesh, Barbados, Belgium, Belize, Benin, Bhutan, Bolivia, Botswana, Brazil, Brunei Darussalam, Bulgaria, Burkina Faso, Burundi, Cambodia, Cameroon, Canada, Cape Verde, Central African Republic, Chad, Chile, China, Colombia, Comoros, Dem. Rep. Congo, Rep. Congo, Costa Rica, Cote d'Ivoire, Cuba, Cyprus, Czech Republic and Slovakia, Denmark, Djibouti, Dominica, Dominican Republic, Ecuador, Arab Rep. Egypt, El Salvador, Equatorial Guinea, Eswatini, Ethiopia and Eritrea, Fiji, Finland, Former Soviet Union nations, Former Yugoslavian nations, France, Gabon, The Gambia, Germany, Ghana, Greece, Grenada, Guatemala, Guinea, Guinea-Bissau, Guyana, Haiti, Honduras, Hungary, Iceland, India, Indonesia and Timor-Leste, Islamic Rep. Iran, Iraq, Ireland, Israel, Italy, Jamaica, Jordan, Kenya, Kiribati, Rep. of Korea, Kuwait, Lao PDR, Lebanon, Lesotho, Liberia, Libya, Liechtenstein, Luxembourg, Madagascar, Malawi, Malaysia, Maldives, Mali, Malta, Marshall Islands, Mauritania, Mauritius, Mexico, Fed. Sts. of Micronesia, Monaco, Mongolia, Morocco, Mozambique, Myanmar, Namibia, Nauru, Nepal, the Netherlands, New Zealand, Nicaragua, Niger, Nigeria, Norway, Oman, Pakistan, Palau, Panama, Papua New Guinea, Paraguay, Peru, the Philippines, Poland, Portugal, Qatar, Romania, Rwanda, Samoa, San Marino, Sao Tome and Principe, Saudi Arabia, Senegal, Seychelles, Sierra Leone, Singapore, Slovak Republic, Solomon Islands, Somalia, South Africa, South Sudan, Spain, Sri Lanka, St. Kitts and Nevis, St. Lucia, St. Vincent and the Grenadines, Sudan, Suriname, Sweden, Switzerland, Syrian Arab Republic, Taiwan, Tanzania, Thailand, Togo, Tonga, Trinidad and Tobago, Tunisia, Turkey, Tuvalu, Uganda, United Arab Emirates, the United Kingdom, the United States, Uruguay, Vanuatu, RB Venezuela, Vietnam, West Bank and Gaza, Rep. of Yemen, Zambia, and Zimbabwe

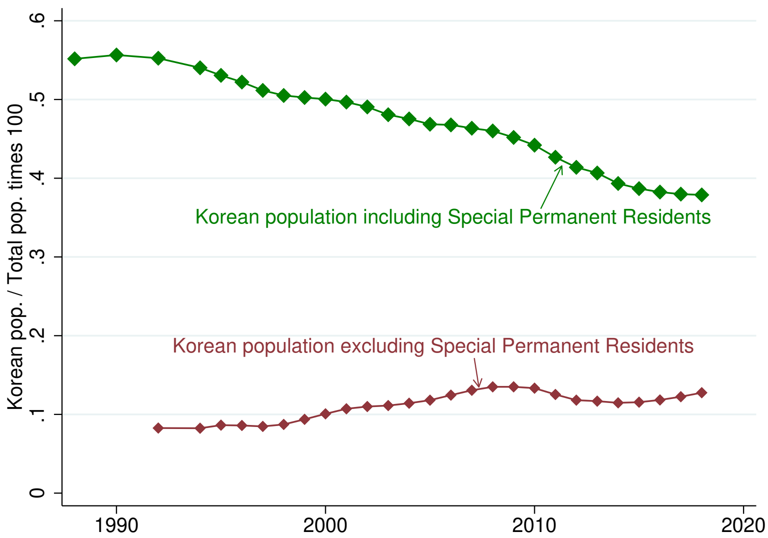
Country borders change over time. As a result, we have the following sets of economies: (1) Indonesia and Timor-Leste; (2) Czech Republic and Slovakia; (3) Ethiopia and Eritrea; (4) Former Yugoslavia nations including Croatia, Bosnia-Herzegovina; Kosovo, Montenegro, North Macedonia, Serbia, Serbia and Montenegro, and Slovenia; and (5) Former Soviet Union nations including Armenia, Azerbaijan, Belarus, Estonia, Georgia, Kazakhstan, Kyrgyzstan, Latvia, Lithuania, Moldova, Russia, Tajikistan, Turkmenistan, Ukraine, and Uzbekistan.

C Korean descents

This section describes the data on Special Permanent Residents (hereafter SPRs). The data from the *Statistics on Foreign Residents* show that 99% of SPRs are of Korean descent. Therefore, we focus on the data from Korean SPRs. The Special Act on Immigration Control was enacted in 1991 and the start year of the SPR resident data is 1992.

Figure C1 shows a continuous decline in the Korean population in Japan since the early 1990s. It also shows that the Korean population excluding SPRs is increasing except for the period of the 2008–2009 Financial Crisis and its aftermath. These suggest that most of the declines of the Korean population including SPRs are caused by the naturalization of SPRs.

FIGURE C1: Korean resident population with and without SPRs



Note: The immigration data are from the *Statistics on Foreign Residents* (*Zairyū Gaikokujin Tōkei*) of the Ministry of Justice.

D Additional summary statistics

TABLE D1: Percentiles of key explanatory variables

Panel A: Immigration variable, Δmig

	1989-1994	1995-2000	2001-2006	2007-2012	2013-2018
90th percentile	8.0	9.7	8.3	0.7	12.3
75th percentile	6.4	5.9	4.3	0.1	8.6
50th percentile	2.1	2.8	2.6	-0.5	5.7
25th percentile	1.3	1.9	1.3	-2.4	3.7
10th percentile	0.9	1.3	0.7	-6.4	2.4
The 75th − the 25th	5.1	4.0	3.0	2.5	4.9

Panel B: Import variable, Δipw^{CHN}

	1989-1994	1995-2000	2001-2006	2007-2012	2013-2018
90th percentile	3.2	5.3	16.0	7.6	4.2
75th percentile	2.9	4.6	14.5	5.2	2.1
50th percentile	2.0	3.9	11.9	2.5	0.1
25th percentile	1.7	2.6	8.2	0.8	-1.4
10th percentile	0.8	2.4	6.3	-0.1	-2.2
The 75th − the 25th	1.1	2.1	6.3	4.4	3.4

Note: The sample size is 47 in each column of the two panels. The unit of Δmig is the change in the number of immigrants per 1,000 people. The unit of Δipw^{CHN} is 10,000 JPY per employee for the top five prefectures, median prefectures, and bottom five prefectures, respectively. See the main text for data sources.

TABLE D2: Correlations between Δmig and Δipw^{CHN}

	Corr.
1989-1994	-0.02
1995-2000	0.49
2001-2006	0.43
2007-2012	-0.60
2013-2018	0.30

Note: The sample size is 47 in each row. See the main text for data sources.

TABLE D3: Percentiles of key dependent variables

Panel A: $100 \times [\ln(wage_{i,t+5}) - \ln(wage_{i,t})]$
of the age 60+ group, medium-sized firms, the construction sector

	1989-1994	1995-2000	2001-2006	2007-2012	2013-2018
90th percentile	8.0	9.7	8.3	0.7	12.3
75th percentile	6.4	5.9	4.3	0.1	8.6
50th percentile	2.1	2.8	2.6	-0.5	5.7
25th percentile	1.3	1.9	1.3	-2.4	3.7
10th percentile	0.9	1.3	0.7	-6.4	2.4
The 75th − the 25th	5.1	4.0	3.0	2.5	4.9

Panel B: $100 \times [\ln(wage_{i,t+5}) - \ln(wage_{i,t})]$
of the age 60+ group, small firms, the manufacturing sector

	1989-1994	1995-2000	2001-2006	2007-2012	2013-2018
90th percentile	3.2	5.3	16.0	7.6	4.2
75th percentile	2.9	4.6	14.5	5.2	2.1
50th percentile	2.0	3.9	11.9	2.5	0.1
25th percentile	1.7	2.6	8.2	0.8	-1.4
10th percentile	0.8	2.4	6.3	-0.1	-2.2
The 75th − the 25th	1.1	2.1	6.3	4.4	3.4

Note: The sample size is 47 in each column of the two panels. See the main text for data sources.

TABLE D4: Additional summary statistics of variables

Panel A: Hourly wage growth rates, all age groups, by firm size

	Obs.	Mean	Std. dev.	Min	Max
Construction, small firms	235	0.9	7.4	-22.7	17.2
Construction, medium-sized firms	233	0.2	11.0	-42.9	36.4
Construction, large firms	221	-0.9	12.3	-52.1	61.8
Manufacturing, small firms	235	0.3	3.6	-9.8	7.9
Manufacturing, medium-sized firms	235	1.1	4.9	-13.5	19.0
Manufacturing, large firms	234	1.6	6.5	-21.2	29.5
Finance, small firms	232	0.9	14.6	-38.3	46.4
Finance, medium-sized firms	235	1.3	7.7	-20.9	25.6
Finance, large firms	235	0.2	5.5	-16.4	19.0

Panel B: Hourly wage growth rates, construction sector, all firms, by age group

	Obs.	Mean	Std. dev.	Min	Max
20s	235	0.3	7.2	-25.8	31.5
30s	235	-0.3	7.5	-32.1	20.4
40s	235	0.4	7.7	-23.0	19.8
50s	235	1.0	9.2	-34.5	30.3
60+	204	-0.6	11.4	-33.8	30.8

Panel C: Hourly wage growth rates, manufacturing sector, all firms, by age group

	Obs.	Mean	Std. dev.	Min	Max
20s	235	1.0	3.5	-13.6	12.2
30s	235	0.6	3.4	-15.9	10.6
40s	235	1.0	4.3	-31.0	11.4
50s	235	1.2	4.9	-31.8	13.4
60+	235	0.8	7.4	-21.1	18.7

Panel D: Hourly wage growth rates, finance sector, all firms, by age group

	Obs.	Mean	Std. dev.	Min	Max
20s	235	1.0	4.6	-14.3	15.4
30s	235	0.5	6.1	-23.3	18.1
40s	235	0.0	6.1	-23.1	15.1
50s	235	-0.3	6.6	-17.5	20.9
60+	171	-0.6	16.9	-36.0	62.8

Panel E: Starting salary growth rates

	Obs.	Mean	Std. dev.	Min	Max
High school, male	235	0.3	2.8	-6.0	10.3
High school, female	235	0.7	3.6	-10.2	29.6
College, male	235	0.3	3.0	-7.8	8.6
Junior college, female	235	0.4	5.1	-29.7	18.4

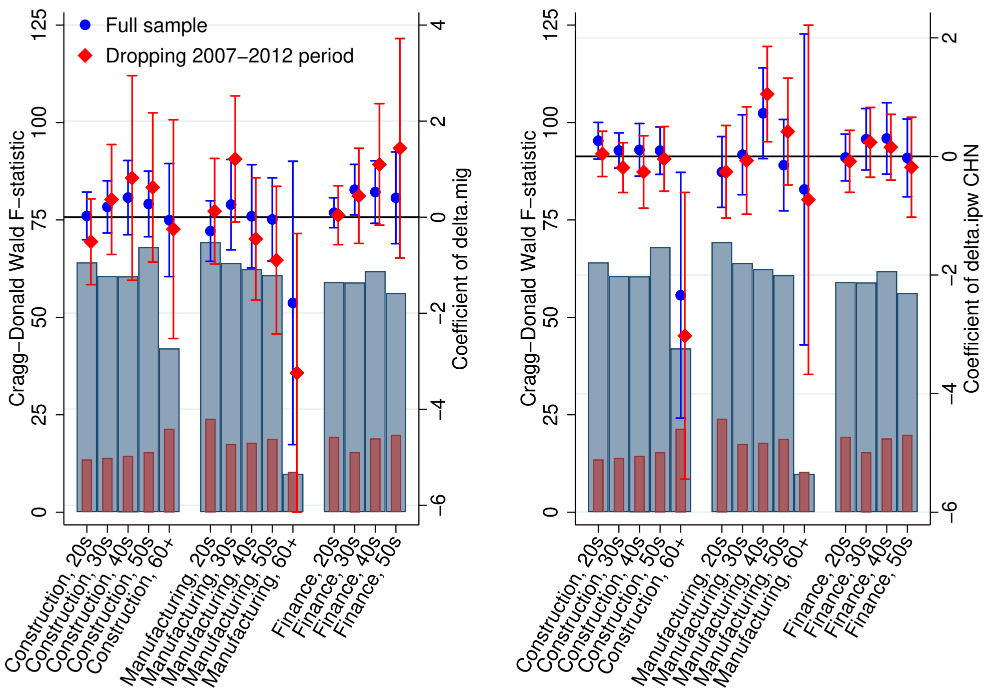
E Additional figures

Figure E1 presents the results for medium-sized firms by age group and sector. This shows that the effects of immigration and imports from China on wages were mostly statistically insignificant. However, significant negative effects come from the age 60+ group in the manufacturing sector, excluding the 2007–2012 period. Figure E2 shows the results for the large firms. Similarly, the effects of the two variables were mostly insignificant. Nevertheless, immigration has a significant positive effect on wages in the manufacturing sector of the age 30s group.

FIGURE E1: Results by sector and by age cohort, medium-sized firms

Panel A: Immigration

Panel B: Imports from China

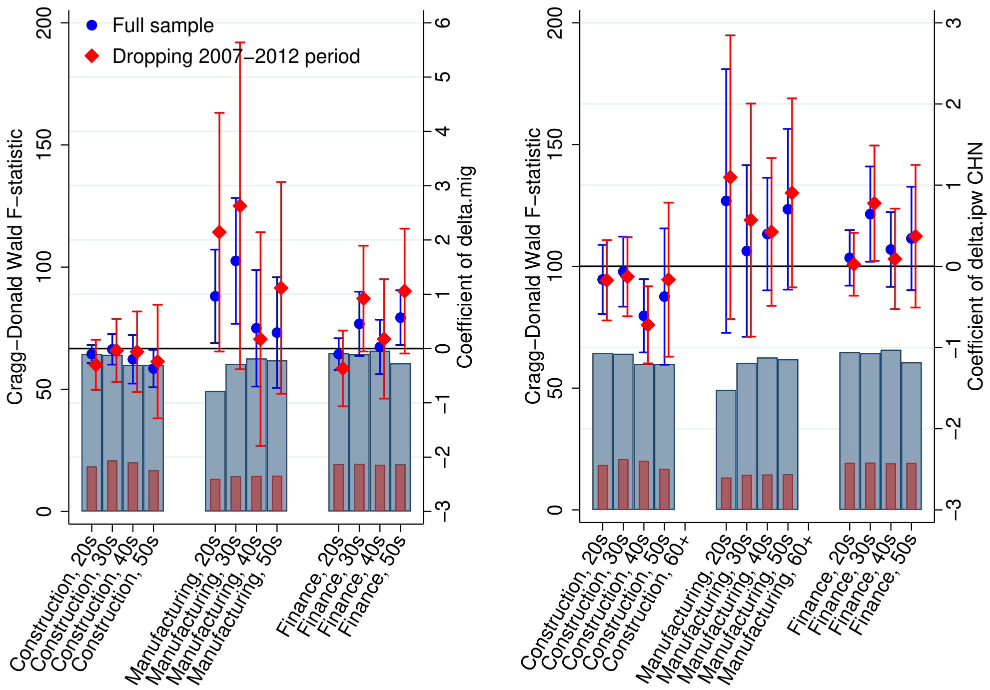


Note: See the note for Figure 7.

FIGURE E2: Results by sector and by age cohort, large firms

Panel A: Immigration

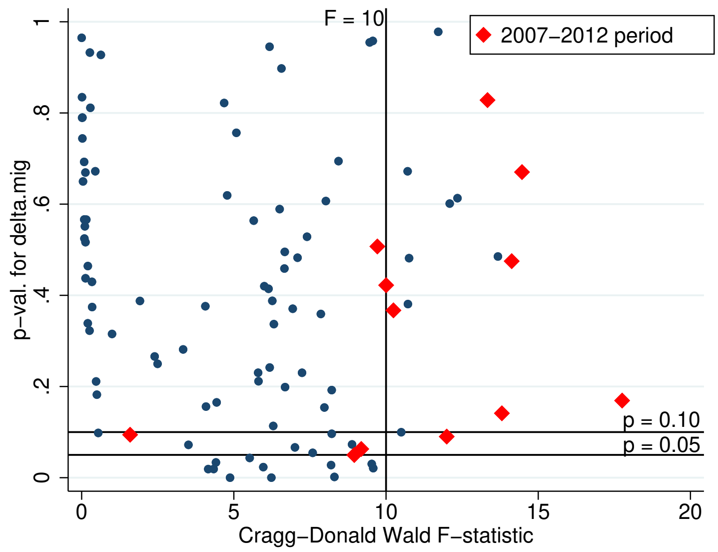
Panel B: Imports from China



Note: See the note for Figure 7.

Figure E3 plots positive coefficients of Δmig when employing the wage growth rate as the dependent variable, obtained from 194 regressions. It shows that none of the coefficients are in the range of p-value < 0.05 and first-stage F-statistic > 10. Figure E4 plots positive coefficients of Δipw^{CHN}. It shows that most coefficients are outside of the valid range. However, seven coefficients are in the valid range and three of them are not from the 2007–2012 period. Table E1 summarizes important statistics of the three coefficients.

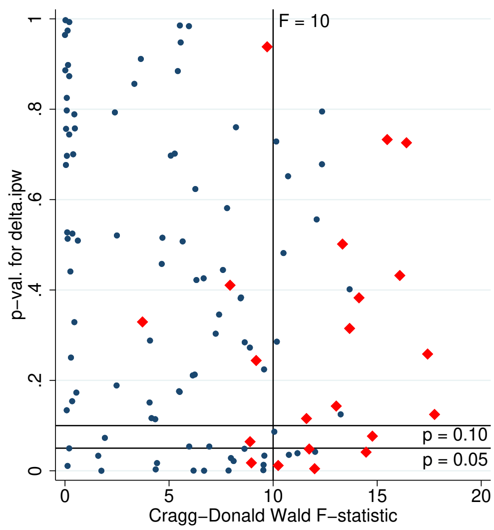
FIGURE E3: Effects on hourly wages, positive coefficients of Δmig



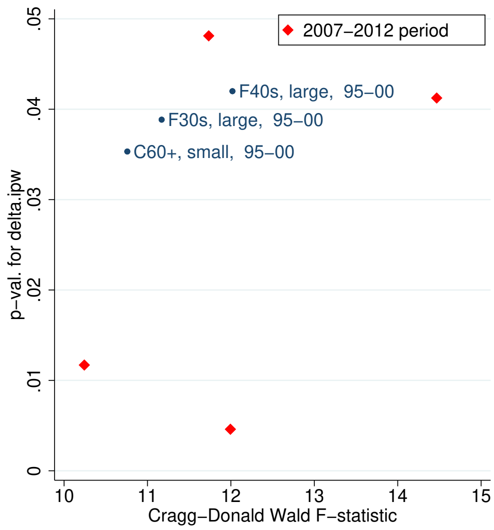
Note: See the note for Figure 9.

FIGURE E4: Effects on hourly wages, positive coefficients of Δipw^{CHN}

Panel A: All coefficients



Panel B: p-value < 0.05 and F-stat. > 10



Note: See the note for Figure 9.

TABLE E1: Positive import effects on wages

Sector, age, firm size, period	Coef.	Std. err.	p-value	C.D. F-stat.	K.-P. F-stat.	Sample size
C60+, small, 95-00	4.04	1.92	0.035	10.76	12.09	47
F30s, large, 95-00	3.12	1.51	0.039	11.17	14.34	47
F40s, large, 95-00	1.79	0.88	0.042	12.02	10.24	47

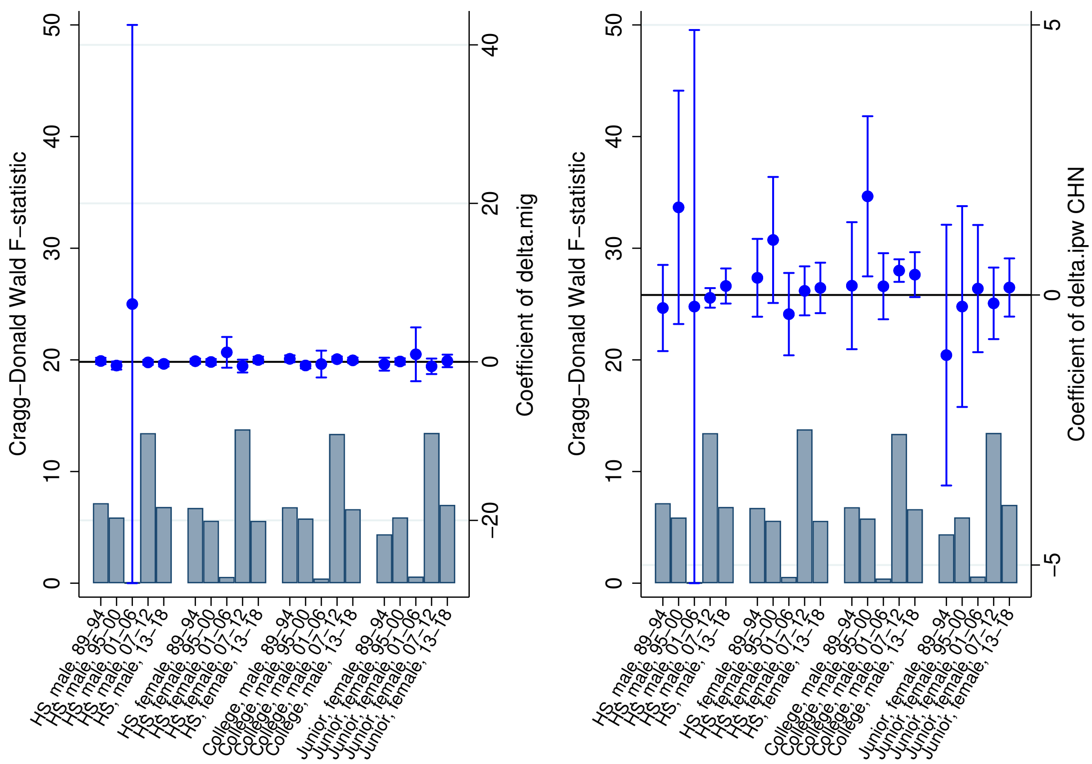
Note: See the note for Table 5.

Figure E5 presents the coefficients of Δmig (in Panel A) and Δipw^{CHN} (in Panel B) when the starting salary growth rate is employed as the dependent variable. It plots coefficients from one period, each of which consists of 47 observations, in contrast to Figure 10, which shows coefficients from two periods, each of which consists of 94 observations. Figure E5 shows that first-stage F-statistics are not sufficiently high to ensure strong IVs, presumably because of the small sample size. First-stage F-statistics are particularly low in regressions for the 2002–2006 period. Appendix F discusses the sources of the low F-statistics.

FIGURE E5: Effects on starting salaries by period, 47 obs. each

Panel A: Immigration

Panel B: Imports from China



Note: See the note for Figure 11.

F First-stage regression results

This section examines the control variables associated with lower first-stage F-statistics. Table F1 shows the results of regressing Δmig on Δmig^{Bartik} for each period. The added controls are summarized at the bottom of the table. This shows that the effect of Δmig^{Bartik} on Δmig remains statistically significant at the 1% level in all periods except 2001–2006 shown in Panel C. In this period, the inclusion of the initial unemployment rate and the initial natural log of population density, or the inclusion of the sectoral value-added share, removes statistical significance. This means that these variables are correlated with Δmig^{Bartik}, which does not have a significant effect on Δmig after controlling for these variables. Table F2 pesents the results of regressing Δipw^{CHN} on Δipw^{OTH}. This shows that, in all periods, the effect of Δipw^{OTH} on Δipw^{CHN} remains statistically significant even after controlling for all variables.

TABLE F1: First-stage regressing Δmig on Δmig^{Bartik} each period

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: 1989-1994						
Δmig^{Bartik}	0.47***	0.35	0.44***	0.57***	0.65***	0.66***
	(0.14)	(0.25)	(0.14)	(0.13)	(0.12)	(0.14)
F-statistic for Δmig^{Bartik}	11.23	2.02	10.31	19.15	31.41	22.51
p-value of F-statistic	0.002	0.162	0.002	0.000	0.000	0.000
Panel B: 1995-2000						
Δmig^{Bartik}	0.78***	1.23***	1.04***	1.33***	1.27***	1.21***
	(0.17)	(0.22)	(0.22)	(0.21)	(0.19)	(0.23)
F-statistic for Δmig^{Bartik}	20.43	30.41	22.17	41.86	45.65	28.16
p-value of F-statistic	0.000	0.000	0.000	0.000	0.000	0.000
Panel C: 2001-2006						
Δmig^{Bartik}	0.69***	0.80***	0.39	0.58	0.47	0.11
	(0.21)	(0.29)	(0.33)	(0.38)	(0.38)	(0.38)
F-statistic for Δmig^{Bartik}	11.00	7.82	1.38	2.35	1.55	0.08
p-value of F-statistic	0.002	0.008	0.246	0.132	0.220	0.775
Panel D: 2007-2012						
Δmig^{Bartik}	1.05***	1.09***	1.03***	1.26***	1.28***	1.29***
	(0.10)	(0.08)	(0.08)	(0.17)	(0.17)	(0.15)
F-statistic for Δmig^{Bartik}	111.53	187.23	166.97	52.38	58.48	77.47
p-value of F-statistic	0.000	0.000	0.000	0.000	0.000	0.000
Panel E: 2013-2018						
Δmig^{Bartik}	0.94***	0.70***	0.78***	0.94***	0.92***	0.65***
	(0.14)	(0.10)	(0.13)	(0.08)	(0.09)	(0.15)
F-statistic for Δmig^{Bartik}	46.08	50.50	37.53	127.15	106.44	19.45
p-value of F-statistic	0.000	0.000	0.000	0.000	0.000	0.000
Controls						
Initial unemployment rate	✓		✓		✓	✓
Initial ln(pop. density)		✓	✓		✓	✓
Sectoral value-added shares				✓	✓	✓
All other controls						✓

Note: The sample size is 47 for each regression. All regressions are estimated using initial populations as weights. ***, **, and * indicate the statistical significance at the 1%, 5%, and 10% level, respectively. Standard errors are in parentheses.

TABLE F2: First-stage regressing Δipw^{CHN} on Δipw^{OTH} each period

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: 1989-1994						
Δipw^{OTH}	0.66***	0.72***	0.78***	1.08***	1.06***	1.00***
	(0.14)	(0.08)	(0.11)	(0.14)	(0.14)	(0.13)
F-statistic for Δipw^{OTH}	22.35	74.41	54.09	60.32	58.64	57.89
p-value of F-statistic	0.000	0.000	0.000	0.000	0.000	0.000
Panel B: 1995-2000						
Δipw^{OTH}	0.83***	0.90***	0.87***	0.84***	0.81***	0.94***
	(0.07)	(0.08)	(0.08)	(0.15)	(0.15)	(0.17)
F-statistic for Δipw^{OTH}	156.44	145.45	123.00	33.36	27.94	29.26
p-value of F-statistic	0.000	0.000	0.000	0.000	0.000	0.000
Panel C: 2001-2006						
Δipw^{OTH}	0.53***	0.53***	0.53***	0.40***	0.38***	0.33***
	(0.03)	(0.03)	(0.04)	(0.05)	(0.05)	(0.05)
F-statistic for Δipw^{OTH}	261.10	307.54	228.07	54.76	62.57	37.88
p-value of F-statistic	0.000	0.000	0.000	0.000	0.000	0.000
Panel D: 2007-2012						
Δipw^{OTH}	0.71***	0.62***	0.72***	0.94***	0.89***	1.04***
	(0.11)	(0.11)	(0.11)	(0.19)	(0.18)	(0.20)
F-statistic for Δipw^{OTH}	41.86	33.33	42.13	25.59	24.43	26.81
p-value of F-statistic	0.000	0.000	0.000	0.000	0.000	0.000
Panel E: 2013-2018						
Δipw^{OTH}	0.32***	0.30***	0.32***	0.31***	0.29***	0.32***
	(0.06)	(0.05)	(0.06)	(0.08)	(0.09)	(0.11)
F-statistic for Δipw^{OTH}	27.38	37.73	24.96	14.32	10.43	8.37
p-value of F-statistic	0.000	0.000	0.000	0.000	0.002	0.006
Controls						
Initial unemployment rate	✓		✓		✓	✓
Initial $\ln$(pop. density)		✓	✓		✓	✓
Sectoral value-added shares				✓	✓	✓
All other controls						✓

Note: See the note for Table F1.

G Different definitions of wages

This section re-estimates the baseline regressions in Table 4 using different wage definitions. The baseline wage data are hourly wages constructed as follows:

- Baseline hourly wage = $\frac{\text{monthly total wages}\times 12+\text{bonuses}}{(\text{planned hours worked}+\text{overtime hours worked})\times 12}$

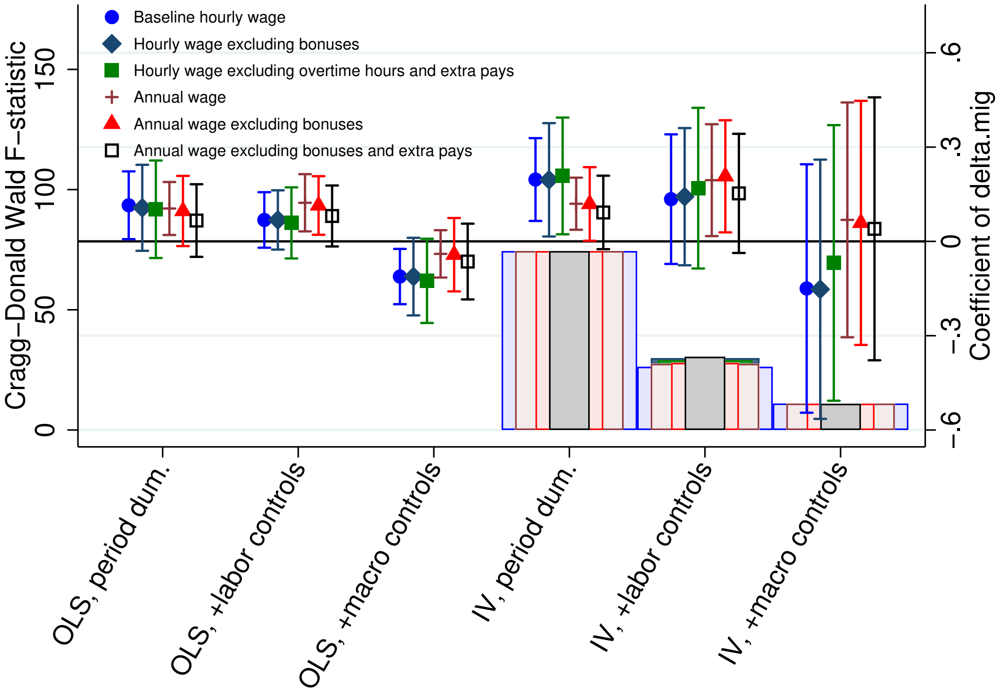
where the "planned hours worked" and "overtime hours worked" are monthly hours worked. Therefore, we multiply 12 to re-express them at an annual level. As a robustness check, we employ the following wage definitions:

- Hourly wage excluding bonuses = $\frac{\text{monthly total wages}\times 12}{(\text{planned hours worked}+\text{overtime hours worked})\times 12}$
- Hourly wage excluding overtime hours and extra pays = $\frac{\text{monthly planned wages}\times 12}{\text{planned hours worked}\times 12}$
- Annual wage = monthly total wages $\times 12$ + bonuses
- Annual wage excluding bonuses = monthly total wages $\times 12$
- Annual wage excluding bonuses and extra pay = monthly planned wages $\times 12$

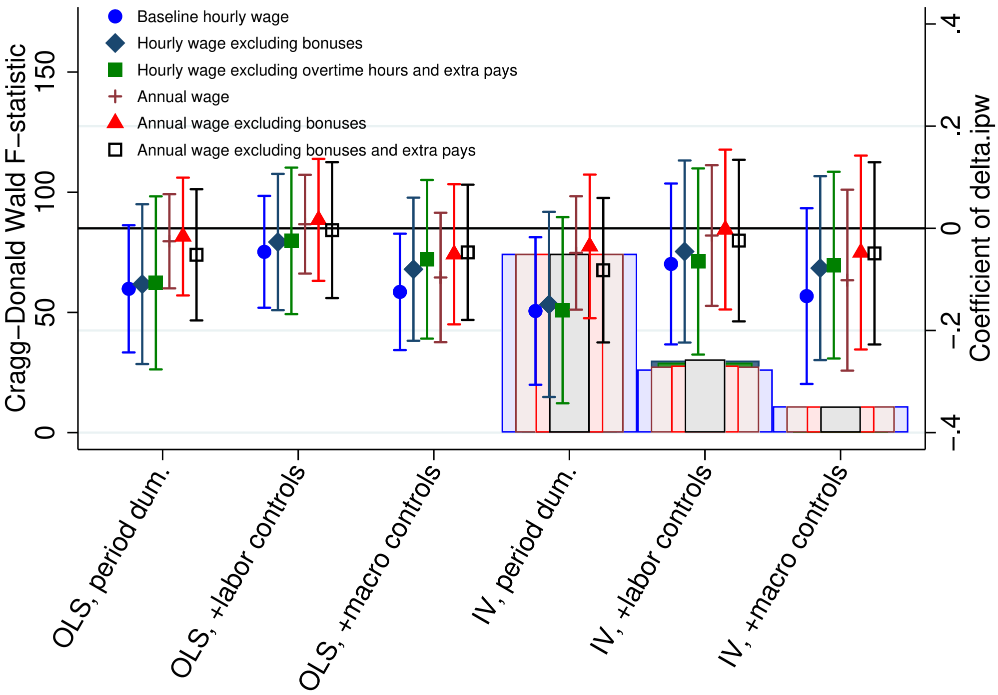
where all wages are deflated using the prefecture-level CPI and expressed in 2020 prices. We rerun the regression models used in Panel B of Table 4–dropping the 2007-12 observations– using each of the wage definitions. Panel A of Figure G1 shows the point estimates and associated confidence intervals of Δmig and Panel B shows those of Δipw^{CHN}. The two panels show that there are no systematic or sizable differences across the six definitions of wages.

FIGURE G1: Baseline regressions with different definitions of wages

Panel A: Immigration



Panel B: Imports from China



Note: The same specifications as Panel B of Table 4 are used. The sample size is 188 in each regression. See the note for Table 4 and Figure 7.

H Different migration variables

This section reruns regressions by employing different definitions when constructing the migration variables. The baseline model uses the following explanatory variable:

$$\Delta mig^{a}_{i,t} = \frac{MIG^{Total}_{i,t+5} - MIG^{Total}_{i,t}}{Pop^{Working}_{i,t}/1000}, \tag{H.1}$$

with the instrument:

$$\Delta mig^{a,Bartik}_{i,t} = \frac{1}{Pop^{Working}_{i,t}/1000} \sum_{g \in G} \frac{MIG^{Total}_{g,i,t-1}}{\sum_i MIG^{Total}_{g,i,t-1}} \times (MIG^{Total}_{g,t+5} - MIG^{Total}_{g,t}), \tag{H.2}$$

where $MIG^{Total}_{i,t}$ denotes the number of immigrants including individuals who are in the labor force and not in the labor force; $Pop^{Working}_{i,t}$ denotes the working age (ages 15-65) population including immigrants and natives.

As a robustness check, we also estimate regressions using the following variables:

$$\Delta mig^{b}_{i,t} = \frac{MIG^{Working}_{i,t+5} - MIG^{Working}_{i,t}}{Pop^{Working}_{i,t}/1000}, \tag{H.3}$$

and

$$\Delta mig^{b,Bartik}_{i,t} = \frac{1}{Pop^{Working}_{i,t}/1000} \sum_{g \in G} \frac{MIG^{Total}_{g,i,t-1}}{\sum_i MIG^{Total}_{g,i,t-1}} \times (MIG^{Total}_{g,t+5} - MIG^{Total}_{g,t}). \tag{H.4}$$

In $\Delta mig^{b}_{i,t}$ (eq. (H.1)), immigrants who are under education or training and dependent immigrants are excluded. As a result, the number of immigrants who are in the labor market–instead of all immigrants–is used to construct the variable. On the other hand, $\Delta mig^{b}_{i,t}$ (eq. (H.4)) is the same as $\Delta mig^{a}_{i,t}$ (eq. (H.3)) because the data on the number of foreign residents by the purpose of stay (e.g., education training, family, or work) are not available at the prefecture-level for each ethnicity.

We also re-estimate regressions using the following variables:

$$\Delta mig^{c}_{i,t} = \frac{MIG^{Total}_{i,t+5} - MIG^{Total}_{i,t}}{Pop^{Total}_{i,t}/1000}, \tag{H.5}$$

and

$$\Delta mig^{c,Bartik}_{i,t} = \frac{1}{Pop^{Total}_{i,t}/1000} \sum_{g \in G} \frac{MIG^{Total}_{g,i,t-1}}{\sum_i MIG^{Total}_{g,i,t-1}} \times (MIG^{Total}_{g,t+5} - MIG^{Total}_{g,t}), \tag{H.6}$$

where $Pop^{Working}_{i,t}$ in equations (H.1) and (H.2) is replaced with $Pop^{Total}_{i,t}$ in equations (H.5) and (H.6), respectively.

We believe that equations (H.1) and (H.2) are the best to quantify the labor market effects of immigration in the Japanese context with our dataset. These variables measure the number of immigrants who participate in economic activities–working and consuming–as a share of the size of the local labor market measured by the working age population. Using the total population–instead of the working age population–would distort the variables to some extent because rural prefectures have greater shares of retired elderly individuals than urban prefectures in Japan.

Table H1 presents summary statistics of the three explanatory variables and the three instruments. Table H2 shows correlation between the three explanatory variables, indicating that the three migration variables are highly positively correlated. Figure H1 presents the regression results with the baseline migration variables and those with two additional sets of migration variables. All regressions exclude the 2007-12 period, leading to a sample of 188 observations. The migration effects are presented in Panel A and the import effects are in Panel B. The estimated coefficients show that there are no sizable differences across coefficients regardless of the definitions of the migration variables.

TABLE H1: Summary statistics of migration variables

	Mean	Std. dev.	Min	Max
Endogenous variable				
$\Delta mig^{a}_{i,t}$ (baseline)	3.21	4.04	-9.57	18.50
$\Delta mig^{b}_{i,t}$	3.25	3.30	-7.85	12.95
$\Delta mig^{c}_{i,t}$	2.10	2.62	-6.15	12.35
Instruments				
$\Delta mig^{a,Bartik}_{i,t}$ (baseline)	3.08	3.73	-8.09	22.11
$\Delta mig^{b,Bartik}_{i,t}$	3.08	3.73	-8.09	22.11
$\Delta mig^{c,Bartik}_{i,t}$	2.00	2.41	-5.20	14.45

Note: The sample size is 235.

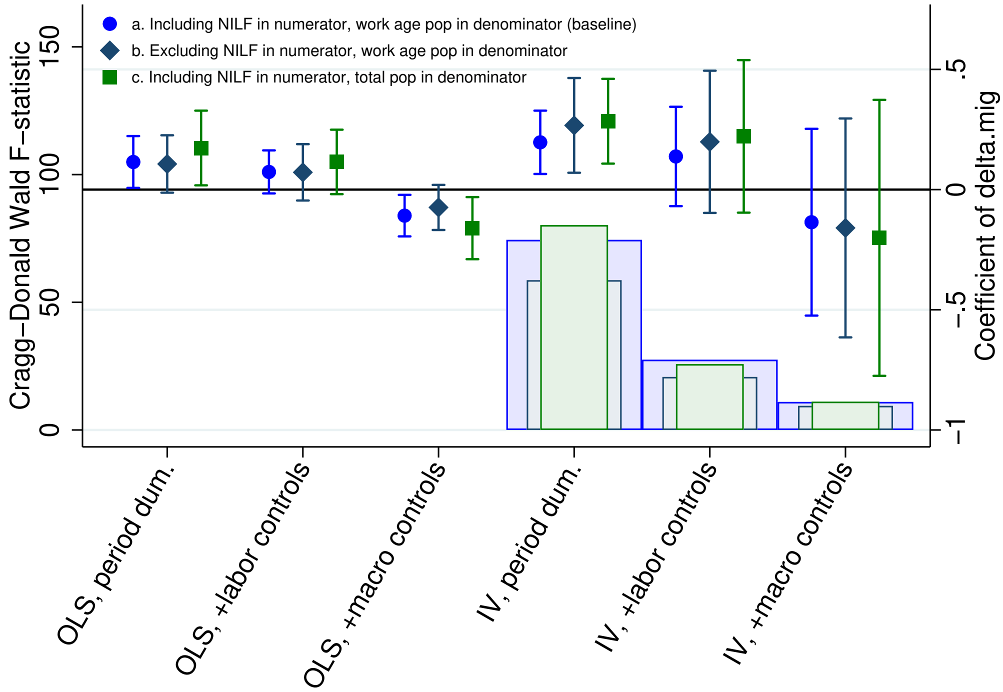
TABLE H2: Correlations between the explanatory variables measuring migrations

	$\Delta mig^{a}_{i,t}$	$\Delta mig^{b}_{i,t}$	$\Delta mig^{c}_{i,t}$
$\Delta mig^{a}_{i,t}$	1		
$\Delta mig^{b}_{i,t}$	0.964	1	
$\Delta mig^{c}_{i,t}$	0.997	0.963	1

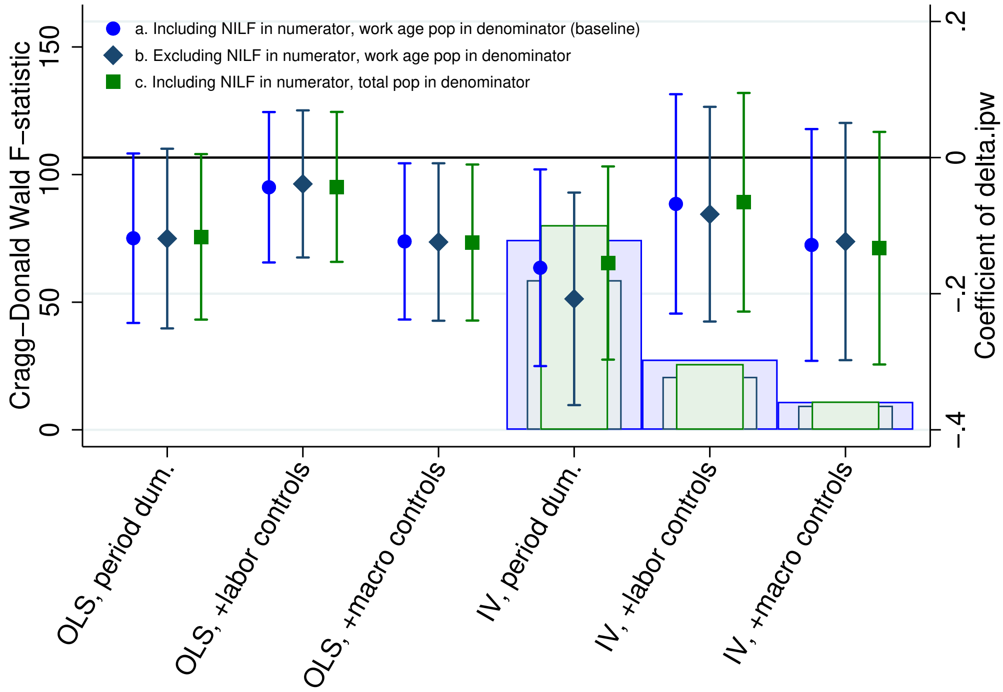
Note: The sample size is 235.

FIGURE H1: Baseline regressions with different migration variables

Panel A: Immigration



Panel B: Imports from China



Note: The same specifications as Panel B of Table 4 are used. The sample size is 188 in each regression. See the note for Table 4 and Figure 7.