

CIRJE-F-1046

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in Japan**

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April 2017

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Transition of spatial distribution of human capital in Japan*

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April 24, 2017

Abstract

We examine the transition of the spatial distribution of human capital by using data on Japanese prefectures. We find substantive concentration of university enrollments in Tokyo and its neighboring prefectures. After graduation, slight dispersal occurs but the movements are limited to neighboring prefectures. Moreover, we examine the relationship between human capital distributions of different cohorts, and find that the concentration of university graduates of a particular age group attracts university graduates of adjacent age groups. However, such an effect becomes insignificant and sometimes opposite as the age differences grow.

Keywords: human capital, spatial distribution, university graduates, transition

JEL Classification Numbers: I23, J24, R12, R23

1 Introduction

The important role of human capital in economic growth has now been established in the literature on Macroeconomics and Endogenous Growth Theory, which has a long history dating back at least to Romer (1986).¹ Its importance is also recognized in understanding the regional and

*This study was conducted as a part of the Project “Spatial Economic Analysis on Trade and Labor Market Interactions in the System of Cities” undertaken at the Research Institute of Economy, Trade and Industry (RIETI). This work was also supported by JSPS KAKENHI Grant Number 15H03348, 15H03344, 16H03615, and 17H02519. We thank Koichi Fukumura, Keita Shiba, and participants of the 56th Annual Meeting of Western Regional Science Association for their helpful comments.

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¹For a recent survey of this literature, see Acemoglu (2009) among others.

urban economy. In fact, it can be a major source of agglomeration economies that make economic agents concentrate on particular places and form larger cities such as New York, London, and Tokyo.² Hence, the human capital distribution across space is considered to be the primary factor that determines distribution of economic activities and local economic conditions.

In this paper, we interpret the distribution of university graduates as a proxy for the human capital distribution, and characterize this by using Japanese prefectural data. We first focus on a particular cohort, and examine how the distribution of university graduates of this cohort changes over time. We find extreme concentration of university enrollments in Tokyo and its neighboring prefectures, and they disperse after graduation but in most cases their movements are limited only within the neighboring prefectures. Thus, Tokyo and its neighborhoods attract human capital from all over Japan, which is considered to be the major force of shaping the largest city in Japan, i.e., the Tokyo Metropolitan Area. Such a concentration of relatively educated people is known as "sorting" in urban economics (Combes et al, 2008).

Moreover, we examine the relationship between human capital distributions of different cohorts, and find that the concentration of university graduates of a particular age group attracts graduates of adjacent age groups. However, such an effect becomes insignificant and sometimes negative as the age differences grow. This implies that human capital formation exhibits positive externalities between close generations although this may turn negative or insignificant between distant generations.

Because there exists a burgeoning literature on migration and distribution of people, it is impossible to refer to it in its entirety. Here, we only present existing empirical works that are closely related to our analysis and explain our study's major departures from this extant research.

Most closely related works are those investigated the regional characteristics that attract human capital. Berry and Glaeser (2005), by using the Public Use Microdata Series in the United States for the years 1970, 1980, 1990, and 2000, showed that cities have a higher share of university graduates as they had a larger pool of university graduates in the past. Betz, Partridge, and Fallah (2016) examined inter-Metropolitan area migration patterns in the United States during the 1990s and 2000s by using four-digit NAICS industry-level proprietary employment data from Economic Modeling Specialists International. They found that cities having large stocks of university graduates attracted university graduates during the 1990s whereas cities having large

²For possible mechanisms of agglomeration economies, see Duranton and Puga (2004) among others. For empirical evidence on the existence of agglomeration economies, see Rosenthal and Strange (2004) among others.

populations attracted university graduates during the 2000s, which is in line with the results of Berry and Glaeser (2005). Brown and Scott (2012) explored the determinants of residential choices among Metropolitan areas of university graduates and non-graduates by using the 2001 Canadian Census of Population and found that university graduates place more importance on thickness of labor markets and less importance on amenities than non-graduates. Dahl and Sorenson (2010), based on panel data on Danish population from 2004 to 2006, showed that wage levels and geographical proximity to family and friends matter for scientists and engineers in choosing their place of work among administrative townships. Faggian and McCann (2009) used the data regarding university graduates for the year 2000 provided by the Higher Education Statistics Agency and the European Patent Office to investigate graduate migration between NUTS2 regions in Great Britain, and showed that graduates are attracted to innovation-active regions especially in England and Wales. Fu and Gabriel (2012) uncovered the effects of human capital distribution on the migration decisions of people with different skill levels in China by using the 1995 One-percent Population Survey. They found that agglomeration of skilled workers attracts skilled workers but has little effect on unskilled workers. Gottlieb and Joseph (2006) used data provided by the National Science Foundation to find that highly educated people such as Ph.D. holders place importance on their migration decisions in the United States for the year 1995, which is in contrast to the Canadian case in the above-mentioned study by Brown and Scott (2012). Based on China's one per cent population sample survey from 2005, Liu and Shen (2013) showed that skilled people prefer to migrate to coastal provinces where wages are high, leading to agglomeration of skilled people. McHenry (2014) examined changes in human capital distribution across commuting zones in the United States during the 1990s using the National Education Longitudinal Study, Integrated Public Use Microdata Series, and Public Use Microdata Area, and showed that labor market size matters in attracting human capital. He also provided insights on intergenerational transmission of skills from parents to children. Miguelez and Moreno (2014) collected data on inventors holding patents in the European Union during the periods 1996-1999 and 2002-2005, and showed that networks among inventors and distance from places of current residence matter in migration decisions. Tano (2014) used data on Swedish individuals born in 1974 and 1976 (Linnaeus Data Base) to uncover a dependence of migration decisions on the ability of university graduates. She showed that high GPA graduates prefer to be located in large cities with large pools of highly-skilled labor, large populations, and good economic conditions.

Our analysis shows a high concentration of human capital in Tokyo and surrounding regions.

Because they constitute the largest Metropolitan area with respect to population size in Japan (Kanemoto and Tokuoka, 2002), and Tokyo has the highest share of university graduates (see e.g., 2015 Population Census, Ministry of Internal Affairs and Communications) and highest wage level (see e.g., 2016 Basic Survey on Wage Structure, Ministry of Health, Labour and Welfare) among Japanese prefectures, our results are mostly consistent with those of existing works.³ However, we depart from the extant literature by investigating the timing and persistence of such concentration, and we show its instigation at the time of university enrollment and its subsequent, highly persistent nature over time in Japan.

Our results are also related to existing works that have examined the possible effects of human capital distribution on local economies.⁴ Faggian and McCann (2009) showed that inflows of university graduates prompt local innovation especially in the high-tech industry. Moretti (2010) examined the effects of changes in labor demand in a particular industry on the labor demand in other industries by using the Census of Population in the United States for the years 1980, 1990, and 2000. He found that an increase in labor demand in the tradable (manufacturing) sector increases labor demand in non-tradable sectors to a larger extent, i.e., there is a multiplier effect across industries. However, it does not increase labor demand in the tradable sector, i.e., it does not exhibit an intra-industry multiplier effect.

Our results in terms of the relationship between human capital distributions of different cohorts are comparable with those shown in Moretti (2010). However, we depart from his analysis by considering relationships between different generations.

The remainder of the paper is structured as follows. Section 2 explains our data. Section 3 investigates the transition of human capital over time. Section 4 examines the relationship between the human capital distributions of different generations. Section 5 provides further analysis by using a different methodology. Finally, Section 6 concludes the paper.

³National economic conditions are also of significance for human capital distribution. Candau and Dienesch (2015) showed that declines in transportation costs fostered agglomeration of human capital in the United States. Also, regional policies can accelerate human capital accumulation and discourage brain drain. Hawley and Rork (2013) showed that state-funded higher education scholarship plans increase state-level university entrance rate and decrease graduates' migration to other states. Similar effects were found by Sjoquist and Winters (2014). Although we acknowledge that these issues impact human capital distribution, they are beyond the scope of this paper.

⁴Some existing research has uncovered effects on individuals. Kazakis and Faggian (2016) showed that interstate migration of people with university degrees or higher has effects of decreasing their wage income.

2 Data

We use two data sources to investigate the transition of human capital distribution across Japanese regions and its consequent impacts. One is the School Basic Survey published by the Ministry of Education, Culture, Sports, Science and Technology (Japan) and the other is the Population Census published by the Statistics Bureau of the Ministry of Internal Affairs and Communications (Japan). From the School Basic Survey, we use the number of people who obtained a high school degree and university admission in each prefecture, and the number of university enrollments in each prefecture. From these figures, we obtained the distribution (in percentage) of those who obtained a high school degree and university admission across prefectures, and the distribution of university enrollments across prefectures. The former is associated to the place where people with university admission obtained a high school degree and the latter is associated to the place where they entered a university. By comparing these two figures, we can see geographical movements associated to university enrollments.

From the Population Census, we use population size by educational attainment level and age group in each prefecture. We can then obtain the distribution of university graduates across prefectures.⁵ By comparing the obtained distributions, we can see the number of people moving from one region to another when entering and graduating from a university and afterwards, that is, we can observe and analyze the transition of human capital distribution over time.

3 Changes in human capital distribution in Japan

The population census is published once every five years in Japan, which shows population size by educational attainment level and age group in each prefecture. Hence, we can capture changes in its distribution over time by focusing on particular cohorts. Specifically, in this section, we focus on cohorts aged between 45-49 in 2010.⁶ Thus, they were aged between 35-39 in 2000, and 25-29 in 1990. In Japan, most people enroll in a university in a year to become 19, we assume

⁵Strictly speaking, we examine the distribution of people who have graduated with at least an undergraduate university degree.

⁶Focusing on other cohorts, very similar results are obtained.

that these cohorts entered a university during 1980-1984.⁷⁸ Since the School Basic Survey is available annually, we can compute the numbers of those who obtained a high school degree and university admission and university enrollments in each prefecture for these cohorts. By comparing the obtained distributions, we can capture the changes in human capital distribution in Japan.

3.1 Sorting at the time of university enrollment

We start by comparing the distribution (in percentage) of those who obtained a high school degree and university admission across prefectures and the distribution of university enrollments across prefectures. In so doing, we take the differences between these two regional shares and present them in Figure 1.

[Figure 1 around here: Place of obtaining a high school degree and place of university enrollment]

If the difference is zero for a particular prefecture, the prefecture experiences no net gains/losses in human capital associated to university enrollment. From Figure 1, we know that Tokyo and its surrounding prefectures markedly attract people at the time of enrollment. If such people remain in these prefectures after they graduate, it results in human capital concentration in and around Tokyo.

3.2 Population distribution after university graduation

We next show the transition of human capital distribution by comparing the distribution (in percentage) of university enrollments across prefectures and the distribution of university graduates. In so doing, we again take the differences between these two regional shares and present them in Figure 2.

[Figure 2 around here: Place of university enrollment and place of residence after university graduation]

⁷Note here that the survey for the Population Census is conducted in October whereas that for the School Basic Survey is conducted on May. Hence, in the cohort of those who were 29 years-old in the 1990 Census, some enrolled in a university in 1980, whereas others enrolled in 1979. Therefore, we also conducted our analysis by assuming the cohorts enrolled in a university during 1979-1983 and obtained very similar results.

⁸Of course, some people spend one or two (or very occasionally more) additional years before/after enrolling in a university. Hence, our analysis is not based on the exact history of particular cohorts. Still, we believe our methodology can serve as a good approximation for general trends.

Figure 2-a compares the place of enrollment and the place of residence soon after graduation from a university (when the cohorts become 25-29 years old). This shows that some people left Tokyo after graduation but the movements are limited to within neighboring prefectures. Figure 2-b (resp. 2-c) compares the place of university enrollment and the place of residence when the cohorts become 35-39 years old (resp. the place of residence when the cohorts become 45-49 years old). Figures 2-b and 2-c show that people continue to leave Tokyo but only to neighborhoods in relatively close proximity.

Thus, we confirmed the sorting of people with higher education into Tokyo and its neighboring prefectures at the time of university enrollment, and its hysteresis over time. This implies that if a region wants to host human capital, it has to attract people at the time of university enrollment. Then, it can retain them as long as their generation remains active.

4 Relationship between human capital distributions of different generations

Next, we use the data on population size by educational attainment level and age group in each prefecture and investigate the relationship between distributions of university graduates of different age groups. Here, we use data for the years 1990, 2000, and 2010 to develop a prefectural panel dataset. Table 1 provides summary statistics of variables used in this section (see also table A-1 for data descriptions).

[Table 1 around here: Summary statistics]

4.1 Estimation methodology

We estimate how the distribution of university graduates of a particular age group is associated with those of other age groups. Letting $Dist_{r,t}^S$ denote the prefecture r 's share of university graduates of age group g in period t , we estimate the following equation.

$$Dist_{r,t}^S = \alpha + \sum_{i \neq g} \beta_i Dist_{r,t}^S + \sum_k \gamma_k X_{krt} + \delta D_r + \tau T_t + \epsilon_{r,t}, \quad (1)$$

where X_{krt} denote a control variable for prefecture r in period t . D_r and T_t represent prefectural and time dummies, respectively. Because we have three periods for this panel data (1990, 2000, 2010), $t = 1, 2, 3$, where $t = 1$ represents that a variable is associated to the year 1990. $\epsilon_{r,t}$ is

the error term. As control variables, we include the number of plants, job-to-applicants ratio, ratio of people over 65 years old, and distance to Tokyo.

It is well known that one of the major reasons for inter-prefectural migration is job opportunities. To control for it, we include the number of plants and job-to-applicants ratio. We expect that a large number of plants attract a large number of skilled workers because they can land a job whose skill requirement matches their skill, and that a high job-to-applicants ratio is usually associated with good economic conditions, which attract skilled workers.

Social characteristics also have potential effects on residential choices. For example, the population structure affects regional policies. If a region has a large elderly population, it tends to operate policies advantaging these people. For this reason, we control for the regional population structure.

In Japan, various factors such as goods, population, and authorities concentrate on the Tokyo prefecture. Hence, one might expect that the accessibility to Tokyo affects residential choices, which leads us to include the distance to Tokyo prefecture.

Moreover, we examine the relationship between distributions of people with different educational attainment levels. Letting $Dist_{rgt}^U$ denote the prefecture r 's share of high school graduates not going to a university of age group g in period t , we estimate the following equation.

$$Dist_{rgt}^U = \alpha + \sum_i \beta_i Dist_{rit}^S + \sum_k \gamma_k X_{krt} + \delta D_r + \tau T_t + \epsilon_{rgt}. \quad (2)$$

Note that the share of university graduates of age group g , $Dist_{rgt}^S$, is not included in the left hand side of (1) to avoid multicollinearity, but it is in the left hand side of (2) because $Dist_{rgt}^S$ and $Dist_{rgt}^U$ differ in educational attainment level.

4.2 Results

Tables 2 and 3 show the estimation results of (1), where the prefectural dummy is not included in Table 2 (i.e., results by the ordinary least squares regression (OLS) without the prefectural dummy) but is included in Table 3 (i.e., results by the fixed effect regression (FE)).

[Table 2 around here: The relationship between distributions of university graduates of different age groups (OLS)]

[Table 3 around here: The relationship between distributions of university graduates of different age groups (FE)]

The estimated results imply that the prefectural share of university graduates of a particular age group is strongly and positively related to that of adjacent age groups. However, the relationship becomes negative as age differences become larger, and becomes weaker and even insignificant when the differences get even larger. For instance, if we look at (4) in Table 3, the prefectural share of university graduates of age group 40 – 44 is positively related to those of age groups 35 – 39 and 45 – 49, but negatively related to those of 30 – 34 and 50 – 54. The significance of the relationship becomes weaker for other age groups. These results have strong policy implications. Educational policies by a local government such as higher education scholarship plans can increase regional human capital, and such an effect persists across adjacent generations. However, it does not continue across generations indefinitely. In this sense, one-off policies have limited impacts on the region even though we can expect certain hysteresis effects.

Tables 4 and 5 show the estimation results of (2), where the prefectural dummy is not included in Table 4 but is included in Table 5.

[Table 4 around here: The relationship between distributions of university graduates and high school graduates (OLS)]

[Table 5 around here: The relationship between distributions of university graduates and high school graduates (FE)]

From Tables 4 and 5, we find no clear-cut relationship between the distributions of university graduates and high school graduates. This indicates that the labor market for university graduates and that for high school graduates are spatially independent.

5 Local multipliers of human capital

Thus far, we have focused on the distribution, that is, regional shares of human capital. This is convenient to capture spatial agglomeration/dispersion of human capital, but is silent on the effects of increases in total amounts of human capital. To analyze such effects, we follow Moretti (2010) and estimate the local multipliers of human capital. More specifically, we estimate the effects of changes in population with university degrees of a particular age group on that with university degrees of different age groups and that with high school degrees. In this section, we again use data on population by educational attainment level and age group in each prefecture.

5.1 Local multipliers on population with university degrees of different age groups

We first examine the effects of changes in population with university degrees of a particular age group on those of other age groups. Letting N_{rgt}^S denote the prefecture r 's population with university degrees of age group g in period t . We follow Moretti (2010) in estimating the following equation.

$$\Delta \log N_{rgt}^S = \zeta + \sum_{i \neq g} \eta_i \Delta \log N_{rit}^S + \tau T_t + \varepsilon_{rgt}, \quad (3)$$

where $\Delta \log N_{rgt}^S$ is defined as

$$\Delta \log N_{rgt}^S \equiv \log N_{rgt}^S - \log N_{rgt-1}^S.$$

We first estimate (3) by the ordinary least squares regression (OLS), and then try the instrumental variable estimation (IV) to confirm the robustness of results. In conducting IV, we follow Moretti (2010) in choosing an instrument for $\Delta \log N_{rit}^S$.⁹ Letting ω_{rit} denote the share of university graduates of age group i among university graduates of all age groups in prefecture r in period t ($= N_{rit}^S / \sum_k N_{rkt}^S$), the instrument we use, IV_{rit} , is given by

$$IV_{rit} = \omega_{rit-1} \Delta \log N_{it}^S,$$

where $\Delta \log N_{it}^S$ is the changes in natural log of Japanese population of age group i with university degrees between t and $t - 1$:

$$\Delta \log N_{it}^S \equiv \log \left(\sum_r N_{rit}^S \right) - \log \left(\sum_r N_{rit-1}^S \right).$$

From the analogy of Moretti (2010), the IV implies that a city with a larger share of graduates of a particular age group at the beginning of the period is more affected by changes in the national stock of graduates of the age group.

In the first stage regression, we estimate

$$\Delta \log N_{rit}^S = \theta + \lambda IV_{rit} + \tau T_t + \varepsilon_{rit}. \quad (4)$$

Then, by using the estimated coefficients, $\hat{\theta}$, $\hat{\lambda}$, and $\hat{\tau}$, we can obtain $\widehat{\Delta \log N_{rit}^S}$ as

$$\widehat{\Delta \log N_{rit}^S} = \hat{\theta} + \hat{\lambda} IV_{rit} + \hat{\tau} T_t,$$

from which we can conduct the second stage estimation by

$$\Delta \log N_{rgt}^S = \zeta + \sum_{i \neq g} \eta_i \widehat{\Delta \log N_{rit}^S} + \tau T_t + \varepsilon_{rgt}. \quad (5)$$

⁹For further details, see Moretti (2010).

Tables 6 and 7 show the estimated results of (5).¹⁰

[Table 6 around here: The effects of changes in population with university degrees of an age group on that of other age groups (OLS)]

[Table 7 around here: The effects of changes in population with university degrees of an age group on that of other age groups (IV)]

Tables 6 and 7 provide the results by OLS and those by IV, respectively. In these tables, each row shows the effects of changes in population with university degrees of a particular age group on that of other age groups, and each column represents the effects of changes in population with university degrees of various age groups on that of a particular age group. From the estimated results, we can confirm our previous findings. An increase in university graduates of a particular age group significantly increases university graduates of adjacent age groups. However, as the age differences grow, such an effect becomes less significant and sometimes negative.

Finally, we conduct similar analysis for the effects on population with high school degrees, of which results are provided in Tables 8 and 9.

[Table 8 around here: The effects of changes in population with university degrees of an age group on population with high school degrees (OLS)]

[Table 9 around here: The effects of changes in population with university degrees of an age group on population with high school degrees (IV)]

From the estimated results, especially from the results by IV shown in Table 9, we again confirm that we find no clear-cut relationship between the distributions of university graduates and of high school graduates. This indicates that the labor market for university graduates and that for high school graduates are independent.

6 Concluding remarks

We examined the transition of the spatial human capital distribution by using data for Japanese prefectures. We focused on a particular cohort, and traced the distribution of university graduates in this cohort over time, starting from the time of university enrollment. We found marked

¹⁰Appendix A provides the results of the first stage regression, (4), of IV.

concentration of university enrollments in Tokyo and its neighboring prefectures. After graduation, they disperse slightly but the movements are limited to neighboring prefectures. Thus, we observed strong hysteresis of human capital distribution. Moreover, we examined the relationship between human capital distributions of different cohorts, and found that the concentration of university graduates of a particular age group attracts university graduates of adjacent age groups. However, such an effect becomes insignificant and sometimes negative as the age differences get larger.

Here, we raise a few potential extensions. First, we didn't distinguish between the types of university graduates. It would be worth exploring the dependence of distribution of university graduates by their field of major or sex. Second, it would be significant to examine the effects of human capital distribution on other economic conditions such as local output or employment levels or land price (i.e., degree of capitalization of human capital). Finally, our analysis is silent about the impact on total human capital level in the whole country. These are important topics for future research.

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Appendices

Appendix A: Data description

[Table A around here: Data description]

Appendix B: First stage regression, (4), of IV.

[Table B around here: Estimation results of the first stage regression, (4), of IV]

TABLE 1: Summary statistics

Variable	Mean	Std. Dev.	Min.	Max.	N
$Dist_{r25-29t}^S$ (%)	2.128	2.972	0.297	17.864	141
$Dist_{r30-34t}^S$ (%)	2.128	2.891	0.293	16.28	141
$Dist_{r35-39t}^S$ (%)	2.128	2.827	0.326	15.746	141
$Dist_{r40-44t}^S$ (%)	2.128	2.864	0.31	16.152	141
$Dist_{r45-49t}^S$ (%)	2.128	2.912	0.314	17.482	141
$Dist_{r50-54t}^S$ (%)	2.128	3.001	0.272	18.771	141
$Dist_{r55-59t}^S$ (%)	2.128	3.133	0.286	20.823	141
$Dist_{r60-64t}^S$ (%)	2.128	3.392	0.278	24.218	141
$Dist_{r25-29t}^U$ (%)	2.128	1.794	0.496	8.851	141
$Dist_{r30-34t}^U$ (%)	2.128	1.732	0.476	8.166	141
$Dist_{r35-39t}^U$ (%)	2.128	1.727	0.499	7.472	141
$Dist_{r40-44t}^U$ (%)	2.128	1.74	0.471	8.177	141
$Dist_{r45-49t}^U$ (%)	2.128	1.813	0.479	9.532	141
$Dist_{r50-54t}^U$ (%)	2.128	1.841	0.502	10.384	141
$Dist_{r55-59t}^U$ (%)	2.128	1.927	0.497	10.982	141
$Dist_{r60-64t}^U$ (%)	2.128	1.907	0.469	10.228	141
log # of plants	11.502	0.698	10.239	13.574	141
job-to-applicants ratio	0.937	0.577	0.28	2.68	141
ratio of people over 65 years rate (%)	19.043	5.152	8.282	29.507	141
log of distance to Tokyo	5.706	1.256	0	7.348	141

Note: $Dist_{rgt}^S$ means the prefecture r 's share of university graduates of age group g in period t . Also, $Dist_{rgt}^U$ means the prefecture r 's share of high school graduates of age group g in period t . See main text.

TABLE 2: The relationship between distributions of university graduates of different age group (OLS)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$Dist_{r25-29t}^S$	$Dist_{r30-34t}^S$	$Dist_{r35-39t}^S$	$Dist_{r40-44t}^S$	$Dist_{r45-49t}^S$	$Dist_{r50-54t}^S$	$Dist_{r55-59t}^S$	$Dist_{r60-64t}^S$
$Dist_{r25-29t}^S$		0.2917*** (0.0391)	-0.2116*** (0.0451)	0.0311 (0.0522)	0.0402 (0.0554)	0.0188 (0.0641)	-0.0096 (0.0466)	0.0494 (0.1133)
$Dist_{r30-34t}^S$	1.8391*** (0.2505)		0.8277*** (0.0514)	-0.1072 (0.1318)	-0.1188 (0.1266)	0.0483 (0.1484)	-0.0485 (0.1303)	0.2001 (0.3154)
$Dist_{r35-39t}^S$	-1.5917*** (0.2975)	0.9877*** (0.0688)		0.4704*** (0.1247)	-0.1785 (0.1193)	0.0117 (0.1525)	0.1624 (0.1571)	-0.5225 (0.3892)
$Dist_{r40-44t}^S$	0.2494 (0.3963)	-0.1366 (0.1575)	0.5020*** (0.0832)		0.8521*** (0.0530)	-0.3158*** (0.1022)	-0.1397 (0.1333)	0.4296 (0.3172)
$Dist_{r45-49t}^S$	0.3524 (0.5289)	-0.1652 (0.1893)	-0.2079* (0.1248)	0.9301*** (0.0551)		0.6912*** (0.0871)	-0.2303** (0.1163)	0.3800 (0.2910)
$Dist_{r50-54t}^S$	0.1249 (0.4217)	0.0508 (0.1549)	0.0103 (0.1349)	-0.2610*** (0.0962)	0.5232*** (0.0841)		0.8311*** (0.0590)	-1.6594*** (0.2517)
$Dist_{r55-59t}^S$	-0.0698 (0.3377)	-0.0560 (0.1477)	0.1570 (0.1401)	-0.1266 (0.1149)	-0.1911* (0.1050)	0.9110*** (0.0548)		2.1929*** (0.1363)
$Dist_{r60-64t}^S$	0.0669 (0.1498)	0.0429 (0.0683)	-0.0939 (0.0684)	0.0724 (0.0544)	0.0586 (0.0450)	-0.3383*** (0.0291)	0.4079*** (0.0192)	

TABLE 2 (count.)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$Dist_{r25-29t}^S$	$Dist_{r30-34t}^S$	$Dist_{r35-39t}^S$	$Dist_{r40-44t}^S$	$Dist_{r45-49t}^S$	$Dist_{r50-54t}^S$	$Dist_{r55-59t}^S$	$Dist_{r60-64t}^S$
log # of plants	0.1118*** (0.0427)	-0.0330* (0.0191)	0.0290 (0.0207)	-0.0088 (0.0144)	0.0200 (0.0139)	-0.0591*** (0.0158)	0.0603*** (0.0161)	-0.1558*** (0.0332)
job-to-applicants ratio	0.0907** (0.0422)	0.0214 (0.0169)	-0.0258* (0.0155)	0.0097 (0.0132)	-0.0164 (0.0136)	0.0242 (0.0180)	-0.0285* (0.0158)	0.0401 (0.0347)
ratio of people over 65 years old	-0.0035 (0.0068)	-0.0014 (0.0031)	0.0013 (0.0028)	0.0003 (0.0027)	-0.0005 (0.0026)	-0.0005 (0.0033)	-0.0004 (0.0032)	0.0073 (0.0066)
distance to Tokyo	0.0356 (0.0229)	0.0024 (0.0104)	-0.0116 (0.0096)	0.0177* (0.0090)	-0.0185** (0.0085)	0.0107 (0.0094)	-0.0020 (0.0076)	-0.0121 (0.0155)
constant	-1.3868** (0.5921)	0.3543 (0.2445)	-0.2478 (0.2410)	-0.0331 (0.1919)	-0.0706 (0.1956)	0.5571** (0.2304)	-0.5944*** (0.2240)	1.5013*** (0.4663)
N	141	141	141	141	141	141	141	141
adj. R^2	0.998	1.000	1.000	1.000	1.000	1.000	1.000	0.999

Note: robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. We consider two cases for preferences. One of two is that preference relate to residential location is homogeneous. The other case is heteroskedasticity preference. We first estimate the effect of distributions of university graduates of different age groups under the homoskedasticity case (Table 2). Second, we also estimate one controlling for fixed effect, that is heteroskedasticity preferences of residents (Table 3).

TABLE 3: The relationship between distributions of university graduates of different age group (FE)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$Dist_{r25-29t}^S$	$Dist_{r30-34t}^S$	$Dist_{r35-39t}^S$	$Dist_{r40-44t}^S$	$Dist_{r45-49t}^S$	$Dist_{r50-54t}^S$	$Dist_{r55-59t}^S$	$Dist_{r60-64t}^S$
$Dist_{r25-29t}^S$		0.3254*** (0.0576)	-0.2472*** (0.0438)	0.1474** (0.0594)	-0.0477 (0.0780)	0.0942 (0.0879)	0.0028 (0.1105)	0.1294 (0.3118)
$Dist_{r30-34t}^S$	1.3997*** (0.1861)		0.8042*** (0.0453)	-0.4369*** (0.1020)	0.2305 (0.1519)	-0.3170 (0.1917)	0.1748 (0.2012)	-0.2538 (0.3413)
$Dist_{r35-39t}^S$	-1.3764*** (0.2878)	1.0413*** (0.0719)		0.7054*** (0.0956)	-0.5146*** (0.1315)	0.4604** (0.2024)	-0.1859 (0.2110)	0.2637 (0.3372)
$Dist_{r40-44t}^S$	0.8054** (0.3377)	-0.5549*** (0.1498)	0.6919*** (0.0927)		0.9138*** (0.0634)	-0.6873*** (0.1232)	0.2605* (0.1411)	-0.4871* (0.2575)
$Dist_{r45-49t}^S$	-0.2618 (0.4393)	0.2940 (0.2031)	-0.5068*** (0.1449)	0.9176*** (0.0473)		0.9096*** (0.0709)	-0.5819*** (0.1144)	1.1871*** (0.2419)
$Dist_{r50-54t}^S$	0.3543 (0.3519)	-0.2773 (0.1874)	0.3111** (0.1519)	-0.4734*** (0.0714)	0.6239*** (0.0523)		0.9389*** (0.0632)	-1.8962*** (0.2467)
$Dist_{r55-59t}^S$	0.0092 (0.3666)	0.1349 (0.1581)	-0.1108 (0.1229)	0.1583** (0.0759)	-0.3520*** (0.0661)	0.8281*** (0.0541)		2.1663*** (0.2371)
$Dist_{r60-64t}^S$	0.0778 (0.1982)	-0.0355 (0.0495)	0.0285 (0.0334)	-0.0536 (0.0356)	0.1301*** (0.0402)	-0.3030*** (0.0533)	0.3925*** (0.0402)	

TABLE 3 (count.)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$Dist_{r25-29t}^S$	$Dist_{r30-34t}^S$	$Dist_{r35-39t}^S$	$Dist_{r40-44t}^S$	$Dist_{r45-49t}^S$	$Dist_{r50-54t}^S$	$Dist_{r55-59t}^S$	$Dist_{r60-64t}^S$
log # of plants	0.5753 (0.4368)	0.0041 (0.1876)	-0.1417 (0.1721)	0.4002** (0.1777)	-0.3861** (0.1585)	-0.0613 (0.1789)	0.0532 (0.1825)	0.3511 (0.4686)
job-to-applicants ratio	0.0084 (0.0313)	0.0181 (0.0156)	-0.0282* (0.0165)	0.0002 (0.0200)	-0.0066 (0.0198)	0.0033 (0.0211)	-0.0198 (0.0196)	0.0731 (0.0489)
ratio of people over 65 years old	0.0583** (0.0223)	-0.0305*** (0.0103)	0.0195** (0.0074)	-0.0037 (0.0055)	-0.0070 (0.0065)	0.0049 (0.0077)	-0.0128 (0.0096)	0.0399* (0.0237)
constant	-8.0277 (5.2610)	0.8405 (2.2405)	1.2248 (2.0080)	-4.4145** (2.1575)	4.6287** (1.9229)	0.6119 (2.0309)	-0.2885 (2.0857)	-5.2672 (5.5796)
N	141	141	141	141	141	141	141	141
adj. R^2	0.914	0.955	0.946	0.976	0.988	0.990	0.993	0.973

Note: robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. We consider two cases for preferences. One of two is that preference relate to residential location is homogeneous. The other case is heteroskedasticity preference. We first estimate the effect of distributions of university graduates of different age groups under the homoskedasticity case (Table 4). Second, we also estimate one controlling for fixed effect, that is heteroskedasticity preferences of residents (Table 5).

TABLE 4: The relationship between distributions of university graduates and of high graduates (OLS)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$Dist_{r25-29t}^U$	$Dist_{r30-34t}^U$	$Dist_{r35-39t}^U$	$Dist_{r40-44t}^U$	$Dist_{r45-49t}^U$	$Dist_{r50-54t}^U$	$Dist_{r55-59t}^U$	$Dist_{r60-64t}^U$
$Dist_{r25-29t}^S$	0.6951** (0.3442)	0.3995 (0.3557)	0.5333 (0.4057)	0.6817* (0.4023)	0.6339 (0.3879)	0.5666* (0.3394)	0.5298 (0.3313)	0.5343* (0.2939)
$Dist_{r30-34t}^S$	-0.5693 (0.8437)	-0.4903 (0.8352)	-1.1683 (0.8934)	-1.4080 (0.9255)	-1.1075 (0.9492)	-0.6583 (0.9535)	-0.7339 (0.9300)	-1.2043 (0.7542)
$Dist_{r35-39t}^S$	0.5406 (0.9413)	1.0638 (0.8558)	1.5760* (0.8431)	1.0391 (0.9286)	0.0904 (1.0286)	-0.3665 (1.1186)	-0.0091 (1.0826)	1.1689 (0.7833)
$Dist_{r40-44t}^S$	-0.9118 (0.9958)	-1.5195 (0.9892)	-1.4842 (0.9136)	-0.4532 (0.8945)	0.4455 (0.9818)	0.5939 (1.0056)	0.7517 (1.0402)	0.0002 (0.9208)
$Dist_{r45-49t}^S$	0.8170 (1.0755)	1.3954 (1.0948)	1.7681 (1.1307)	1.3847 (1.0774)	0.5161 (1.0766)	-0.1644 (1.0315)	-0.7088 (1.0554)	-0.1579 (0.9851)
$Dist_{r50-54t}^S$	-0.8927 (0.8277)	-1.2491 (0.8537)	-1.6818* (0.8804)	-2.0095** (0.8587)	-1.3741* (0.7393)	-0.6803 (0.7311)	-0.7562 (0.8574)	-1.1960 (0.7664)
$Dist_{r55-59t}^S$	1.7104** (0.8533)	1.7583** (0.8608)	1.9066** (0.7624)	2.4807*** (0.7488)	2.7206*** (0.7127)	2.5184*** (0.7909)	2.6048*** (0.9320)	2.2433*** (0.7905)
$Dist_{r60-64t}^S$	-1.0249*** (0.3866)	-1.0122*** (0.3783)	-1.0709*** (0.3304)	-1.3153*** (0.3323)	-1.5030*** (0.3471)	-1.4002*** (0.3982)	-1.2225*** (0.4349)	-0.8907*** (0.3378)

TABLE 4 (count.)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$Dist_{r25-29t}^U$	$Dist_{r25-29t}^U$	$Dist_{r25-29t}^U$	$Dist_{r25-29t}^U$	$Dist_{r25-29t}^U$	$Dist_{r25-29t}^U$	$Dist_{r25-29t}^U$	$Dist_{r25-29t}^U$
log # of plants	1.2867*** (0.1373)	1.3020*** (0.1348)	1.2627*** (0.1269)	1.2365*** (0.1223)	1.2100*** (0.1294)	1.2421*** (0.1327)	1.1861*** (0.1354)	1.1631*** (0.1176)
job-to-applicants ratio	-0.0155 (0.0979)	-0.1055 (0.0963)	-0.0749 (0.0982)	-0.0115 (0.1000)	0.0626 (0.1024)	0.0592 (0.1010)	0.0957 (0.0993)	0.1091 (0.0936)
ratio of people over 65 years old	-0.0253 (0.0174)	-0.0161 (0.0177)	-0.0098 (0.0169)	0.0025 (0.0170)	0.0004 (0.0165)	0.0061 (0.0166)	0.0067 (0.0198)	0.0296 (0.0199)
distance to Tokyo	0.1163* (0.0592)	0.0727 (0.0590)	0.0795 (0.0567)	0.0822 (0.0534)	0.1030* (0.0527)	0.1228** (0.0584)	0.1713*** (0.0650)	0.2291*** (0.0613)
constant	-13.4133*** (1.6362)	-13.4727*** (1.6288)	-13.3016*** (1.5168)	-13.3983*** (1.4774)	-13.2514*** (1.5472)	-13.8421*** (1.5831)	-13.6150*** (1.7014)	-14.3342*** (1.5589)
N	141	141	141	141	141	141	141	141
adj. R^2	0.951	0.949	0.953	0.954	0.955	0.957	0.960	0.967

Note: robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. We consider two cases for preferences. One of two is that preference relate to residential location is homogeneous. The other case is heteroskedasticity preference. We first estimate the effect of distributions of university graduates of different age groups under the homoskedasticity case (Table 4). Second, we also estimate one controlling for fixed effect, that is heteroskedasticity preferences of residents (Table 5).

TABLE 5: The relationship between distributions of university graduates and of high graduates (FE)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$Dist_{r25-29t}^U$	$Dist_{r30-34t}^U$	$Dist_{r35-39t}^U$	$Dist_{r40-44t}^U$	$Dist_{r45-49t}^U$	$Dist_{r50-54t}^U$	$Dist_{r55-59t}^U$	$Dist_{r60-64t}^U$
$Dist_{r25-29t}^S$	0.1449 (0.2193)	0.1252 (0.1485)	0.2054* (0.1190)	-0.2963* (0.1537)	-0.7176*** (0.2586)	-0.6082* (0.3318)	-0.4731 (0.2886)	0.1497 (0.2267)
$Dist_{r30-34t}^S$	0.6325 (0.8770)	0.3396 (0.8453)	-0.0035 (0.3375)	1.2279* (0.6221)	2.8114*** (0.5714)	3.7046*** (0.8624)	3.6530*** (1.2951)	1.7889* (1.0429)
$Dist_{r35-39t}^S$	-0.6695 (0.8686)	0.4032 (0.7180)	0.8018* (0.4234)	-1.4554** (0.5466)	-3.8881*** (0.5375)	-4.8209*** (0.8730)	-4.4306*** (1.2626)	-1.6979 (1.0565)
$Dist_{r40-44t}^S$	0.9155* (0.5044)	-0.8085** (0.3337)	-1.2191*** (0.3976)	1.2906** (0.5424)	3.9397*** (1.0006)	4.4454*** (1.0610)	3.5358*** (1.0271)	0.7837 (0.8040)
$Dist_{r45-49t}^S$	-1.4670*** (0.4894)	0.1985 (0.3529)	1.4925*** (0.3574)	0.2835 (0.6004)	-2.0929* (1.0488)	-3.4336*** (1.0485)	-3.0255*** (1.0059)	-0.7076 (0.7926)
$Dist_{r50-54t}^S$	1.4341** (0.5590)	0.1365 (0.3810)	-1.0311*** (0.3161)	-0.7886* (0.4375)	0.9189 (0.7410)	2.1374** (0.9526)	1.3813 (1.1220)	-0.2971 (0.9488)
$Dist_{r55-59t}^S$	-0.6065 (0.4453)	0.0429 (0.3643)	0.5585 (0.3661)	0.8808** (0.3547)	0.5337 (0.4525)	0.0828 (0.6632)	0.5600 (0.8404)	0.7843 (0.7501)
$Dist_{r60-64t}^S$	0.0272 (0.2594)	-0.3460 (0.2662)	-0.3798 (0.2552)	-0.3967 (0.2752)	-0.3905 (0.3746)	-0.6538 (0.4561)	-0.8206* (0.4637)	-0.5674 (0.3631)

TABLE 5 (count.)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$Dist_{r25-29t}^U$	$Dist_{r30-34t}^U$	$Dist_{r35-39t}^U$	$Dist_{r40-44t}^U$	$Dist_{r45-49t}^U$	$Dist_{r50-54t}^U$	$Dist_{r55-59t}^U$	$Dist_{r60-64t}^U$
log # of plants	1.0857 (0.7232)	1.5045** (0.7441)	1.0030*** (0.3663)	0.5641 (0.7905)	-0.5757 (1.0026)	-0.0099 (1.0280)	1.0805 (1.0056)	1.5180** (0.6612)
job-to-applicants ratio	0.0836* (0.0495)	-0.0867 (0.0551)	-0.1072** (0.0410)	-0.0146 (0.0683)	0.0887 (0.1026)	0.0506 (0.1057)	-0.0781 (0.0920)	-0.1941*** (0.0656)
ratio of people over 65 years old	-0.0643* (0.0338)	-0.0278 (0.0280)	0.0595*** (0.0211)	0.1292*** (0.0319)	0.1018*** (0.0329)	0.0136 (0.0519)	0.0107 (0.0576)	0.0663* (0.0353)
constant	-9.5841 (8.4219)	-14.5669* (8.3759)	-11.5817*** (4.2525)	-8.9191 (8.7748)	4.0105 (11.1076)	0.2127 (12.1653)	-11.2108 (11.9770)	-17.2376** (7.7465)
N	138	138	138	138	138	138	138	138
adj. R^2	0.557	0.509	0.515	0.562	0.606	0.663	0.602	0.560

Note: robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. We consider two cases for preferences. One of two is that preference relate to residential location is homogeneous. The other case is heteroskedasticity preference. We first estimate the effect of distributions of university graduates of different age groups under the homoskedasticity case (Table 4). Second, we also estimate one controlling for fixed effect, that is heteroskedasticity preferences of residents (Table 5).

TABLE 6: The effects of changes in population size with university degree of an age group on those of other age groups (OLS)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$\Delta \log N_{r25-29t}^S$	$\Delta \log N_{r30-34t}^S$	$\Delta \log N_{r35-39t}^S$	$\Delta \log N_{r40-44t}^S$	$\Delta \log N_{r45-49t}^S$	$\Delta \log N_{r50-54t}^S$	$\Delta \log N_{r55-59t}^S$	$\Delta \log N_{r60-64t}^S$
$\Delta \log N_{r25-29t}^S$		0.4636*** (0.0520)	-0.3817*** (0.0608)	0.3709*** (0.0693)	-0.1865** (0.0810)	0.3198*** (0.0780)	-0.3444*** (0.1004)	0.5807*** (0.1865)
$\Delta \log N_{r30-34t}^S$	1.1320*** (0.1009)		0.8415*** (0.0432)	-0.6831*** (0.0673)	0.3472*** (0.1194)	-0.5603*** (0.1276)	0.6134*** (0.1595)	-0.5666* (0.3185)
$\Delta \log N_{r35-39t}^S$	-1.0376*** (0.1287)	0.9367*** (0.0501)		0.8277*** (0.0586)	-0.5476*** (0.1159)	0.6166*** (0.1349)	-0.5480*** (0.1741)	0.6283* (0.3271)
$\Delta \log N_{r40-44t}^S$	0.9419*** (0.1518)	-0.7105*** (0.0817)	0.7734*** (0.0662)		0.8852*** (0.0679)	-0.9082*** (0.0795)	0.8218*** (0.1336)	-1.4824*** (0.2572)
$\Delta \log N_{r45-49t}^S$	-0.4462** (0.1698)	0.3401*** (0.1083)	-0.4818*** (0.0821)	0.8336*** (0.0397)		0.9649*** (0.0438)	-0.8960*** (0.0939)	1.7356*** (0.1771)
$\Delta \log N_{r50-54t}^S$	0.6045*** (0.1336)	-0.4337*** (0.0857)	0.4288*** (0.0728)	-0.6759*** (0.0648)	0.7625*** (0.0602)		1.0707*** (0.0467)	-1.7789*** (0.1538)
$\Delta \log N_{r55-59t}^S$	-0.4697*** (0.1194)	0.3425*** (0.0698)	-0.2749*** (0.0663)	0.4412*** (0.0731)	-0.5108*** (0.0718)	0.7724*** (0.0349)		1.5782*** (0.1122)
$\Delta \log N_{r60-64t}^S$	0.2213*** (0.0584)	-0.0884** (0.0421)	0.0881** (0.0367)	-0.2225*** (0.0356)	0.2766*** (0.0420)	-0.3587*** (0.0356)	0.4412*** (0.0292)	

TABLE 6 (count.)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$\Delta \log N_{r25-29t}^S$	$\Delta \log N_{r30-34t}^S$	$\Delta \log N_{r35-39t}^S$	$\Delta \log N_{r40-44t}^S$	$\Delta \log N_{r45-49t}^S$	$\Delta \log N_{r50-54t}^S$	$\Delta \log N_{r55-59t}^S$	$\Delta \log N_{r60-64t}^S$
2nd period	0.0313	-0.0888***	0.0730***	-0.1099***	0.1129***	-0.2287***	0.2778***	-0.3713***
dummy	(0.0488)	(0.0245)	(0.0254)	(0.0282)	(0.0278)	(0.0200)	(0.0281)	(0.0607)
constant	-0.0484	0.0210	0.0024	0.0738**	-0.0856***	0.1942***	-0.2149***	0.4960***
	(0.0497)	(0.0263)	(0.0277)	(0.0342)	(0.0323)	(0.0267)	(0.0336)	(0.0563)
N	94	94	94	94	94	94	94	94
adj. R^2	0.929	0.956	0.899	0.985	0.992	0.989	0.938	0.826

Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

TABLE 7: The effects of changes in population size with university degree of an age group on those of other age groups (IV)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$\Delta \log N_{r25-29t}^S$	$\Delta \log N_{r30-34t}^S$	$\Delta \log N_{r35-39t}^S$	$\Delta \log N_{r40-44t}^S$	$\Delta \log N_{r45-49t}^S$	$\Delta \log N_{r50-54t}^S$	$\Delta \log N_{r55-59t}^S$	$\Delta \log N_{r60-64t}^S$
$\Delta \log N_{r25-29t}^S$		-6.8064 (35.7340)	-0.1271 (0.1920)	1.0424*** (0.3517)	0.2431 (0.3036)	-0.1738 (0.2949)	-0.1608 (0.2440)	0.7283 (0.4868)
$\Delta \log N_{r30-34t}^S$	9.7116 (19.6337)		1.0504*** (0.1168)	-0.4571 (0.3713)	0.6485* (0.3670)	-0.0143 (0.4587)	0.9340*** (0.2705)	-1.6244** (0.8021)
$\Delta \log N_{r35-39t}^S$	-6.4885 (13.0801)	-0.5144 (6.5426)		0.7037*** (0.2039)	-0.9029*** (0.2666)	0.4546 (0.3015)	-0.8541*** (0.2440)	1.2725** (0.6147)
$\Delta \log N_{r40-44t}^S$	3.4451 (6.6902)	-1.8282 (6.4880)	0.4143*** (0.1553)		0.9803*** (0.1320)	-0.8994*** (0.1110)	0.8955*** (0.2192)	-1.8929*** (0.4318)
$\Delta \log N_{r45-49t}^S$	-0.6286 (2.1167)	1.2998 (5.3275)	-0.0279 (0.2090)	0.6640*** (0.1408)		1.3351*** (0.2041)	-0.9087*** (0.2283)	1.9445*** (0.3385)
$\Delta \log N_{r50-54t}^S$	3.8206 (7.8561)	0.7767 (7.0325)	0.2582 (0.1697)	-0.3882* (0.2069)	0.6218*** (0.1995)		1.1105*** (0.0863)	-2.4085*** (0.3514)
$\Delta \log N_{r55-59t}^S$	-4.1143 (8.4206)	-0.5342 (5.5694)	-0.2525* (0.1469)	0.1370 (0.2628)	-0.2898 (0.2268)	0.5491*** (0.1001)		2.1533*** (0.3454)
$\Delta \log N_{r60-64t}^S$	0.0481 (0.6031)	0.8810 (5.1528)	-0.0573 (0.0802)	-0.2557*** (0.0929)	0.0616 (0.1128)	-0.2410*** (0.0772)	0.3316*** (0.0723)	

TABLE 7 (count.)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$\Delta \log N_{r25-29t}^S$	$\Delta \log N_{r30-34t}^S$	$\Delta \log N_{r35-39t}^S$	$\Delta \log N_{r40-44t}^S$	$\Delta \log N_{r45-49t}^S$	$\Delta \log N_{r50-54t}^S$	$\Delta \log N_{r55-59t}^S$	$\Delta \log N_{r60-64t}^S$
2nd period	2.0245	-1.3288	0.1703**	0.1641	0.1648*	-0.2194***	0.3521***	-0.6406***
dummy	(4.5923)	(5.7851)	(0.0663)	(0.1577)	(0.0942)	(0.0772)	(0.0570)	(0.1936)
constant	-0.6901	0.3699	-0.0089	-0.0274	-0.0233	0.1311***	-0.1947***	0.5953***
	(1.5480)	(1.5363)	(0.0443)	(0.0804)	(0.0716)	(0.0357)	(0.0398)	(0.1103)
N	94	94	94	94	94	94	94	94
adj. R^2	.	.	0.775	0.929	0.978	0.976	0.912	0.746

Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

TABLE 8: The effects of changes in population size with university degree of an age group on population size with high school degree (OLS)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$\Delta \log N_{r25-29t}^U$	$\Delta \log N_{r30-34t}^U$	$\Delta \log N_{r35-39t}^U$	$\Delta \log N_{r40-44t}^U$	$\Delta \log N_{r45-49t}^U$	$\Delta \log N_{r50-54t}^U$	$\Delta \log N_{r55-59t}^U$	$\Delta \log N_{r60-64t}^U$
$\Delta \log N_{r25-29t}^S$	0.2494 (0.1982)	0.2329 (0.1936)	0.2046 (0.1629)	-0.2262 (0.2568)	-0.0575 (0.3032)	0.6180 (0.3747)	0.3182 (0.3275)	0.6180 (0.3747)
$\Delta \log N_{r30-34t}^S$	-0.0316 (0.3317)	-0.1209 (0.3276)	-0.2545 (0.2635)	0.7003* (0.3750)	0.9962* (0.5045)	0.6463 (0.5605)	0.7575 (0.5623)	0.6463 (0.5605)
$\Delta \log N_{r35-39t}^S$	0.0824 (0.3589)	0.7381** (0.3441)	0.7278*** (0.2614)	-0.9053** (0.3927)	-1.6396*** (0.5153)	-1.3398** (0.6155)	-0.8049 (0.6336)	-1.3398** (0.6155)
$\Delta \log N_{r40-44t}^S$	0.2404 (0.3372)	-0.4750 (0.3100)	-0.5398** (0.2502)	0.6056 (0.4086)	1.0648* (0.5399)	1.1296* (0.6600)	0.8184 (0.6267)	1.1296* (0.6600)
$\Delta \log N_{r45-49t}^S$	-0.8974*** (0.3307)	-0.1811 (0.2646)	0.7154*** (0.2570)	0.7938** (0.3631)	0.3016 (0.4732)	-1.0107* (0.6070)	-1.1173* (0.5906)	-1.0107* (0.6070)
$\Delta \log N_{r50-54t}^S$	0.7284** (0.2952)	0.0193 (0.2565)	-0.5774*** (0.2179)	-0.5978** (0.2873)	-0.1679 (0.4241)	0.6724 (0.4850)	0.4860 (0.4830)	0.6724 (0.4850)
$\Delta \log N_{r55-59t}^S$	-0.0396 (0.2135)	0.4449** (0.1989)	0.2855 (0.1859)	-0.0302 (0.2774)	0.1706 (0.3487)	0.4337 (0.3761)	0.6874* (0.3483)	0.4337 (0.3761)
$\Delta \log N_{r60-64t}^S$	-0.0002 (0.1159)	-0.3500*** (0.0969)	-0.0528 (0.0947)	0.3768** (0.1437)	0.2075 (0.1845)	-0.2649 (0.1977)	-0.3131* (0.1855)	-0.2649 (0.1977)

TABLE 8 (count.)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$\Delta \log N_{r25-29t}^U$	$\Delta \log N_{r30-34t}^U$	$\Delta \log N_{r35-39t}^U$	$\Delta \log N_{r40-44t}^U$	$\Delta \log N_{r45-49t}^U$	$\Delta \log N_{r50-54t}^U$	$\Delta \log N_{r55-59t}^U$	$\Delta \log N_{r60-64t}^U$
2nd period	-0.5721***	-0.6006***	0.0237	0.4343***	-0.0797	-0.5603***	-0.3221**	-0.5603***
dummy	(0.0881)	(0.0816)	(0.0688)	(0.1041)	(0.1234)	(0.1369)	(0.1402)	(0.1369)
constant	-0.1146	0.1411	-0.2420***	-0.6339***	-0.2620**	0.1891	0.2422*	0.1891
	(0.0919)	(0.0867)	(0.0734)	(0.1181)	(0.1232)	(0.1437)	(0.1435)	(0.1437)
N	94	94	94	94	94	94	94	94
adj. R^2	0.930	0.857	0.405	0.751	0.814	0.915	0.534	0.915

Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

TABLE 9: The effects of changes in population size with university degree of an age group on population size with high school degree (IV)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$\Delta \log N_{r25-29t}^U$	$\Delta \log N_{r30-34t}^U$	$\Delta \log N_{r35-39t}^U$	$\Delta \log N_{r40-44t}^U$	$\Delta \log N_{r45-49t}^U$	$\Delta \log N_{r50-54t}^U$	$\Delta \log N_{r55-59t}^U$	$\Delta \log N_{r60-64t}^U$
$\Delta \log N_{r25-29t}^S$	0.4215 (0.5681)	-0.2063 (0.4462)	-0.9838* (0.5504)	-2.4613*** (0.8404)	-2.8610** (1.3372)	-0.4956 (1.2384)	0.0004 (1.0551)	-0.6267 (0.7551)
$\Delta \log N_{r30-34t}^S$	-1.4046 (0.8731)	0.4935 (0.6474)	1.4832* (0.8264)	1.7067 (1.2935)	-0.1937 (2.2581)	-1.7659 (2.0508)	-1.4336 (1.5338)	-0.1515 (0.9415)
$\Delta \log N_{r35-39t}^S$	1.1598 (0.7579)	0.3074 (0.5405)	-0.7320 (0.6581)	-2.1538** (1.0496)	-1.1100 (1.7937)	0.7273 (1.6441)	0.9145 (1.2780)	0.4114 (0.8559)
$\Delta \log N_{r40-44t}^S$	-1.0442* (0.6118)	-0.4017 (0.4532)	0.6890 (0.5794)	1.9220** (0.8616)	0.9072 (1.4590)	-1.0922 (1.3415)	-1.1239 (1.0684)	-0.3628 (0.7942)
$\Delta \log N_{r45-49t}^S$	0.1116 (0.5210)	0.0174 (0.3828)	0.1376 (0.4937)	0.2744 (0.7463)	0.9911 (1.2340)	1.3425 (1.0890)	0.8632 (0.8849)	0.4285 (0.7011)
$\Delta \log N_{r50-54t}^S$	-0.3997 (0.5895)	0.1198 (0.4261)	0.3733 (0.5196)	-0.1381 (0.8411)	-1.1156 (1.4562)	-1.7116 (1.4117)	-1.8710* (1.0629)	-1.0731 (0.6925)
$\Delta \log N_{r55-59t}^S$	0.8685* (0.5033)	0.2673 (0.3641)	-0.5502 (0.4455)	-0.3266 (0.7671)	1.0204 (1.4146)	2.2419 (1.3682)	2.5576** (1.0177)	1.1927** (0.5976)
$\Delta \log N_{r60-64t}^S$	-0.3104 (0.2157)	-0.3742** (0.1610)	0.2438 (0.1823)	0.8364*** (0.3246)	0.6043 (0.5633)	-0.5582 (0.5489)	-0.7337* (0.4169)	-0.0494 (0.2849)

TABLE 9 (count.)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$\Delta \log N_{r25-29t}^U$	$\Delta \log N_{r30-34t}^U$	$\Delta \log N_{r35-39t}^U$	$\Delta \log N_{r40-44t}^U$	$\Delta \log N_{r45-49t}^U$	$\Delta \log N_{r50-54t}^U$	$\Delta \log N_{r55-59t}^U$	$\Delta \log N_{r60-64t}^U$
2nd period	-0.9418***	-0.5812***	0.1829	0.0974	-1.0785*	-1.5660***	-1.2027***	-0.6532**
dummy	(0.2056)	(0.1835)	(0.2341)	(0.3554)	(0.5967)	(0.5309)	(0.4108)	(0.2901)
constant	0.1398	0.1741	-0.3485***	-0.5650***	0.0261	0.6327*	0.7203***	0.5086***
	(0.1376)	(0.1119)	(0.1127)	(0.1865)	(0.3415)	(0.3458)	(0.2615)	(0.1619)
N	94	94	94	94	94	94	94	94
adj. R^2	0.894	0.840	0.017	0.351	0.135	0.771	0.114	0.380

Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

TABLE A: Data description.

Variable	Definition	Data Source
$Dist_{r,g,t}^S$ (%)	The prefecture r 's share of university graduates of age group g in period t .	Population Census
$Dist_{r,g,t}^U$ (%)	The prefecture r 's share of high school graduates of age group g in period t .	Population Census
log # of plants	Logarithm of the number of plants in each prefecture.	Establishment and Enterprise Census
job-to-applicants ratio	Annual average of job-applicants ratio in each prefecture.	Monthly Labour Survey
ratio of people over 65 years rate (%)	The share of population over 65 years old in each prefecture.	Population Census
log of distance to Tokyo	The distance from each jurisdictional government offices to Tokyo government office.	Geospatial Information Authority of Japan

TABLE B-1: The results of first stage regression, (4), of IV (for column (1) in table 7)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	$\Delta \log N_{r30-34t}^S$	$\Delta \log N_{r35-39t}^S$	$\Delta \log N_{r40-44t}^S$	$\Delta \log N_{r45-49t}^S$	$\Delta \log N_{r50-54t}^S$	$\Delta \log N_{r55-59t}^S$	$\Delta \log N_{r60-64t}^S$
$IV_{r30-34t}$	-0.4561 (9.0150)	49.7391*** (7.2280)	119.4898*** (8.0973)	44.5472*** (5.4550)	-58.6476*** (8.5021)	-49.3769*** (5.7692)	-14.5839 (12.1942)
$IV_{r35-39t}$	-53.3432*** (7.9756)	-77.2217*** (5.5734)	2.7708 (6.8605)	44.6842*** (3.8772)	17.1496** (7.0433)	4.7592 (4.0282)	21.8089* (12.2263)
$IV_{r40-44t}$	-1.6548 (7.6661)	-10.9224** (4.4541)	-25.7817*** (4.0651)	6.4857** (3.1759)	6.5534 (5.3653)	-6.5798** (2.9154)	24.6698** (9.8794)
$IV_{r45-49t}$	2.3910 (5.7123)	-2.1544 (3.2068)	2.2408 (3.4473)	-16.0005*** (2.6063)	7.9520* (4.7176)	19.4824*** (2.0215)	-8.1547 (8.1259)
$IV_{r50-54t}$	9.1392** (3.8841)	3.2885 (2.3486)	0.0432 (2.5483)	1.7954 (1.5686)	-24.5314*** (3.7641)	-6.5690*** (1.8636)	21.8543** (8.5664)
$IV_{r54-59t}$	-21.8615*** (5.1885)	-14.2824*** (3.7392)	2.6359 (4.1146)	-1.2456 (2.5911)	-11.1431** (4.5874)	-37.6712*** (2.5244)	-1.4530 (8.5685)
$IV_{r60-64t}$	-1.6048 (3.4194)	-2.6108 (2.7211)	2.5394 (2.8237)	1.1730 (2.0941)	-2.7445 (2.8955)	0.4686 (1.6571)	-31.0349*** (3.9971)

TABLE B-1 (count.)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	$\Delta \log N_{r30-34t}^S$	$\Delta \log N_{r35-39t}^S$	$\Delta \log N_{r40-44t}^S$	$\Delta \log N_{r45-49t}^S$	$\Delta \log N_{r50-54t}^S$	$\Delta \log N_{r55-59t}^S$	$\Delta \log N_{r60-64t}^S$
2nd period dummy	0.6189*** (0.1908)	-0.3808*** (0.1147)	-1.5145*** (0.1298)	-1.0288*** (0.0975)	-0.4777*** (0.1664)	0.9461*** (0.0839)	1.7942*** (0.3305)
constant	1.2866*** (0.3420)	1.9661*** (0.2230)	-0.6691** (0.3018)	-0.4438** (0.2028)	2.0932*** (0.3069)	1.4902*** (0.1746)	-0.4003 (0.5188)
N	94	94	94	94	94	94	94
adj. R^2	0.828	0.784	0.965	0.992	0.977	0.973	0.878

Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

TABLE B-2: The results of first stage regression, (4), of IV (for column (2) in table 7)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	$\Delta \log N_{r25-29t}^S$	$\Delta \log N_{r35-39t}^S$	$\Delta \log N_{r40-44t}^S$	$\Delta \log N_{r45-49t}^S$	$\Delta \log N_{r50-54t}^S$	$\Delta \log N_{r55-59t}^S$	$\Delta \log N_{r60-64t}^S$
$IV_{r25-29t}$	3.5199 (6.4038)	-6.4052 (5.0541)	-15.7598* (8.2603)	-3.2399 (4.1101)	-2.9304 (5.8196)	1.6283 (4.0051)	16.0338** (6.9071)
$IV_{r35-39t}$	23.0214** (10.3592)	-73.8646*** (9.1978)	10.4071 (15.7456)	50.5640*** (7.8714)	1.1280 (11.2188)	-4.0168 (7.7325)	37.1144** (16.0866)
$IV_{r40-44t}$	15.0223** (6.5501)	-13.1567*** (4.5574)	-31.2142*** (7.7653)	4.9189 (3.7424)	7.3643 (6.9461)	-5.1846 (4.1287)	27.7875*** (9.3350)
$IV_{r45-49t}$	-0.1826 (5.8949)	-10.5646*** (3.8440)	-18.0055*** (6.8180)	-23.2503*** (3.2566)	16.6822*** (5.6972)	27.2961*** (3.2407)	-4.0868 (6.1914)
$IV_{r50-54t}$	0.4533 (3.9142)	1.3535 (2.8224)	-4.6526 (4.5891)	0.3794 (2.2528)	-23.5808*** (3.8209)	-5.2487* (2.9270)	24.2190*** (7.9062)
$IV_{r55-59t}$	5.0132 (7.0378)	-14.8808*** (5.3899)	1.0654 (8.8523)	-0.8900 (3.8644)	-14.1809** (6.0489)	-38.7663*** (3.7107)	3.7774 (6.5769)
$IV_{r60-64t}$	-4.9575 (4.4802)	-1.6006 (3.8189)	5.0184 (6.5060)	1.7266 (2.9032)	-2.4614 (4.3662)	0.1310 (2.5950)	-33.3218*** (3.2872)

TABLE B-2 (count.)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	$\Delta \log N_{r25-29t}^S$	$\Delta \log N_{r35-39t}^S$	$\Delta \log N_{r40-44t}^S$	$\Delta \log N_{r45-49t}^S$	$\Delta \log N_{r50-54t}^S$	$\Delta \log N_{r55-59t}^S$	$\Delta \log N_{r60-64t}^S$
2nd period dummy	0.3852 (0.3916)	-0.9478*** (0.3274)	-2.8990*** (0.5263)	-1.3873*** (0.2593)	-0.4362 (0.4134)	1.2261*** (0.2961)	2.8073*** (0.6427)
constant	-0.9048 (0.6157)	3.2691*** (0.5305)	2.4928*** (0.8930)	0.5093 (0.4500)	1.4548** (0.6554)	0.6020 (0.4674)	-1.9949** (0.9503)
N	94	94	94	94	94	94	94
adj. R^2	0.839	0.670	0.874	0.986	0.964	0.936	0.885

Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

TABLE B-3: The results of first stage regression, (4), of IV (for column (3) in table 7)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	$\Delta \log N_{r25-29t}^S$	$\Delta \log N_{r30-34t}^S$	$\Delta \log N_{r40-44t}^S$	$\Delta \log N_{r45-49t}^S$	$\Delta \log N_{r50-54t}^S$	$\Delta \log N_{r55-59t}^S$	$\Delta \log N_{r60-64t}^S$
$IV_{r25-29t}$	-0.3620 (5.1511)	28.2749*** (4.0872)	-5.3960 (3.3669)	-15.9938*** (2.8425)	-10.5617*** (2.9155)	-2.8997 (1.8920)	1.4576 (4.4912)
$IV_{r30-34t}$	39.0005*** (10.9121)	-2.0964 (12.4400)	116.9813*** (7.6136)	51.0006*** (8.4191)	-59.0920*** (8.3276)	-49.4796*** (5.5415)	-5.3164 (12.7282)
$IV_{r40-44t}$	15.9840** (7.1446)	1.6971 (6.7837)	-26.9937*** (4.2263)	5.7104 (5.5185)	5.0869 (4.6442)	-6.9785** (3.2354)	26.7394** (12.2561)
$IV_{r45-49t}$	3.2051 (5.7930)	9.7717** (4.7016)	1.8708 (3.3194)	-22.2094*** (3.7710)	5.5842 (4.0089)	18.8252*** (2.2849)	-11.2167 (10.2555)
$IV_{r50-54t}$	0.6174 (4.1038)	13.1411*** (3.5436)	-0.6350 (2.8142)	-0.6358 (3.4342)	-25.9941*** (2.7970)	-6.9712*** (2.1587)	21.7769** (9.9148)
$IV_{r55-59t}$	3.0400 (6.3711)	-13.1956** (5.5530)	0.5835 (4.3900)	-5.3669 (4.4185)	-14.5294*** (4.3393)	-38.5982*** (2.7284)	0.3148 (9.2377)
$IV_{r60-64t}$	-6.2640 (4.2213)	-2.0150 (3.9148)	3.8085 (2.9633)	-0.9270 (3.0483)	-2.1451 (3.0424)	0.6250 (1.6791)	-35.0031*** (3.2818)

TABLE B-3 (count.)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	$\Delta \log N_{r25-29t}^S$	$\Delta \log N_{r30-34t}^S$	$\Delta \log N_{r40-44t}^S$	$\Delta \log N_{r45-49t}^S$	$\Delta \log N_{r50-54t}^S$	$\Delta \log N_{r55-59t}^S$	$\Delta \log N_{r60-64t}^S$
2nd period dummy	0.2312 (0.3346)	2.4373*** (0.2943)	-1.8277*** (0.1923)	-2.1236*** (0.2097)	-1.1443*** (0.2129)	0.7629*** (0.1387)	1.7758*** (0.4353)
constant	-0.8149* (0.4416)	-1.8138*** (0.4234)	-0.2685 (0.2610)	1.6842*** (0.3022)	3.1797*** (0.2920)	1.7898*** (0.1862)	0.0732 (0.4702)
N	94	94	94	94	94	94	94
adj. R^2	0.851	0.815	0.966	0.985	0.978	0.973	0.868

Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

TABLE B-4: The results of first stage regression, (4), of IV (for column (4) in table 7)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	$\Delta \log N_{r25-29t}^S$	$\Delta \log N_{r30-34t}^S$	$\Delta \log N_{r35-39t}^S$	$\Delta \log N_{r45-49t}^S$	$\Delta \log N_{r50-54t}^S$	$\Delta \log N_{r55-59t}^S$	$\Delta \log N_{r60-64t}^S$
$IV_{r25-29t}$	4.3060 (6.3040)	15.0299*** (5.0810)	-1.5708 (4.0369)	-0.7547 (3.0031)	-7.8867* (4.5243)	-1.1896 (2.4713)	12.1515 (7.3887)
$IV_{r30-34t}$	35.1617*** (11.3513)	3.1327 (9.8003)	49.8927*** (7.0613)	44.0619*** (5.5467)	-60.8016*** (8.3536)	-49.3412*** (5.9007)	-12.9217 (12.1847)
$IV_{r35-39t}$	17.6560 (10.8734)	-36.7357*** (9.0165)	-79.9843*** (7.1606)	44.4430*** (5.1071)	8.9613 (9.4854)	2.8235 (4.8726)	37.6431* (20.1241)
$IV_{r45-49t}$	10.2585* (5.8830)	4.9673 (4.1823)	-5.7600* (3.0940)	-14.2046*** (2.6273)	8.3097* (4.3084)	17.2605*** (1.7930)	1.7488 (5.4500)
$IV_{r50-54t}$	-0.3556 (3.9013)	11.0175*** (3.0127)	4.2866* (2.2128)	1.0119 (1.5414)	-26.1289*** (2.8941)	-5.9953*** (1.6635)	20.5732** (8.8520)
$IV_{r55-59t}$	4.7865 (6.5645)	-16.5714*** (4.9022)	-15.3302*** (4.1116)	-1.2256 (2.8685)	-13.6653*** (4.5096)	-38.3893*** (2.6065)	3.9842 (7.9105)
$IV_{r60-64t}$	-5.9489 (4.2891)	-3.7787 (3.4074)	-1.8264 (2.8283)	0.9606 (2.1646)	-1.8893 (2.9023)	0.9777 (1.6943)	-34.0986*** (3.7123)

TABLE B-4 (count.)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	$\Delta \log N_{r25-29t}^S$	$\Delta \log N_{r30-34t}^S$	$\Delta \log N_{r35-39t}^S$	$\Delta \log N_{r45-49t}^S$	$\Delta \log N_{r50-54t}^S$	$\Delta \log N_{r55-59t}^S$	$\Delta \log N_{r60-64t}^S$
2nd period dummy	0.2279 (0.3777)	1.5094*** (0.3082)	-0.2396 (0.2394)	-1.2087*** (0.1599)	-1.0650*** (0.2954)	1.0173*** (0.1535)	1.9651*** (0.5526)
constant	-1.2199* (0.6603)	-0.0367 (0.5339)	1.8981*** (0.4105)	-0.2583 (0.2896)	2.8932*** (0.5255)	1.4702*** (0.2675)	-0.9866 (0.9297)
N	94	94	94	94	94	94	94
adj. R^2	0.849	0.842	0.773	0.992	0.978	0.971	0.868

Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

TABLE B-5: The results of first stage regression, (4), of IV (for column (5) in table 7)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	$\Delta \log N_{r25-29t}^S$	$\Delta \log N_{r30-34t}^S$	$\Delta \log N_{r35-39t}^S$	$\Delta \log N_{r40-44t}^S$	$\Delta \log N_{r50-54t}^S$	$\Delta \log N_{r55-59t}^S$	$\Delta \log N_{r60-64t}^S$
$IV_{r25-29t}$	5.1696 (6.0712)	14.3537*** (4.9135)	-2.4219 (4.0274)	-7.4513* (4.3201)	-8.4624* (4.7827)	-5.2427* (3.0989)	16.2456** (7.5510)
$IV_{r30-34t}$	32.8293*** (10.9909)	0.3279 (9.2658)	50.6418*** (6.7651)	117.0247*** (7.3818)	-64.6433*** (7.8888)	-61.6951*** (5.8384)	-7.2770 (11.0195)
$IV_{r35-39t}$	15.4299 (10.2433)	-38.9576*** (8.2678)	-79.1171*** (7.4794)	-5.7546 (8.2700)	5.8251 (10.4018)	-6.6777 (5.1732)	41.3892** (18.8196)
$IV_{r40-44t}$	19.1604*** (6.4222)	3.3953 (5.9439)	-12.7264*** (4.3344)	-26.5103*** (4.3184)	8.6656* (4.6207)	2.6422 (3.7457)	24.4810*** (7.4440)
$IV_{r50-54t}$	4.2136 (2.7557)	13.2694*** (2.2862)	1.7342 (1.9319)	-0.3957 (2.2349)	-22.3818*** (2.7654)	1.8909 (1.3966)	21.2101*** (6.0989)
$IV_{r55-59t}$	2.5513 (6.2146)	-18.3401*** (5.0085)	-14.3048*** (3.7865)	-0.3290 (4.2505)	-16.2757*** (4.2973)	-45.6035*** (3.3505)	6.0785 (5.6427)
$IV_{r60-64t}$	-4.6950 (4.1635)	-3.1634 (3.4526)	-2.5277 (2.6930)	3.7061 (2.8039)	-0.8640 (2.8885)	3.1289 (2.1424)	-33.9146*** (3.0832)

TABLE B-5 (count.)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	$\Delta \log N_{r25-29t}^S$	$\Delta \log N_{r30-34t}^S$	$\Delta \log N_{r35-39t}^S$	$\Delta \log N_{r40-44t}^S$	$\Delta \log N_{r50-54t}^S$	$\Delta \log N_{r55-59t}^S$	$\Delta \log N_{r60-64t}^S$
2nd period dummy	0.6001 (0.3910)	1.4762*** (0.3333)	-0.5200* (0.2845)	-1.9704*** (0.2902)	-1.0122*** (0.3675)	0.5697*** (0.1932)	2.7983*** (0.7082)
constant	-1.4375** (0.6260)	0.1319 (0.4969)	2.1119*** (0.4275)	0.0278 (0.4495)	3.0361*** (0.5802)	2.4821*** (0.2834)	-2.0114* (1.1128)
N	94	94	94	94	94	94	94
adj. R^2	0.854	0.841	0.785	0.966	0.977	0.952	0.885

Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

TABLE B-6: The results of first stage regression, (4), of IV (for column (6) in table 7)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	$\Delta \log N_{r25-29t}^S$	$\Delta \log N_{r30-34t}^S$	$\Delta \log N_{r35-39t}^S$	$\Delta \log N_{r40-44t}^S$	$\Delta \log N_{r45-49t}^S$	$\Delta \log N_{r55-59t}^S$	$\Delta \log N_{r60-64t}^S$
$IV_{r25-29t}$	5.6315 (6.3272)	11.5752** (5.5577)	-3.7957 (3.9644)	-6.9612* (4.1068)	-0.5975 (2.9201)	0.2180 (2.6678)	7.5897 (7.8463)
$IV_{r30-34t}$	35.9544*** (11.4425)	0.3414 (10.2020)	48.2969*** (7.0442)	117.9697*** (7.7400)	44.0802*** (5.3871)	-48.0957*** (6.5844)	-17.0404 (13.5297)
$IV_{r35-39t}$	17.5503 (11.0296)	-41.2089*** (11.1375)	-81.5432*** (7.7982)	-4.8286 (8.4933)	43.9344*** (5.1067)	5.3550 (4.9122)	28.9008 (24.3222)
$IV_{r40-44t}$	15.5538** (7.0259)	-4.1001 (7.1703)	-12.7838*** (4.5670)	-26.6583*** (4.3015)	5.6513* (3.1279)	-3.7694 (2.5772)	16.3454 (10.4331)
$IV_{r45-49t}$	7.2971 (4.3980)	15.5127*** (4.2350)	0.2445 (2.5300)	0.2557 (2.6729)	-14.2605*** (1.8750)	12.5420*** (1.6517)	17.3612** (7.2212)
$IV_{r55-59t}$	6.1238 (5.7397)	-6.8147 (5.1966)	-12.7329*** (3.5371)	-0.6991 (3.6865)	0.3163 (2.7296)	-44.3414*** (2.4128)	24.7747*** (6.3345)
$IV_{r60-64t}$	-6.0848 (4.0041)	-8.4448** (3.7385)	-3.4340 (2.5654)	3.9507 (2.5741)	0.4201 (2.1004)	3.6283** (1.6329)	-43.2576*** (3.9873)

TABLE B-6 (count.)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	$\Delta \log N_{r25-29t}^S$	$\Delta \log N_{r30-34t}^S$	$\Delta \log N_{r35-39t}^S$	$\Delta \log N_{r40-44t}^S$	$\Delta \log N_{r45-49t}^S$	$\Delta \log N_{r55-59t}^S$	$\Delta \log N_{r60-64t}^S$
2nd period dummy	0.6376 (0.4198)	1.2666*** (0.4104)	-0.6256** (0.2795)	-1.9326*** (0.2722)	-1.0739*** (0.1788)	0.9931*** (0.1734)	2.1371** (0.8587)
constant	-1.6379** (0.7037)	0.2338 (0.6343)	2.3003*** (0.4449)	-0.0457 (0.4622)	-0.3934 (0.3012)	1.4823*** (0.2958)	-1.1186 (1.3594)
N	94	94	94	94	94	94	94
adj. R^2	0.856	0.823	0.782	0.966	0.992	0.967	0.833

Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

TABLE B-7: The results of first stage regression, (4), of IV (for column (7) in table 7)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	$\Delta \log N_{r25-29t}^S$	$\Delta \log N_{r30-34t}^S$	$\Delta \log N_{r35-39t}^S$	$\Delta \log N_{r40-44t}^S$	$\Delta \log N_{r45-49t}^S$	$\Delta \log N_{r50-54t}^S$	$\Delta \log N_{r60-64t}^S$
$IV_{r25-29t}$	4.4566 (5.4451)	21.0907*** (5.3673)	2.6141 (4.6023)	-7.2931* (4.1150)	0.4267 (2.6583)	-2.3886 (3.8808)	13.8613* (7.3788)
$IV_{r30-34t}$	36.5007*** (11.4466)	2.7456 (10.7637)	48.6168*** (7.7637)	117.7363*** (7.6781)	44.5065*** (5.3387)	-60.7980*** (8.9141)	-10.7843 (11.7458)
$IV_{r35-39t}$	16.8296 (10.3311)	-31.8823*** (10.1729)	-75.9248*** (9.1721)	-5.2302 (8.4913)	45.0238*** (4.8329)	13.1149 (8.7060)	37.4347** (16.6763)
$IV_{r40-44t}$	16.3314** (7.0720)	0.9469 (6.7938)	-11.5433** (5.0284)	-27.0827*** (4.5521)	6.4729** (3.1144)	5.1486 (4.8087)	27.4325*** (9.1692)
$IV_{r45-49t}$	4.1179 (6.0328)	10.3521** (4.6724)	2.6509 (3.2545)	1.1125 (3.3800)	-15.5744*** (2.6554)	11.5441** (4.4377)	-7.1838 (5.7883)
$IV_{r50-54t}$	3.3590 (3.5250)	4.9882 (3.2605)	-2.7669 (2.8117)	-0.8788 (2.4916)	1.3268 (1.5330)	-30.5819*** (2.3410)	25.3096*** (5.9517)
$IV_{r60-64t}$	-2.8321 (2.3240)	-12.7925*** (2.0371)	-10.5489*** (1.5111)	3.6207** (1.3852)	0.4919 (1.1243)	-9.1873*** (1.7472)	-31.0765*** (1.9259)

TABLE B-7 (count.)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	$\Delta \log N_{r25-29t}^S$	$\Delta \log N_{r30-34t}^S$	$\Delta \log N_{r35-39t}^S$	$\Delta \log N_{r40-44t}^S$	$\Delta \log N_{r45-49t}^S$	$\Delta \log N_{r50-54t}^S$	$\Delta \log N_{r60-64t}^S$
2nd period dummy	0.5944 (0.3750)	1.8284*** (0.3703)	-0.2876 (0.3302)	-1.9568*** (0.2885)	-1.0083*** (0.1674)	-0.6814** (0.2997)	2.6524*** (0.6605)
constant	-1.5335** (0.6443)	-0.5862 (0.6079)	1.7430*** (0.5212)	-0.0177 (0.4635)	-0.4810* (0.2848)	2.3158*** (0.4873)	-1.6412 (0.9888)
N	94	94	94	94	94	94	94
adj. R^2	0.855	0.824	0.747	0.966	0.992	0.976	0.886

Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

TABLE B-8: The results of first stage regression, (4), of IV (for column (8) in table 7)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	$\Delta \log N_{r25-29t}^S$	$\Delta \log N_{r30-34t}^S$	$\Delta \log N_{r35-39t}^S$	$\Delta \log N_{r40-44t}^S$	$\Delta \log N_{r45-49t}^S$	$\Delta \log N_{r50-54t}^S$	$\Delta \log N_{r55-59t}^S$
$IV_{r25-29t}$	4.2256 (6.1909)	13.8198*** (5.1994)	-3.6466 (4.0391)	-5.9893 (4.3144)	0.3954 (2.8696)	-7.9036* (4.5457)	-1.7073 (2.6080)
$IV_{r30-34t}$	35.8046*** (11.9977)	2.8211 (9.9763)	48.8161*** (7.0058)	118.1049*** (7.9200)	44.6644*** (5.4978)	-60.5922*** (8.3886)	-49.7766*** (5.7472)
$IV_{r35-39t}$	20.1693* (11.0442)	-35.3370*** (8.8292)	-79.5627*** (7.2371)	-6.4975 (9.1055)	44.2312*** (5.1393)	9.7610 (10.0006)	2.3199 (5.4997)
$IV_{r40-44t}$	17.0172** (7.3631)	1.5610 (6.8892)	-11.1425** (4.7868)	-27.5573*** (4.6526)	6.3253** (3.1333)	5.4727 (5.1926)	-7.0331** (3.1135)
$IV_{r45-49t}$	4.2414 (6.3871)	3.6387 (5.0433)	-3.1946 (3.4535)	2.1321 (3.5731)	-15.6792*** (2.6915)	6.3803 (4.5738)	19.3916*** (1.9566)
$IV_{r50-54t}$	3.9775 (3.8575)	12.7867*** (3.1049)	3.8769 (2.3584)	-2.4800 (2.9366)	1.2768 (1.6030)	-24.7455*** (3.1662)	-7.1578*** (1.9385)
$IV_{r55-59t}$	-2.5166 (3.6981)	-21.5836*** (2.8067)	-18.2330*** (2.0348)	4.8717** (2.2100)	0.3199 (1.5319)	-15.9819*** (2.5510)	-37.3600*** (1.4387)

TABLE B-8 (count.)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	$\Delta \log N_{r25-29t}^S$	$\Delta \log N_{r30-34t}^S$	$\Delta \log N_{r35-39t}^S$	$\Delta \log N_{r40-44t}^S$	$\Delta \log N_{r45-49t}^S$	$\Delta \log N_{r50-54t}^S$	$\Delta \log N_{r55-59t}^S$
2nd period dummy	0.6162 (0.4266)	1.4968*** (0.3532)	-0.5793** (0.2760)	-1.9151*** (0.3028)	-1.0170*** (0.1791)	-0.9398*** (0.3552)	0.8347*** (0.2069)
constant	-1.6449** (0.7393)	-0.0416 (0.5641)	2.2367*** (0.4318)	-0.0449 (0.4905)	-0.4497 (0.3048)	2.7563*** (0.5756)	1.6614*** (0.3207)
N	94	94	94	94	94	94	94
adj. R^2	0.853	0.840	0.784	0.965	0.992	0.978	0.973

Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

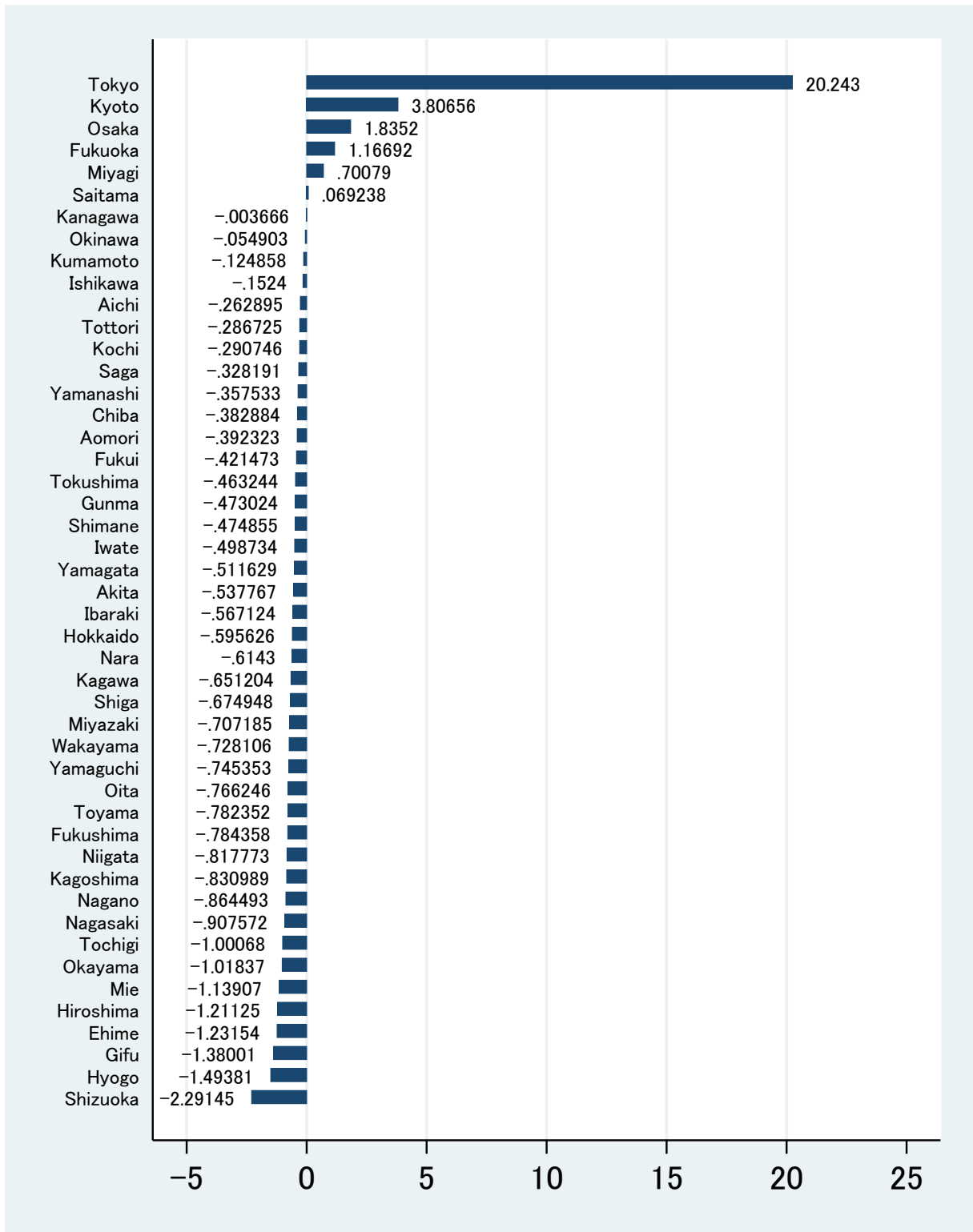
TABLE B-9: The results of first stage regression, (4), of IV (for columns in table 9)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$\Delta \log N_{r25-29t}^S$	$\Delta \log N_{r30-34t}^S$	$\Delta \log N_{r35-39t}^S$	$\Delta \log N_{r40-44t}^S$	$\Delta \log N_{r45-49t}^S$	$\Delta \log N_{r50-54t}^S$	$\Delta \log N_{r55-59t}^S$	$\Delta \log N_{r60-64t}^S$
$IV_{r25-29t}$	6.1469 (6.3561)	15.1500*** (5.1331)	-2.8625 (4.0272)	-7.2556 (4.3753)	-0.0225 (2.9952)	-7.2943 (4.7013)	-1.9728 (2.6042)	15.2470** (6.7879)
$IV_{r30-34t}$	36.3682*** (11.6876)	3.2114 (9.8472)	49.0461*** (7.0646)	117.7334*** (7.7405)	44.5418*** (5.4026)	-60.4134*** (8.3552)	-49.8545*** (5.7223)	-10.8930 (11.7686)
$IV_{r35-39t}$	18.2004* (10.8902)	-36.7002*** (9.0184)	-80.3663*** (7.4773)	-5.1998 (8.7541)	44.6595*** (5.1256)	9.1365 (9.8672)	2.5920 (5.4598)	38.5584** (16.4673)
$IV_{r40-44t}$	16.2983** (6.9662)	1.0633 (6.7136)	-11.4359** (4.7172)	-27.0835*** (4.5792)	6.4817** (3.1801)	5.2447 (5.1411)	-6.9337** (3.1660)	27.4053*** (9.4200)
$IV_{r45-49t}$	5.7341 (6.1138)	4.6721 (4.7143)	-2.5854 (3.4238)	1.1483 (3.6455)	-16.0039*** (2.5761)	6.8537 (4.6114)	19.1853*** (2.0178)	-5.8589 (6.7956)
$IV_{r50-54t}$	1.6071 (3.8345)	11.1455*** (3.0857)	2.9095 (2.5817)	-0.9177 (3.0927)	1.7924 (1.6307)	-25.4974*** (3.3215)	-6.8303*** (2.1363)	23.8734*** (7.8619)
$IV_{r55-59t}$	4.7164 (6.3950)	-16.5760*** (4.9298)	-15.2810*** (4.0030)	0.1046 (4.5862)	-1.2535 (2.9264)	-13.6879*** (4.6063)	-38.3594*** (2.6734)	3.8663 (6.6583)
$IV_{r60-64t}$	-5.4069 (4.1515)	-3.7434 (3.3907)	-2.2067 (2.7198)	3.5636 (2.8792)	1.1762 (2.1944)	-1.7149 (2.9359)	0.7471 (1.6839)	-33.1872*** (3.4065)

TABLE B-9 (count.)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$\Delta \log N_{r25-29t}^S$	$\Delta \log N_{r30-34t}^S$	$\Delta \log N_{r35-39t}^S$	$\Delta \log N_{r40-44t}^S$	$\Delta \log N_{r45-49t}^S$	$\Delta \log N_{r50-54t}^S$	$\Delta \log N_{r55-59t}^S$	$\Delta \log N_{r60-64t}^S$
2nd period	0.6768	1.5387***	-0.5546**	-1.9550***	-1.0302***	-0.9206**	0.8263***	2.7199***
dummy	(0.4151)	(0.3474)	(0.2776)	(0.2981)	(0.1828)	(0.3536)	(0.2026)	(0.6318)
constant	-1.6813**	-0.0668	2.2219***	-0.0210	-0.4418	2.7447***	1.6664***	-1.7623*
	(0.7068)	(0.5542)	(0.4339)	(0.4837)	(0.3024)	(0.5738)	(0.3183)	(0.9361)
N	94	94	94	94	94	94	94	94
adj. R^2	0.854	0.840	0.783	0.966	0.992	0.978	0.973	0.885

Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.



Note: vertical axis is prefectures and horizontal axis is differences between the regional share (in percentage) of people obtaining a high school degree and college/university admission and that of college/ university enrollment

Fig. 1: Place of obtaining a high school degree and place of college/university enrollment

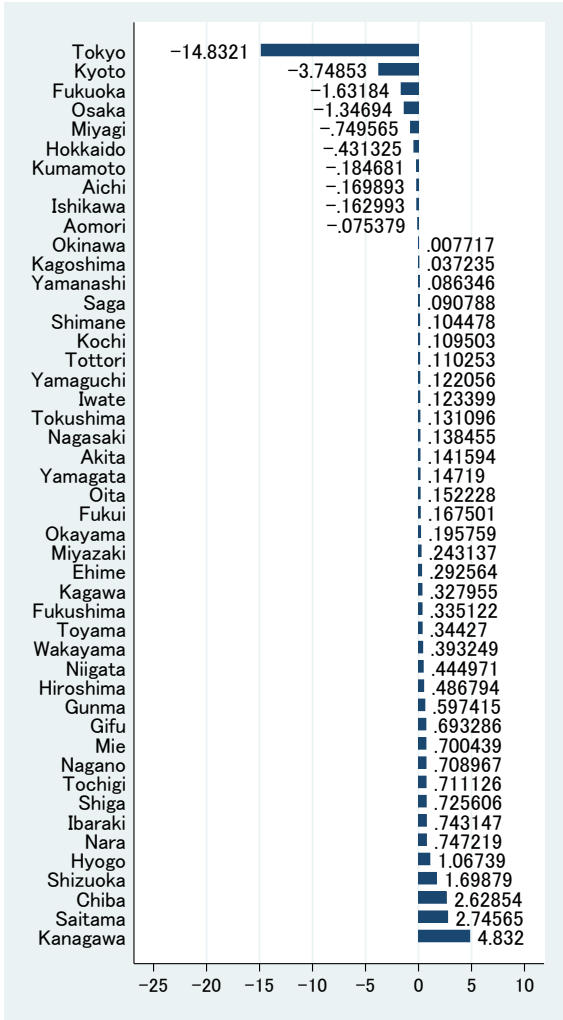


Fig.2-a: 25-29 years old

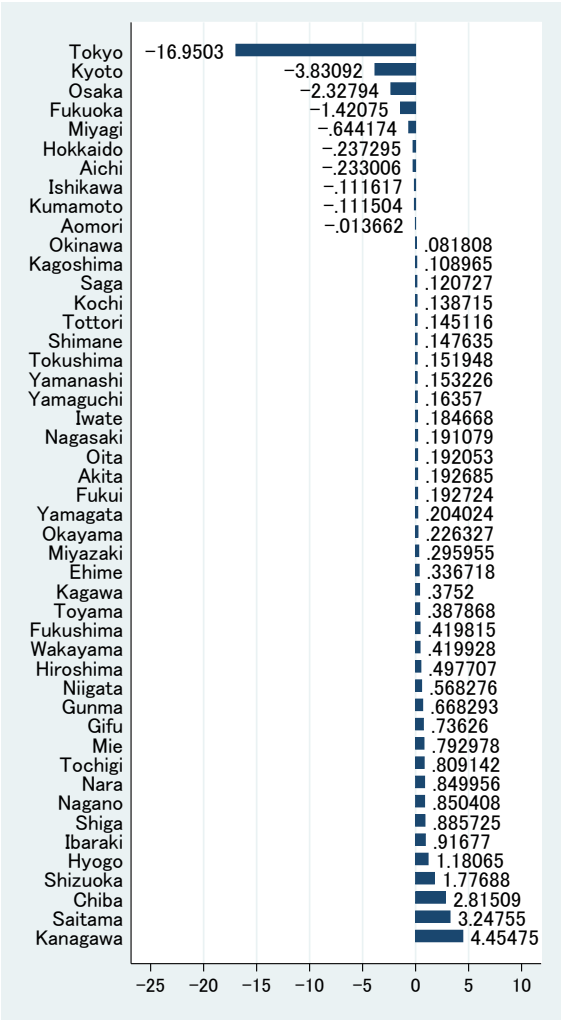


Fig. 2-b: 35-39 years old

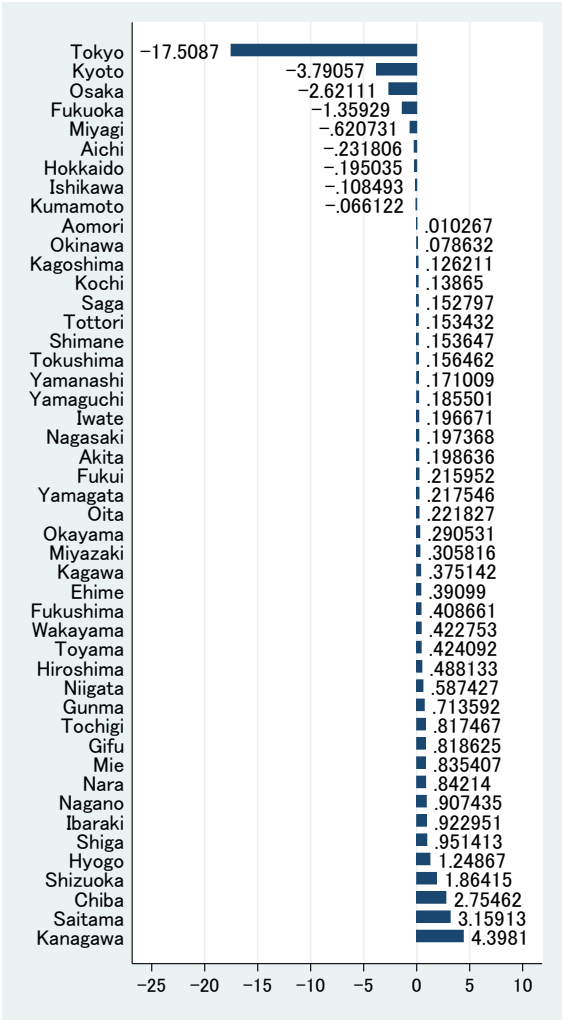


Fig.2-c: 45-49 years old

Note: vertical axis is prefectures and horizontal axis is differences between the regional share (in percentage) of college/university enrollment and that of college/ university graduates.

Fig.2: Place of college/university enrollment and place of residence after college/university graduation