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**Urbanization Effects on
Job Search Decision***

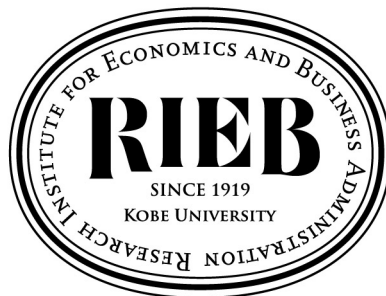
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September 17, 2020

*This Discussion Paper won the Kanematsu Prize (FY 2019).

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Urbanization effects on job search decision*

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Abstract

This paper examines the effect of industrial agglomeration on a non-working individual's decision to search for a job. The theory implies that agglomeration reduces search costs, enabling non-working individuals to search for jobs. The empirical analyses, using Japanese microdata, find that agglomeration raises the probability of searching for a job, supporting the theoretical prediction. Furthermore, this effect is significant only for females who are less educated, middle-aged and older, and married without children. Such groups tend to benefit from agglomeration because they have relatively higher potential search costs than do other groups.

Keywords: Agglomeration; Local labor market; Labor force participation; Heterogenous individual

JEL classification: J64; R11; R23

* I would like to thank anonymous reviewers of the 2019 Kanematsu Prize, Kazufumi Yugami, Nobuaki Hamaguchi, Tamotsu Nakamura, Yasuhiro Sato, and participants at the 22nd Labor Economics Conference, the 2019 Autumn Meeting of the Japanese Economic Association, and the 33rd Annual Meeting of the Applied Regional Science Conference for helpful comments. I would also like to thank the Ministry of Internal Affairs and Communications (MIC) of Japan for providing the microdata of the Employment Status Survey (ESS). The results using the ESS in this paper are calculated by the author; therefore, they are not necessarily consistent with the survey results that the MIC makes public. Remaining errors are my own. This research was supported by the Grant-in-Aid for Japan Society for the Promotion of Science (JSPS) Fellows (JSPS KAKENHI Grant Number JP18J11560).

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1. Introduction

Some studies have recently confirmed the urban premium with regard to job search and matching. In urbanized areas, which generate greater labor market pooling in thick markets, job seekers might encounter vacancies easily because of the high frequency of wage offers (Wheeler, 2001; Andini et al., 2013). This urbanization effects suggest an improvement in job matching between job seekers and vacancies by firms. Petrongolo and Pissarides (2006) run structural estimations to find that the scale effects of urbanization of local labor markets increase the distribution of wage offers.

Industrial agglomeration, which is a factor of urbanization, has a significant effect on the probability of job matching for job seekers residing in urban areas (de Blasio and Di Addario, 2005; Di Addario, 2011; Andini et al., 2013; Abel and Deitz, 2015). In addition, agglomeration affects matching quality, namely, the gap between the skills of heterogenous workers and the productivity of firms, enabling workers to earn high wages (Sato, 2001; Abel and Deitz, 2015). Simultaneously, according to Di Addario (2011), agglomeration effects do not entirely arise in any dimension of job search and marching. Specifically, agglomeration effects in a worker's search intensity (i.e., effort of job search) are not significant, unlike the likelihood of matching.

This paper aims to examine the effects of industrial agglomeration on the decision of a non-working individual to search for a job, that is, participate in the labor force. Previous studies examine job search behaviors, matching processes, or employment. In these cases, individuals already participate in the labor force. This study contributes to the literature by focusing on the decision of non-working individuals to search for jobs, that is, their transition into labor force participation. This dimension seems to be a substantial issue because whether individuals succeed in finding jobs or

earning wages occurs only after they participate in the labor market. If there are agglomeration effects in the job search decision, Di Addario's (2011) finding of search intensity not depending on urbanization level might be natural.

This study also focuses on the heterogeneity of individuals' attributes. According to the estimation of matching functions, matching efficiencies vary across heterogeneous individuals (e.g., Petrongolo, 2001; Sasaki et al., 2013; Barnichon and Figura, 2015). Thus, we consider that agglomeration effects on job search decision exhibit different natures across heterogeneous individuals. The following evidence seems to support the significance of this dimension. The female probability of employment and wage benefits from urbanization, while males do not (Phimister, 2005). Job matching is efficient in urban areas, resulting in wage inequality, since firms with higher productivity match with higher skilled workers (Wheeler, 2001; Abel and Deitz, 2015). Heterogeneity of other attributes, such as gender, age, and skills, also exhibit different urban premium in terms of job finding rates and wages (Andini et al., 2013).

Before empirical analyses, this paper develops a theoretical framework of agglomeration effects on the job search decision. We find that the significance of agglomeration effects is determined by the size of individual value of leisure, assumed to be heterogeneous across attributes. Non-working individuals with too low or high value of leisure do not benefit from agglomeration. The former's search does not depend on agglomeration, while the latter does.

Next, we run the empirical analyses using Japanese microdata on employment, which provide us information on status of job search, and individual and household characteristics. Instrumental variables (IV) in the models cope with potential endogeneity, stemming from the simultaneity of job search and residential location

choice.

According to the estimation results, agglomeration is a trigger for a non-working individual's decision to search for a job. This result suggests that non-working individuals could find lower search cost in urbanized areas, supporting the theoretical explanation. Focusing on the heterogeneity of individual attributes, we find that agglomeration effects are significant for females who are less educated, middle-aged and older, married without children. In contrast, others tend to search for jobs regardless of the level of agglomeration. Those married with children face too high value of leisure to benefit from a decrease in search cost through agglomeration. Females whose job search decisions are affected by agglomeration tend to exhibit higher value of leisure than non-working individuals with other attributes do.

The rest of this paper is organized as follows. Section 2 presents the theoretical model of agglomeration effect and job search decision. Section 3 presents the empirical specification to confirm the theory. Section 4 describes the dataset and provides an overview of rates of search by levels of agglomeration in Japan. Section 5 discusses the estimation results. Section 6 concludes the paper.

2. Theoretical background

Mortensen (1986) provides the theoretical framework that illustrates the mechanism of whether non-working individuals search for jobs, that is, participate in the labor force. Based on his model, this section develops a model accounting for the agglomeration effect.

First, we briefly describe Mortensen's (1986) search decision model.¹ A

¹ See Mortensen (1986, pp. 852–859) for the development of this formula in detail.

non-working individual faces the decision problem of job search in continuous time, given by the following Bellman equation:

$$rV = b - c + \lambda \int_0^{\infty} \max[0, W(x) - V] dF(x), \quad (1)$$

where V represents the value of searching for a job and r is the interest rates. b denotes the value of leisure, or the value of time other than is spent searching for a job, c is the search cost, and λ is the offer arrival rate. x denotes the best of random offer wage in the next period, and $W(x)$ is the value of accepting it. $F(\cdot)$ is the distribution of the wage offers. Equation (1) implies that the discounted present value of job search is determined by the gap of the expected value of accepting the offer wage and the expected value of searching in the future. In addition, it is also determined by the value of leisure (i.e., the value of not searching) minus search cost.

Equation (1) yields the reservation wage $w^* = rV = rW(w^*)$. Substituting w^* in equation (1), we obtain

$$\frac{\lambda}{r} \int_{w^*}^{\infty} [x - w^*] dF(x) = c + w^* - b. \quad (2)$$

Equation (2) shows that the expected marginal benefit of searching for a job in the next periods (i.e., the left-hand-side) equals the cost of searching in the current period (i.e., the right-hand-side) if the reservation wage is offered. Here, we can suppose that the value of leisure b is an opportunity cost of job search, while c is the out-of-pocket cost of job search.

If a non-working individual finds that the present value of search is large, he/she decides to search for a job, that is, participate in the labor force. In other words, the reservation wage exceeds the value of leisure, or the opportunity cost of a job search (i.e., $V > b/r$). Therefore, based on equations (1) and (2), the participation condition

(i.e., the condition of deciding to search for a job) is as follows:

$$rV = w^* > b, \text{ if and only if } \frac{\lambda}{r} \int_b^{\infty} [x - b] dF(x) > c. \quad (3)$$

Equation (3) implies that a non-working individual decides to start searching for a job (i.e., participating in the labor force) only when the reservation wage is larger than the opportunity cost of job search, if and only if the return of job search is larger than the out-of-pocket cost of job search.

Next, we extend Mortensen's (1986) participation condition by incorporating the agglomeration effect. Wheeler (2001) develops the firm's search model, which considers the agglomeration effect. His model assumes that population agglomeration determines firm's search cost. We consider that it is possible to apply this assumption of firm's search cost directly to a worker's search model.

Following Wheeler (2001), but substituting workers for firms in his assumption, the out-of-pocket cost of job search is assumed to be the function of industrial agglomeration, given by $c(a) = \frac{C}{\lambda(a)}$, where a is the level of industrial agglomeration, C is the fixed search cost, and $\lambda(a)$ is the offer arrival rate, which is determined by the level of industrial agglomeration. This offer arrival rate is assumed to be $\frac{\partial \lambda(a)}{\partial a} > 0$. In agglomerated areas, job seekers can meet potential vacancies more often. Therefore, it implies $\frac{\partial c(a)}{\partial a} < 0$.² In more agglomerated areas, job seekers receive more offers by paying a certain fixed cost C , resulting in lower search cost $c(a)$.

² $c(a)$ does not contain the congestion effect. Wheeler (2001) describes the congestion effect in addition to the agglomeration effect in the search cost, by multiplying the level of agglomeration and $c(a)$, yielding $ac(a)$. Instead of following it, to simplify our model, we suppose that $\frac{\partial c(a)}{\partial a} < 0$ is a case where the congestion effect is less than the agglomeration effect. The validity of this assumption can be confirmed by the empirical analyses in the following section.

To develop the participation condition model incorporating the agglomeration effect, we apply $c(a)$ and $\lambda(a)$ to the equation (1), leading to

$$rV(a) = b - c(a) + \lambda(a) \int_0^{\infty} \max[0, W(x) - V(a)] dF(x). \quad (4)$$

Thus, the value of searching for a job is the function of the level of agglomeration. According to equation (4), the larger the level of agglomeration, the larger the value of job search becomes. Considering the reservation wage with agglomeration, $w^* = rV(a) = rW(w^*)$, it satisfies $\frac{\partial w^*}{\partial a} > 0$. Consequently, we obtain the new participation condition, which simply replaces c and λ with $c(a)$ and $\lambda(a)$ in equation (3), respectively:

$$rV = w^* > b, \text{ if and only if } \frac{\lambda(a)}{r} \int_b^{\infty} [x - b] dF(x) > c(a). \quad (5)$$

Intuitively, agglomeration seems to be a trigger of the decision to search for a job. In the more agglomerated region, $\frac{\lambda(a)}{r} \int_b^{\infty} [x - b] dF(x)$ is larger and $c(a)$ is smaller. Therefore, the participation condition could be easily satisfied in the agglomerated areas.

We assume that the fixed search cost C and the offer arrival rate $\lambda(a)$ are identical among all individual attributes, yielding that $c(a)$ is also identical. In contrast, the opportunity cost of search (i.e., the value of leisure) b is heterogenous across individual attributes, stemming from the difference in preference (Pissarides, 2000).

The size of opportunity cost of search determines whether the agglomeration effect arises in the job search decision. Based on the size of opportunity cost of search, we classify individuals into three types in terms of the relationship between the participation condition of equation (5) and level of industrial agglomeration.

Figure 1 shows three types of individuals by comparing the sizes of the search benefit (i.e., $\frac{\lambda(a)}{r} \int_b^\infty [x - b] dF(x)$) and the search cost (i.e., $c(a)$), which are in equation (5). The horizontal axis represents the level of agglomeration. The line of search benefit is upward sloping, while that of search cost is downward sloping. These slopes come from the offer arrival rate and search cost, as the function of the level of agglomeration. An intercept of the line of search benefit reflects the size of the opportunity cost of search.

[Figure 1 about here]

Panel (a) presents non-working individuals who have the largest opportunity cost of search among the three types of individuals. The search benefit is consistently smaller than the search cost, regardless of the level of agglomeration. In this case, the participation condition in equation (5) is not satisfied. The non-working individuals do not search for jobs at all. We call them the *never-search type*.

In panel (b), the lines of the search benefit and the search cost cross each other in a certain level of agglomeration \bar{a} . Non-working individuals satisfy the participation condition, that is, search for a job, when the agglomeration level is \bar{a} or higher. In other words, their search decision depends on the urbanization of their residential areas. We call them the *agglomeration-search type*. The opportunity cost of search of this type is smaller than the *never-search type*.

Panel (c) illustrates that the line of the search benefit is above the line of the search cost. Therefore, non-working individuals always satisfy the participation condition, regardless of the level of agglomeration. We label them the *always-search type*. Their opportunity cost of search is lowest among the three types.

To sum up, the agglomeration effect does not arise when the opportunity cost of

search is so high that the participation condition cannot be satisfied, resulting in not searching. In contrast, the opportunity cost of search is sufficiently low to satisfy the participation condition; the non-working individual is unaffected by the level of agglomeration but searches. When the size of opportunity cost of search falls into the interval of one of the above two cases, the agglomeration effect occurs. The non-working individual decides to search for a job at a certain level of agglomeration, which becomes the point to satisfy the participation condition.

3. Empirical specification

This section presents the empirical specification to confirm the theory of agglomeration effect on job search decision in the previous section. We cannot observe the processes of job search decision from the data. Instead, we examine the relationship between the level of agglomeration and an individual's state of job search residing there. Furthermore, the type of a non-working individual is theoretically deterministic, depending on the size of opportunity cost of search. In reality, however, individuals are not entirely classified into the three types with regard to our interest attributes for the empirical analyses. Some observable and unobservable individual factors also affect the job search decision. Therefore, we empirically estimate the probability of searching for a job after controlling for observable individual and household characteristics.

Let s_{ij} denote the dummy variable taking one if an individual i who resides in municipality j is searching for a job, and zero otherwise. This is the dependent variable, which regresses to the variable of level of agglomeration in our empirical model. The specification is probit model given by

$$P(s_{ij} = 1) = \Phi(\alpha + A_j'\beta + X_{ij}'\gamma), \quad (6)$$

where $A_j = (I_j^{a \in (20,40]}, I_j^{a \in (40,60]}, I_j^{a \in (60,80]}, I_j^{a \in (80,100]})'$ is the vector of dummy variables of levels of employees' density in municipality j , representing the level of agglomeration. Each element represents that $I_j^{a \in (r,s]}$ equals one if the employees' density of municipality j is in the interval of $(r, s]$ percentiles, and zero otherwise.³ The $[0,20]$ percentile dummy is omitted as a benchmark. X_{ij} is the vector of the individual and household characteristics, controlling for observable factors. $\Phi(\cdot)$ is the normal cumulative distribution function. α is a constant, β and γ are the vectors of parameters.

The result from this estimation distinguishes the *agglomeration-search type* from others. If β , our interest parameter, in equation (6) is positive, the probability of the agglomeration-search type is high. If β is zero, the probability of non-agglomeration-search type is high. In this case, we interpret that the sample tends to exhibit the *never-search type* or the *always-search type*. Besides, if β is negative, the congestion effect could be larger than the *agglomeration effect*. Our theory does not explain this case.

4. Data

We utilize two types of data from Japan. First, we use the individual level cross-sectional microdata from the Employment Status Survey (ESS). The data contain the necessary variables for our analyses, such as whether an individual is searching for a job and his/her observable characteristics. Second, to create variables of the level of agglomeration, we use the municipality level data on the number of employees from the

³ Section 4 explains why the number of employees is not directly used as the variable of agglomeration.

Economic Census (EC).⁴ Both the ESS and EC are provided by the Statistics Bureau, Ministry of Internal Affairs and Communications (MIC). The ESS reports individuals' places of residence at the municipality level. We then create the dataset by merging the ESS with the EC based on the municipality codes.

The ESS is conducted every five years. Each wave covers approximately one million members of 15 years and over in 500 thousand households, which are collected through a stratified two-stage sampling method. They are asked their employment status as of October 1 in the survey year, in addition to essential information, for example, sex, birthdate, educational background, and income.⁵

Our dataset pools two waves of the 2012 and 2017 ESS, since they have consistent variables. Our sample contains individuals who answer not working and wishing to work. Their records report status of whether to search for a job, which is the dependent variable of the empirical specification (equation (6)). Individuals who answer that they are preparing to open a business, other than searching for a job, are omitted.

We restrict the sample as follows. We restrict individuals to working age (i.e., 15–64 years old) and omit students. We also omit individuals who are not searching for a job because of unavoidable reasons, such as childbirth/childcare, nursing care, disease/injury, old age, attending school, and qualification acquisition. Finally, we obtain a sample size of 47,806 after omitting individuals who lack one or more necessary variables.

Next, the EC, which surveys the activities of establishments and enterprises of

⁴ Municipality is a minimum administrative district in Japan.

⁵ See the website of the Statistics Bureau of the MIC for details (<https://www.stat.go.jp/english/data/shugyou/index.html>, accessed on October 10, 2019).

industries in Japan, was conducted in 2009 and 2014, as of July 1 in each census year.⁶ We obtain the variable of level of agglomeration from the municipality level aggregated data of the EC with 1719 municipalities.⁷ We create the dataset for our analyses by merging the 2012 and 2017 ESS with the 2009 and 2014 EC, respectively, based on the municipality of residence of sample non-working individuals. Note that the numbers of municipalities in our dataset are 1474 in the 2012 ESS and 1377 in the 2017 ESS because the ESS does not cover whole municipalities.

As the indices of level of agglomeration, we calculate the densities of the number of employees, that is, the number of employees per square kilometer of inhabitable area.⁸ We then employ five dummy variables, representing the five classes of agglomeration level, instead of using the continuous variable of the densities as it is. These dummy variables are established by every 20 percentile points of the municipalities' density.^{9,10} This is because less agglomerated municipalities have small number of observations in our dataset (i.e., the number of sample individuals in the ESS), resulting in too much disparity in rates of individuals searching for jobs (see Figure A1). In extreme cases, the rate of searching individuals in some municipalities is zero, and one in others. This tendency arises from small sample sizes in rural municipalities, rather than job search behavior itself.

Table 1 shows the summary statistics of the variables of the individual and its

⁶ See the website of the Statistics Bureau of the MIC for details (<https://www.stat.go.jp/english/data/e-census.html>, accessed on October 10, 2019).

⁷ We arrange the number of municipalities in the 2009 EC as of 2014 to deal with the municipal mergers.

⁸ The data on municipal areas is from the Population Census, provided by the Statistics Bureau of the MIC.

⁹ Percentiles are calculated from the densities of whole municipalities, including where no observation appears in the ESS.

¹⁰ See Table A1 for the densities of employees by percentiles as thresholds.

household characteristics for our analyses. They are described by five classes of percentiles of density of the number of employees, as the agglomeration level. For all variables, their means are quite similar across five agglomeration level areas.

[Table 1 about here]

Here, we capture an overview of the relationship between agglomerations and the job search decisions of non-working individuals. Figure 2 illustrates the rates of individuals searching for jobs by agglomeration levels. Panel (a) presents the whole sample of individuals in our dataset. The rates seem to increase depending on the level of agglomeration. Especially, the rates of the (60,80] and (80,100] percentile areas exhibit higher than the [0,20] percentile areas, which is statistically significant at the 5 percent level. On average, there might be agglomeration effects on the decision of non-working individuals to search for jobs.

[Figure 2 about here]

We now check the difference in agglomeration effects on the job search decision of non-working individuals with heterogenous attributes. Panel (b) focuses on the gender gap in the agglomeration effect. The rates of individuals searching for a job are quite different between genders, that is, rates for males are about 60 percent or higher, while those for females are about 40–50 percent. For males, the agglomeration effect seems to exist from the (40,60] percentile areas and larger agglomerated areas. Females' rates of searching constantly increase. We consider that agglomeration effects on the search decision exhibit a gender gap.

In terms of educational background, panel (c) shows that rates of non-working individuals with university degree or higher, searching for jobs, are higher than those with less than university degrees. Agglomeration effects on job search decision arise for

non-working individuals with less than university degrees. Agglomeration effects seem to disappear for highly educated non-working individuals.

Similarly, we find age class differentials in the rates of non-working individuals searching for jobs and the agglomeration effects, shown in panel (d). Around 65–70 percent of the non-working youth (aged 15–34) are searching for a job, while 45–50 percent of and the middle-aged and older (aged 35–64) are searching. The former finds no agglomeration effects. In contrast, the latter increases depending on levels of agglomeration.

The above descriptive evidence finds agglomeration effects on the job search decisions of non-working individuals, indicating that urban non-working inhabitants tend to decide to search for a job. According to the theory, agglomeration could reduce search costs, which allows non-working individuals to participate in the labor force. We also find a gap in agglomeration effects in heterogenous individual attributes. Specifically, less educated, middle-aged and older females exhibit low probability of searching. They seem to benefit from agglomeration effects, indicating that their opportunity cost of job search (i.e., the value of leisure) is higher than it is for others. These findings are not controlled for individual characteristics. The regression analyses in the next section minutely examine such agglomeration effects.

5. Results

This section estimates the empirical model of equation (6). First, we consider agglomeration effect on the search decision for whole non-working individuals. Next, we focus on the difference in agglomeration effects among some individual attributes.

5.1. *Whole non-working individuals*

Table 2 provides the estimation results of the marginal effects of the probit and probit IV models for the whole sample of non-working individuals.¹¹ Column (1) shows that the marginal effects of the dummy variables of the (20,40], (60,80], and (80,100] percentile of agglomeration levels are positive and significant, comparing with the benchmark of the [0,20] percentile, when the specifications do not control for the individual and household characteristics. Their magnitudes are similarly 0.05. After controlling for the individual and household characteristics in column (2), their magnitudes become gradually larger, depending on the level of agglomeration, except for the (40,60] percentile dummy, while their signs and statistical significances do not change. These results indicate that agglomeration can be the trigger for an individual's decision to search for a job.

[Table 2 about here]

Here, we do not find any significantly negative marginal effects. Therefore, we consider that the congestion effect is less than the agglomeration effect. The assumption that search cost is a decreasing function of agglomeration in the theory in Section 2 is valid.

There is a possibility of suffering from endogenous bias in the results of simple probit models in columns (1) and (2). This is because the job search and residential search exhibit simultaneity (e.g., Smith and Zenou, 2003; Patacchini and Zenou, 2006). To cope with this endogenous problem, we additionally estimate the probit IV models.

¹¹ All specifications contain prefecture dummies to control for unobservable region effects. We also estimate the specifications with municipality dummies to control unobservable municipality-specific effects. However, many municipality dummies are omitted because of multicollinearity. Most of remaining municipality dummies are statistically insignificant. Consequently, there is little to no effect on the estimates of agglomeration and other covariates whether the city dummies are included or not.

The IVs are the dummies of (20,40] to (80,100] percentile of the density of the number of employees in 1981.^{12,13}

Columns (3) and (4) are the results of the probit IV models. In the model without individual and household covariates, the marginal effects of (60,80] and (80,100] percentile dummies are significantly positive (column (3)). After controlling for individual and household characteristics, the (60,80] percentile dummy is also significantly positive, in addition to the (60,80] and (80,100] percentile dummies (column (4)). Both results are almost similar to that in columns (1) and (2).

Although the Wald tests do not reject the null hypothesis of exogeneity, we focus on the result of the probit IV model. This is because we maintain the consistency of interpretation for analyses in the following subsection, when some of them show endogeneity. We primarily interpret the results of the probit IV models hereafter.

We now consider the result of column (4), which controls for individual and household characteristics, and estimate using IVs. The effect of the (20,40] percentile agglomeration is not different from zero (i.e., same as the [0,20] percentile agglomeration), and the marginal effect of (40,60] percentile agglomeration is 0.05. The effects increase depending on the level of agglomeration, that is, the marginal effects are 0.08 and 0.09 for (60,80] and (80,100] percentile agglomeration, respectively. This result suggests that non-working residents in urban areas tend to search for a job comparing with those in rural areas. This is because the agglomeration effect influences individuals to search for jobs by reducing their search costs. We consider that Japan

¹² The source of data on the number of employees in 1981 is the Establishment and Enterprise Census, the predecessor of the EC, provided by the Statistics Bureau of the MIC.

¹³ We re-aggregate the municipal level data on the number of employees in 1981 at the municipal level as of 2017, to deal with municipal mergers during the periods.

would have a significant rate of agglomeration-search type individuals.

Di Addario (2011) does not find the agglomeration effect in search intensity. Our finding of the agglomeration effect on job search decision is consistent with it. Search intensities appear in only those non-working individuals who decide to search for jobs on the basis of the level of agglomeration. Therefore, search intensities are independent of agglomeration because non-working job seekers already benefit from agglomeration.

Here, the density of the number of employees in the Tokyo wards area and Osaka City is more than 10,000 per square kilometer of inhabitable area. This density is far larger than other municipalities (see Figure A2). We guess that the Tokyo wards area and Osaka City have some peculiar features. To manage this, we run additional estimations, except for the Tokyo wards area and Osaka City.¹⁴ Columns (5) to (8) of Table 2 show these results, corresponding columns (1) to (4), respectively. All the magnitudes and sign of marginal effects, and their statistical significance are coincident with the corresponding models for the whole area sample. Thus, such megalopolises do not seem to have peculiar features other than the sizes of agglomeration in Japan. Hereafter, we do not show any results for the sample, except for the Tokyo wards area and Osaka City, as the case for our remainder analyses is the same.

5.2. *Heterogenous attributes of individuals*

The above estimation results of agglomeration effect on job search decision are the average of whole attributes of individuals. The theory in Section 2 implies that there are three types of individuals with different responses of search decisions to the level of agglomeration, because of the heterogenous opportunity cost of search (i.e., the value of

¹⁴ Petrongolo and Pissarides (2006), studying agglomeration and job search and matching, also try to analyze their models for sample, treating London as a megalopolis.

leisure). We now investigate the difference in the agglomeration effect using subsamples with regard to genders, educational backgrounds, and age classes. Table 3 provides the marginal effects of probit IV models by these attributes. Note that although we run both the probit and probit IV models as estimations for the whole sample, Table 3 shows only the results of the probit IV models because both models obtain similar results.

[Table 3 about here]

First, we focus on the gender difference, shown in columns (1) and (2). Females exhibit positive and significant marginal effects of all agglomeration levels on their search decisions, while males do not find statistically significant agglomeration effect.

For females, as the level of agglomeration becomes larger, the magnitudes of marginal effects increase. This tendency is roughly similar to the whole sample estimations in Table 2. We also find that when comparing the results for the whole sample, the marginal effect of (20,40] percentile dummy becomes statistically significant, and the magnitudes of the marginal effects of (40,60] to (80,100] percentile dummies become 1.5–1.8 times larger. These results suggest that a part of agglomeration effects, confirmed by Table 2 for whole sample, stems from females. Therefore, non-working females could show high probability of the agglomeration-search type.

In contrast, we do not find evidence that the level of agglomeration does not affect the search decisions of males, suggesting that, on average, males would not be the agglomeration-search type. However, whether males are the never-search type or always-search type is ambiguous. We suppose their type by the descriptive fact, shown in panel (b) of Figure 2. About 60 percent or higher of non-working males in areas of all

level of agglomeration are searching for a job, indicating that the male proportion of the always-search type is larger than other types.

Consequently, females tend to have the higher opportunity cost of search than males. The evidence of gender gap from our estimations seems to be consistent with Phimister (2005), that is, females benefit from larger urbanization premium in probability of employment and wage than males.

Second, we consider educational background. Columns (3) and (4) of Table 3 present the estimation results for non-working individuals with less than a university degree and university degree or higher, respectively. Agglomeration effects on job search decision significantly arise in non-working individuals with less than a university degree, while it is insignificant in those with a university degree or higher. The magnitudes of marginal effects of agglomeration level dummies for the less than university degree holders become larger depending on the level of agglomeration (column (3)), suggesting that a significant rate are the agglomeration-search type. On the other hand, we guess that non-working individuals with university degree or higher are generally classified into the always-search type because panel (c) of Figure 2 describes that more than half of them in all regions are searching for a job. Furthermore, column (4) of Table 3 shows insignificant marginal effects of percentile dummies.

These results suggest that less educated individuals would have higher opportunity cost of search than the highly educated. Hence, human capital accumulation from school education might release individuals from the restrictions of search cost.

Third, we compare two age classes, namely, the youth (aged 15–34) and the middle-aged and older (aged 35–64). Columns (5) and (6) show the estimation results for the age ranges of 15–34 and 35–64, respectively. Only the age range of 35–64

significantly confirms the agglomeration effect. Panel (d) of Figure 2 illustrates that about 60 to 70 percent of non-working individuals aged 15–34 are searching for a job. These results suggest that the youth tend to be classified into the always-search type, while the middle-aged and older are the agglomeration-search type.

Eventually, Table 3 reveals that female, less educated, middle-aged and older individuals have a high probability of being the agglomeration-search type. In other words, urban regions provide more job search opportunities for such groups of attributes. A decrease in the variable search cost allows them to search because of their high opportunity cost of search.

5.3. Gender gap in educational background and age classes

Table 3 in the previous subsection finds a significant gender gap in the agglomeration effect on job search decision. We also find that the magnitudes of percentile dummies for females (column (2)) are larger than those for the less educated (column (3)) and the 35–64 age range (column (6)), which show significant agglomeration effects. We then suppose that agglomeration effects for the less educated and those aged 35–64 are larger for females in such groups of attributes. To confirm this conjecture, we further explore the gender gap in educational background and age. All models are estimated as the probit IV model.

First, we focus on the gender gap in educational background, shown in Table 4. Females with less than university degree exhibit significant and positive marginal effects for all percentile dummies (column (2)). Comparing with the previous analyses, the magnitudes of marginal effects of all percentile dummies are larger than the corresponding dummies for the only female sample (column (2) of Table 3) and the less

than university degree sample (column (3) of Table 3).

[Table 4 about here]

In contrast, for the remainder attributes (i.e., males with less than university degree and both genders with university degree or higher), the marginal effects of agglomeration level dummies are statistically insignificant (columns (1), (3), and (4) of Table 4).

Panel (a) of Figure 3 plots the rates of non-working individuals who are searching for jobs by attributes crossing educational background and gender. Males with both education levels tend to be the always-search type because 60 percent or more of them in regions of all levels of agglomeration are searching jobs. Although the rates of non-working females who are searching for jobs at all levels of agglomeration are similar with both education levels, the standard deviations of the rates of searching for females with university degree or higher are large. Females with university degree or higher who are searching for jobs constitute about 50 percent with large standard deviation. We cannot judge which proportion is larger, the always-search or never-search types. At least, on average, they do not seem to be classified into the agglomeration-search type.

[Figure 3 about here]

These results suggest that the educational level differential in the agglomeration effect on search decision tend to be a substantial issue for females. The less educated females could have high opportunity cost of search, as the agglomeration level affects their search decision. Regardless of educational background, males would have similar opportunity cost of search. Their search decision is independent of the agglomeration level.

Next, Table 5 investigates the difference in agglomeration effect on the job search decision of age classes in gender. Column (4) for females aged 35–64 shows significantly positive marginal effects of all variables of agglomeration levels. This result suggests that they tend to be the agglomeration-search type. The magnitudes of marginal effects of all percentile dummies are larger than just the female sample and the 35–64 age range sample, shown in columns (2) and (6) of Table 3, respectively.

[Table 5 about here]

For other attributes (i.e., males of both age classes and females aged 15–34), significant agglomeration effects are not confirmed (columns (1) to (3) of Table 5). Simultaneously, panel (b) of Figure 3 describes that more than half the individuals of such attributes are searching for a job, indicating that they tend to be the always-search type.

Thus, we find a significant age gap in the agglomeration effect on the job search decision in females. The opportunity cost of search for middle-aged and older females is higher than for younger females. However, males do not exhibit this age gap. The opportunity cost of search for males might be similar over age ranges.

To sum up, there is a remarkable gender gap in the agglomeration effect on job search decision, in terms of gaps in educational levels and age classes. Less educated, middle-aged, and older non-working females constitute a significant proportion of the agglomeration-search types.

5.4. Female marital status and presence of children

The previous subsection finds significant gender gap in the agglomeration effect on job search decision in terms of educational background and age classes. Next, we

focus on the difference in the agglomeration effects in terms of female heterogeneous attributes. Marital status and presence of children are significant issues with regard to the regional variety of female employment in Japan (Abe, 2013; Kawabata and Abe, 2018). We compare the results for four female subsamples on the basis of marital status and presence of preschool children (i.e., under six years old). Thus far, the dataset for the analyses does not contain non-working individuals who are not searching for a job owing to childbirth/childcare as one of the unavoidable reasons not to search, as mentioned in Section 4. To examine the effect of the presence of children, this subsection also includes these females in the dataset.

Table 6 shows the estimation results for females by marital status and presence of children. We find significant marginal effects of density percentile dummies only for married females without children (column (3)). This result indicates that they tend to be the agglomeration-search type.

[Table 6 about here]

Figure 4 illustrates the rates of individuals searching for jobs by marital status and presence of children. A high proportion of unmarried females without children seem to be the always-search type because about 60 percent of them in all regions are searching for jobs. We do not judge whether unmarried females with children tend to be the always-search or never-search type, since the small sample size results in large standard deviations. At least, they might not generally be the agglomeration-search type. Only 20 to 30 percent of married females with children in regions of all levels of agglomeration are searching for jobs. They do not tend to search for a job, regardless of their residential areas. They could be classified into the never-search type. Although the result in column (3) of Table 6 suggests that married females without children are the

agglomeration-search type, Figure 4 shows that about 30 to 40 percent of them are indeed searching for jobs. Therefore, we consider that a substantial proportion might be the never-search type. Some of them could be the agglomeration-search type; however, their proportion is less than the never-search type.

[Figure 4 about here]

These results suggest that married females could have much higher opportunity costs of search than unmarried females, regardless of the presence of children. Married females without children decide to search for jobs if the variable search cost decreases through agglomeration. Simultaneously, married females with children experience much higher opportunity costs of search, on average, resulting in not searching.

6. Conclusion

This paper examined agglomeration effects on the decision of non-working individual to search for a job. This study focused on the job search decision, which is a step before search intensity and matching occur. We also focus on the difference in the agglomeration effects across heterogeneous individual attributes.

First, we theoretically demonstrated the agglomeration effect on the job search decision. The out-of-pocket cost of job search was assumed as a decreasing function of the level of agglomeration. Therefore, non-working individuals residing in urban areas might search for jobs because of lower search costs than the search benefits. Simultaneously, the value of leisure, namely, the opportunity cost of job search, was assumed to be heterogeneous across individual attributes, while it was independent on agglomeration. The size of the opportunity cost of job search determines that a non-working individual benefits from the agglomeration effect on job search decision.

The above framework reveals three types of individuals in terms of the relationship between agglomeration and job search decision. The first type does not search for a job because the search benefit is constantly smaller than the search cost, regardless of the level of agglomeration, because of the high opportunity cost of job search (the *never-search type*). The second type decides to search for a job at a certain level of agglomeration. A decrease in the variable search cost stemming from agglomeration allows the search benefit to become higher than the search cost (the *agglomeration-search type*). The last type always searches, regardless of the level of agglomeration, because their opportunity cost of search is so low that the search benefit is constantly higher than the search cost (the *always-search type*).

Next, we empirically explored the agglomeration effect on job search decision. We estimated the probability of searching for a job using microdata of the Japanese ESS and municipality level data on the number of employees as the level of industrial agglomeration. The results of probit IV models for the non-working individual sample showed statistically significant agglomeration effects, suggesting that non-working individuals in urban areas exhibit high probability of searching for jobs because agglomeration reduces search cost.

Other estimations focused on the difference in agglomeration effects across gender, educational level, and age classes. According to the results, depending on the level of agglomeration, less educated females, and middle-aged and older females exhibit high probability of searching for jobs. Such non-working females benefit from agglomeration through a decrease in their search cost. Thus, they could be generally classified into the agglomeration-search type. These results also suggested that others, who do not show significant agglomeration effects, are the always-search type. Married

females without children also showed high probability of being the agglomeration-search type. Married females with children, in contrast, tend to be the never-search type. Overall, the difference in the agglomeration effect on job search decision across individual attributes arises only in females.

Appendix

[Table A1 here]

[Figures A1 and A2 here]

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Table 1: Summary statistics of non-working individuals and their household characteristics in five classes of percentiles of density of the number of employees as agglomeration level

Variables	[0,20] percentile		(20,40] percentile		(40,60] percentile		(60,80] percentile		(80,100] percentile	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Searching for a job	0.50	0.50	0.54	0.50	0.53	0.50	0.55	0.50	0.55	0.50
Female	0.64	0.48	0.63	0.48	0.65	0.48	0.69	0.46	0.73	0.45
Age	45.45	13.58	45.56	13.52	45.04	13.23	44.34	12.90	44.13	12.10
Univ. degree or higher	0.08	0.27	0.08	0.27	0.10	0.30	0.13	0.34	0.19	0.39
Marriage	0.55	0.50	0.54	0.50	0.56	0.50	0.59	0.49	0.63	0.48
Household head	0.20	0.40	0.22	0.42	0.21	0.40	0.20	0.40	0.19	0.39
Job experience	0.85	0.36	0.86	0.34	0.86	0.35	0.87	0.34	0.88	0.32
No. of under 6-year-old child	0.16	0.50	0.15	0.45	0.17	0.49	0.17	0.48	0.16	0.46
Living alone	0.08	0.27	0.09	0.28	0.08	0.28	0.09	0.29	0.09	0.29
Employed member	0.74	0.44	0.74	0.44	0.75	0.43	0.76	0.43	0.76	0.42
Not employed member	0.18	0.38	0.17	0.37	0.17	0.37	0.15	0.36	0.14	0.35
<i>Individual income type</i>										
Employment insurance	0.02	0.13	0.02	0.12	0.02	0.13	0.02	0.12	0.01	0.11
Social benefit	0.19	0.39	0.19	0.39	0.18	0.39	0.16	0.37	0.13	0.33
Other	0.08	0.27	0.08	0.27	0.07	0.26	0.07	0.26	0.08	0.27
<i>Household yearly income (JPY in millions)</i>										
Less than 1	0.14	0.35	0.13	0.34	0.11	0.32	0.11	0.32	0.10	0.30
1–1.99	0.12	0.33	0.13	0.33	0.13	0.33	0.11	0.31	0.10	0.29
2–2.99	0.15	0.36	0.18	0.38	0.15	0.36	0.14	0.34	0.12	0.33
3–3.99	0.15	0.36	0.14	0.35	0.14	0.34	0.14	0.34	0.12	0.33

4–4.99	0.11	0.32	0.11	0.31	0.12	0.32	0.12	0.33	0.11	0.32
5–5.99	0.09	0.28	0.09	0.29	0.10	0.30	0.11	0.31	0.10	0.30
6–6.99	0.07	0.25	0.07	0.25	0.08	0.27	0.08	0.27	0.09	0.28
7–7.99	0.04	0.20	0.05	0.21	0.06	0.23	0.06	0.24	0.07	0.25
8–8.99	0.05	0.23	0.04	0.19	0.04	0.20	0.04	0.21	0.05	0.23
9–9.99	0.02	0.14	0.02	0.14	0.03	0.16	0.03	0.17	0.04	0.19
10–12.49	0.03	0.18	0.03	0.16	0.03	0.17	0.04	0.19	0.05	0.23
12.5–14.99	0.01	0.11	0.01	0.10	0.01	0.10	0.01	0.12	0.02	0.14
15–19.99	0.01	0.07	0.01	0.07	0.01	0.08	0.01	0.09	0.01	0.12
20 or higher	0.01	0.07	0.00	0.06	0.00	0.05	0.00	0.06	0.01	0.08
Observations	1074		3905		6845		12464		23518	

Note: Pooled data of the 2012 and 2017 ESS.

Table 2: Marginal effects of the probit and probit IV models for whole sample

Variables	Whole area				Except the Tokyo wards area and Osaka city			
	Probit		Probit IV		Probit		Probit IV	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(Reference: [0,20] percentile)								
(20,40] percentile	0.045** (0.019)	0.037** (0.018)	0.047 (0.035)	0.051 (0.033)	0.045** (0.019)	0.037** (0.018)	0.047 (0.035)	0.051 (0.033)
(40,60] percentile	0.030 (0.019)	0.023 (0.018)	0.041 (0.027)	0.050** (0.025)	0.030 (0.019)	0.023 (0.018)	0.041 (0.027)	0.050** (0.025)
(60,80] percentile	0.048*** (0.018)	0.040** (0.017)	0.064** (0.027)	0.075*** (0.026)	0.048*** (0.018)	0.040** (0.017)	0.064** (0.027)	0.075*** (0.026)
(80,100] percentile	0.047*** (0.018)	0.046*** (0.017)	0.068*** (0.025)	0.086*** (0.024)	0.047*** (0.018)	0.046*** (0.017)	0.068*** (0.025)	0.086*** (0.024)
Individual and household characteristics	No	Yes	No	Yes	No	Yes	No	Yes
Observations	47806	47806	47806	47806	46513	46513	46513	46513
Pseudo R ²	0.003	0.060			0.003	0.060		
Log pseudolikelihood	-32839.266	-30970.336	23339.620	25439.498	-31946.960	-30116.630	20163.071	22226.177
Wald test of exogeneity (chi2)			1.335	3.939			1.336	3.911
p-value			0.855	0.414			0.855	0.418

Notes: Standard errors clustered at the municipality level are in parentheses. ***, **, and * represent statistical significance at 1%, 5%, and 10% level, respectively. All models contain a constant, prefecture dummies, and the survey year dummy. Instrumental variables are the corresponding dummies of the percentile of density in 1981.

Table 3: Marginal effects of the probit IV models for individual attributes

Variables	Gender		Educational background		Age	
	Male	Female	Less than univ. degree	Univ. degree or higher	15–34	35–64
	(1)	(2)	(3)	(4)	(5)	(6)
(Reference: [0,20] percentile)						
(20,40] percentile	-0.010 (0.050)	0.089** (0.044)	0.055 (0.033)	0.014 (0.147)	0.046 (0.069)	0.059 (0.038)
(40,60] percentile	-0.020 (0.041)	0.092*** (0.034)	0.053** (0.026)	0.041 (0.118)	0.019 (0.051)	0.069** (0.030)
(60,80] percentile	-0.001 (0.042)	0.122*** (0.035)	0.080*** (0.026)	0.053 (0.117)	0.047 (0.052)	0.094*** (0.031)
(80,100] percentile	0.008 (0.039)	0.136*** (0.032)	0.092*** (0.024)	0.055 (0.115)	0.034 (0.049)	0.114*** (0.028)
Individual and household characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Observations	14559	33247	40726	7080	11206	36600
Log pseudolikelihood	5341.862	20956.870	18174.720	8742.497	5084.293	20895.301
Wald test of exogeneity (chi2)	0.544	7.237	4.303	4.748	5.224	3.391
p-value	0.969	0.124	0.367	0.314	0.265	0.495

Notes: Standard errors clustered at the municipality level are in parentheses. ***, **, and * represent statistical significance at 1%, 5%, and 10% level, respectively. All models contain a constant, prefecture dummies, and the survey year dummy. Instrumental variables are the corresponding dummies of the percentile of density in 1981.

Table 4: Marginal effects of the probit IV models for educational background in gender

Variables	Less than univ. degree		Univ. degree or higher	
	Male	Female	Male	Female
	(1)	(2)	(3)	(4)
(Reference: [0,20] percentile)				
(20,40] percentile	-0.013 (0.052)	0.094** (0.046)	0.049 (0.194)	0.007 (0.227)
(40,60] percentile	-0.034 (0.043)	0.100*** (0.035)	0.104 (0.155)	-0.012 (0.172)
(60,80] percentile	-0.012 (0.044)	0.130*** (0.036)	0.090 (0.157)	0.040 (0.174)
(80,100] percentile	-0.004 (0.040)	0.146*** (0.033)	0.092 (0.154)	0.047 (0.168)
Individual and household characteristics	Yes	Yes	Yes	Yes
Observations	11554	29172	3005	4075
Log pseudolikelihood	2995.955	15947.654	2991.482	6376.081
Wald test of exogeneity (chi2)	0.248	8.419	5.205	1.436
p-value	0.993	0.077	0.267	0.838

Notes: Standard errors clustered at the municipality level are in parentheses. ***, **, and * represent statistical significance at 1%, 5%, and 10% level, respectively. All models contain a constant, prefecture dummies, and the survey year dummy. Instrumental variables are the corresponding dummies of the percentile of density in 1981.

Table 5: Marginal effects of the probit IV models for age classes in gender

Variables	15–34		35–64	
	Male (1)	Female (2)	Male (3)	Female (4)
(Reference: [0,20] percentile)				
(20,40] percentile	0.022 (0.098)	0.089 (0.096)	-0.008 (0.064)	0.101** (0.049)
(40,60] percentile	0.019 (0.074)	0.031 (0.066)	-0.023 (0.053)	0.121*** (0.039)
(60,80] percentile	0.031 (0.078)	0.076 (0.068)	-0.001 (0.053)	0.149*** (0.040)
(80,100] percentile	0.019 (0.073)	0.064 (0.064)	0.019 (0.051)	0.172*** (0.037)
Individual and household characteristics	Yes	Yes	Yes	Yes
Observations	4864	6342	9695	26905
Log pseudolikelihood	2400.702	3016.078	3345.180	18446.871
Wald test of exogeneity (chi2)	0.986	5.610	0.256	7.213
p-value	0.912	0.230	0.992	0.125

Notes: Standard errors clustered at the municipality level are in parentheses. ***, **, and * represent statistical significance at 1%, 5%, and 10% level, respectively. All models contain a constant, prefecture dummies, and the survey year dummy. Instrumental variables are the corresponding dummies of the percentile of density in 1981.

Table 6: Marginal effects of the probit IV models for females' marital status and presence of children, including sample not searching for jobs because of childbearing or childcare

Variables	Unmarried		Married	
	No child	With child	No child	With child
	(1)	(2)	(3)	(4)
(Reference: [0,20] percentile)				
(20,40] percentile	0.021 (0.085)	0.058 (0.369)	0.126** (0.058)	0.042 (0.076)
(40,60] percentile	0.036 (0.063)	0.065 (0.241)	0.140*** (0.047)	0.043 (0.055)
(60,80] percentile	0.048 (0.064)	0.103 (0.253)	0.170*** (0.047)	0.058 (0.057)
(80,100] percentile	0.066 (0.061)	0.112 (0.241)	0.181*** (0.045)	0.045 (0.054)
Individual and household characteristics	Yes	Yes	Yes	Yes
Observations	7787	588	21023	14936
Log pseudolikelihood	3770.398	517.423	15715.622	14181.010
Wald test of exogeneity (chi2)	2.586	2.792	5.453	7.941
p-value	0.629	0.593	0.244	0.094

Notes: Standard errors clustered at the municipality level are in parentheses. ***, **, and * represent statistical significance at 1%, 5%, and 10% level, respectively. All models contain a constant, prefecture dummies, and the survey year dummy. Instrumental variables are the corresponding dummies of the percentile of density in 1981.

Table A1: Densities of the number of employees of percentile points as thresholds of agglomeration levels (per square kilometer of inhabitable area)

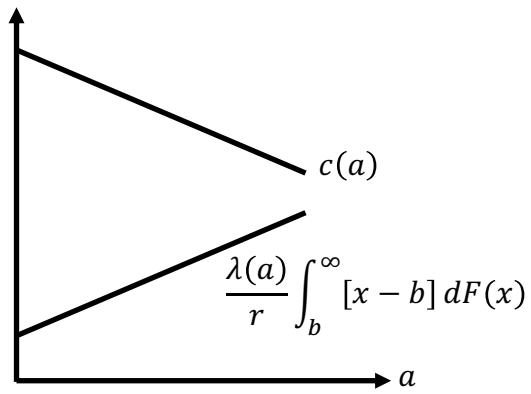
	20 percentile	40 percentile	60 percentile	80 percentile
2009 (for the 2012 ESS)	85.37	162.04	298.81	649.98
2014 (for the 2017 ESS)	78.19	151.97	290.34	624.89

Source: Author's calculation by the EC.

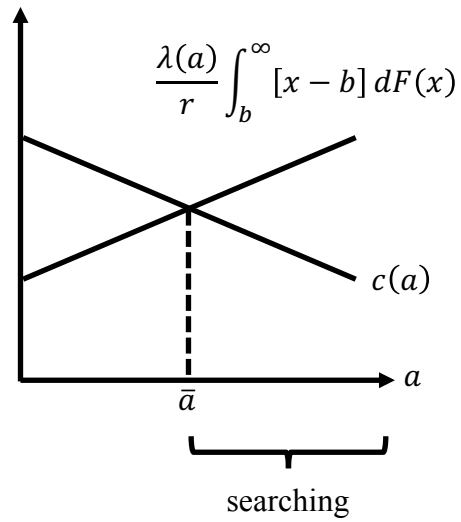
Note: Percentiles are calculated using data for whole municipalities, including omitted municipalities for the analyses due to the lack of samples in the ESS.

Figure 1: Three types of individuals with regard to relationship between agglomeration and search decision

(a) Never-search type



(b) Agglomeration-search type



(c) Always-search type

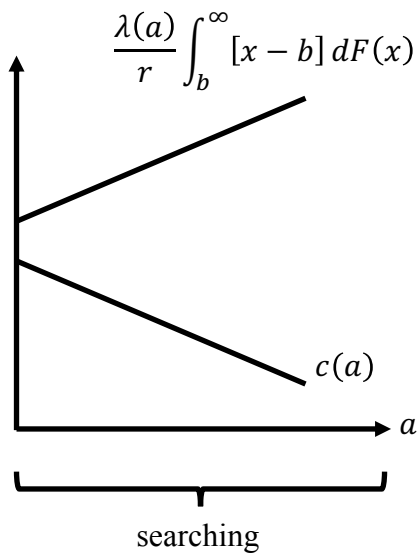
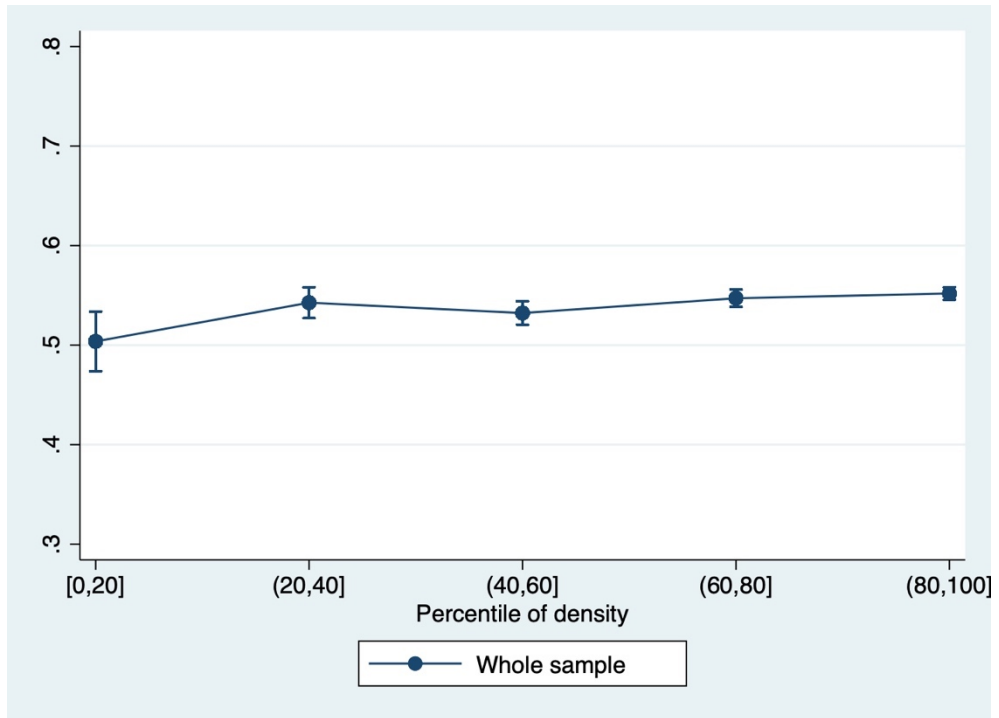
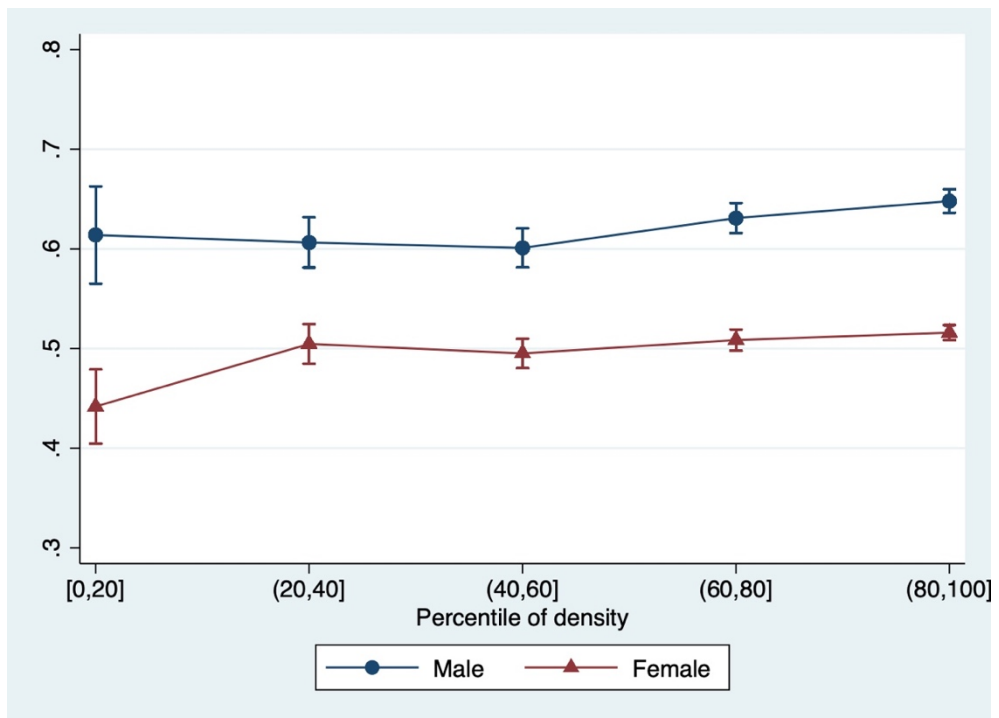


Figure 2: Rates of non-working individuals who are searching for jobs by agglomeration levels

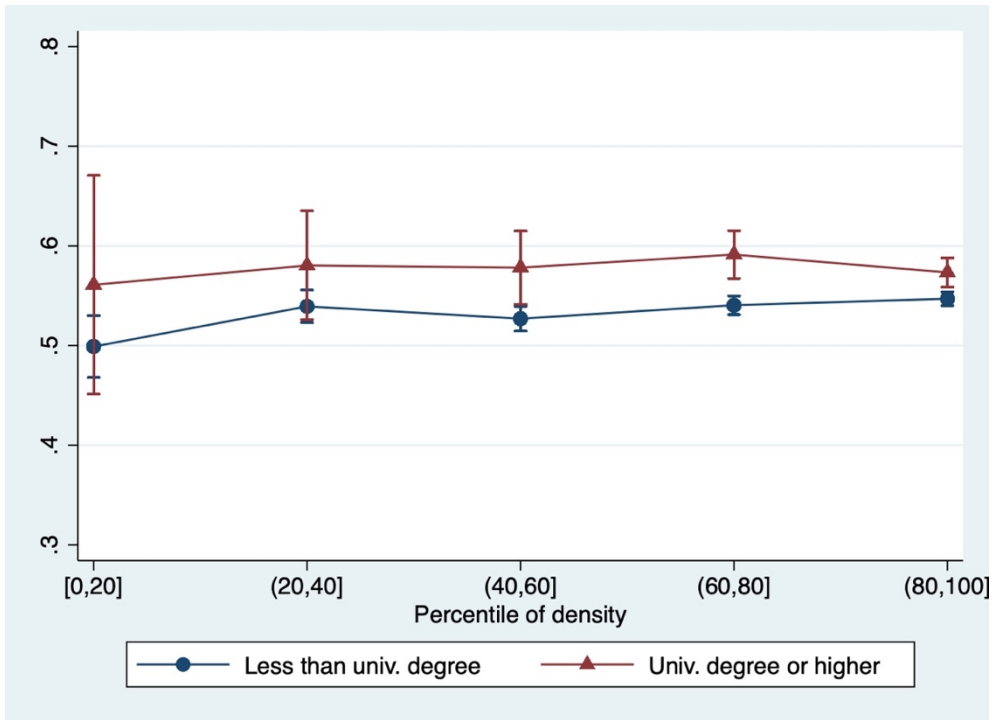
(a) Whole sample



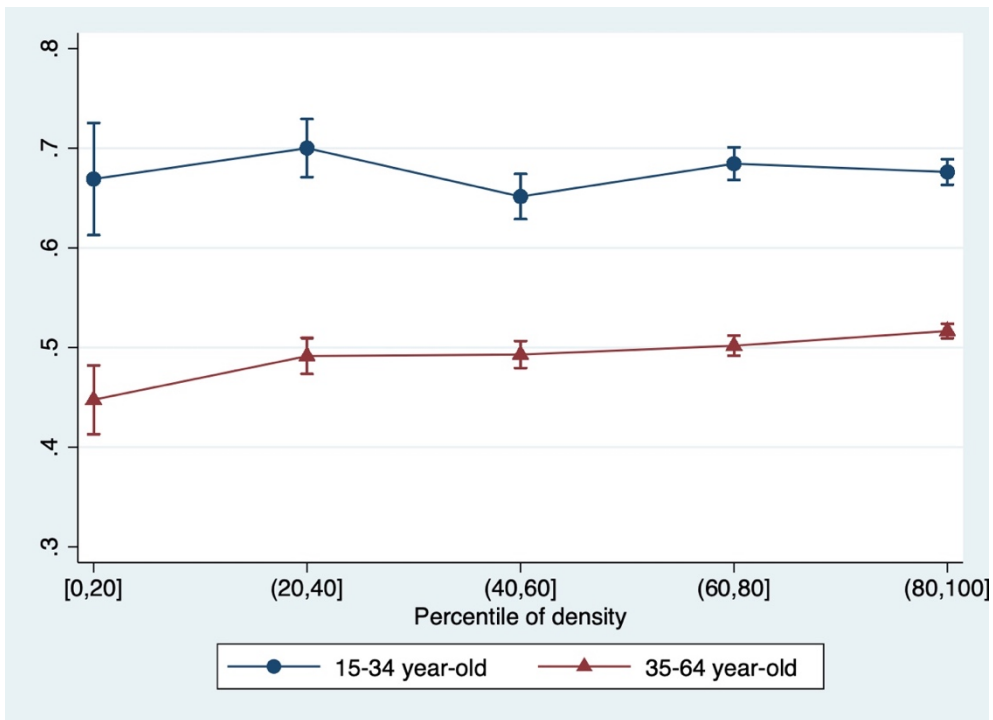
(b) Gender



(c) Educational background



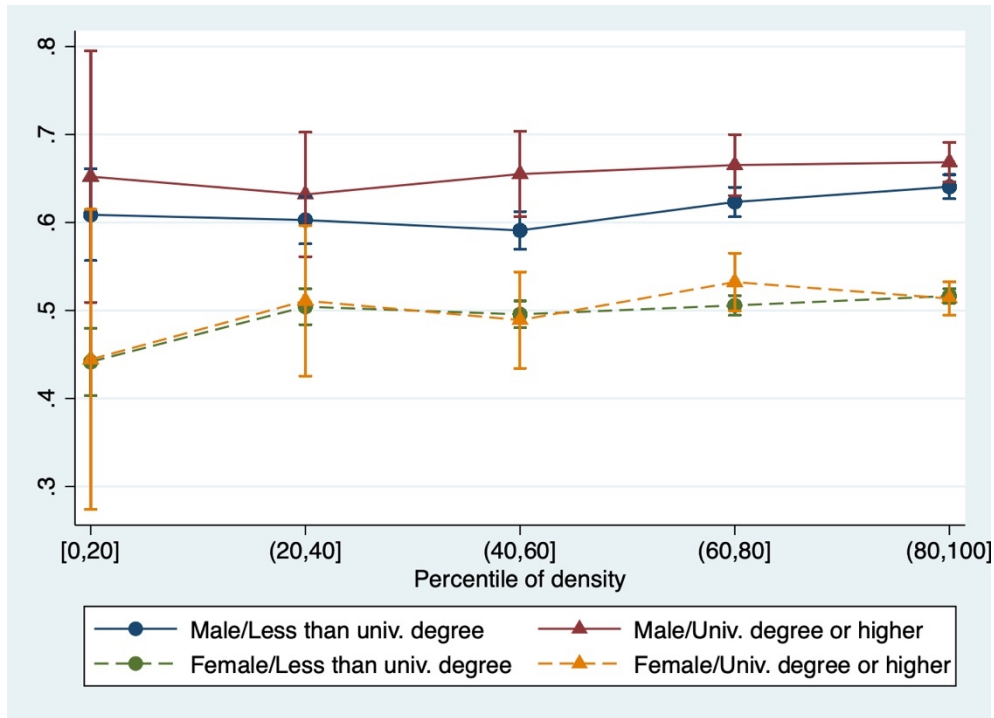
(d) Age



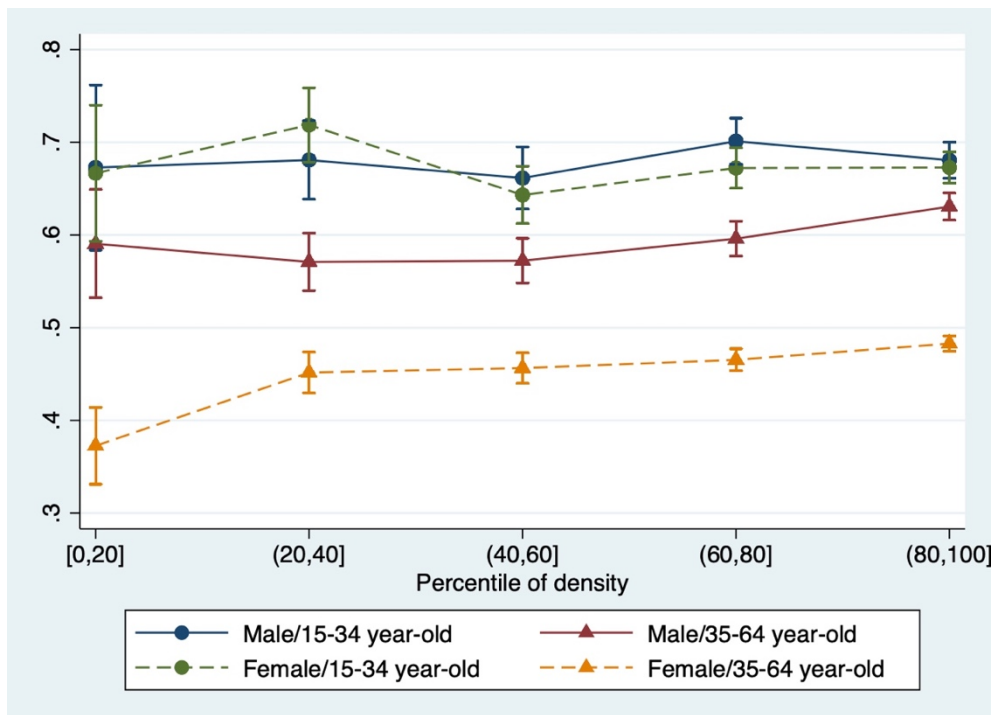
Note: Error bars represent 95 percent confidence interval.

Figure 3: Gender gaps in educational background and age classes with regard to rates of non-working individuals searching for jobs by agglomeration levels

(a) Educational background \times gender

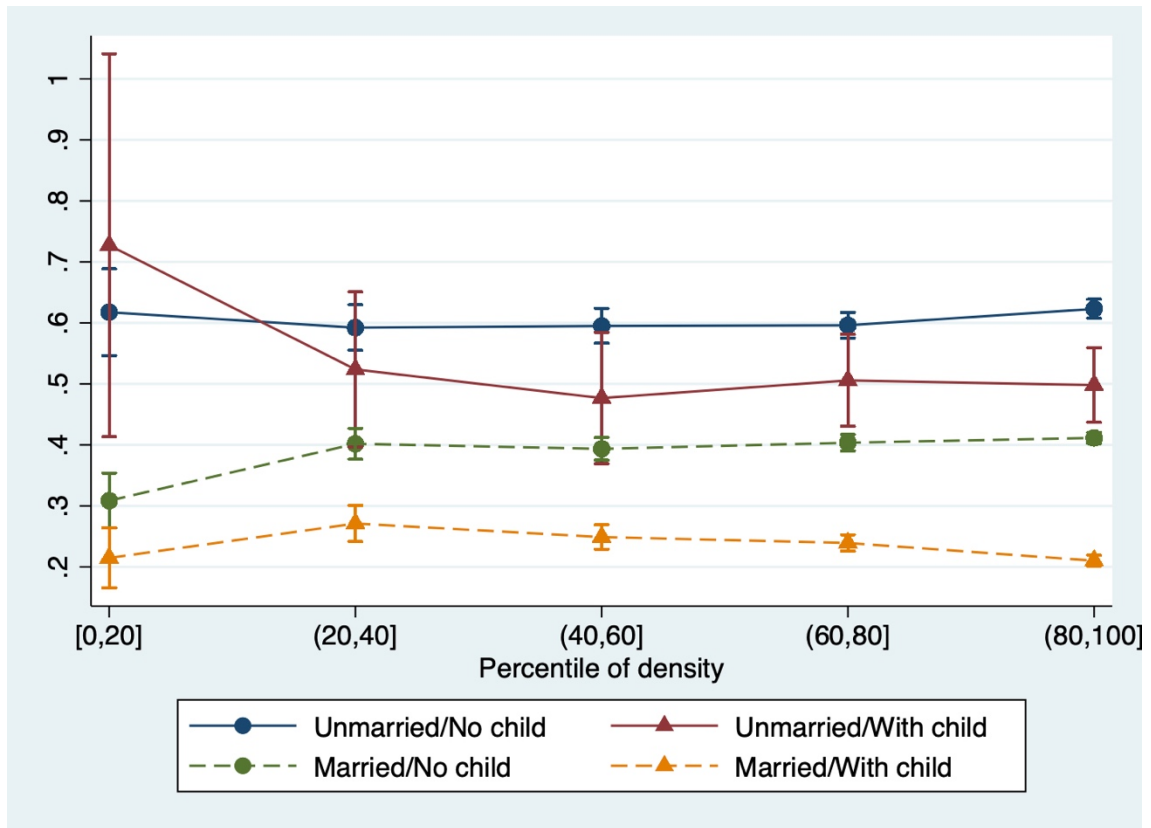


(b) Age \times gender



Note: Error bars represent 95 percent confidence interval.

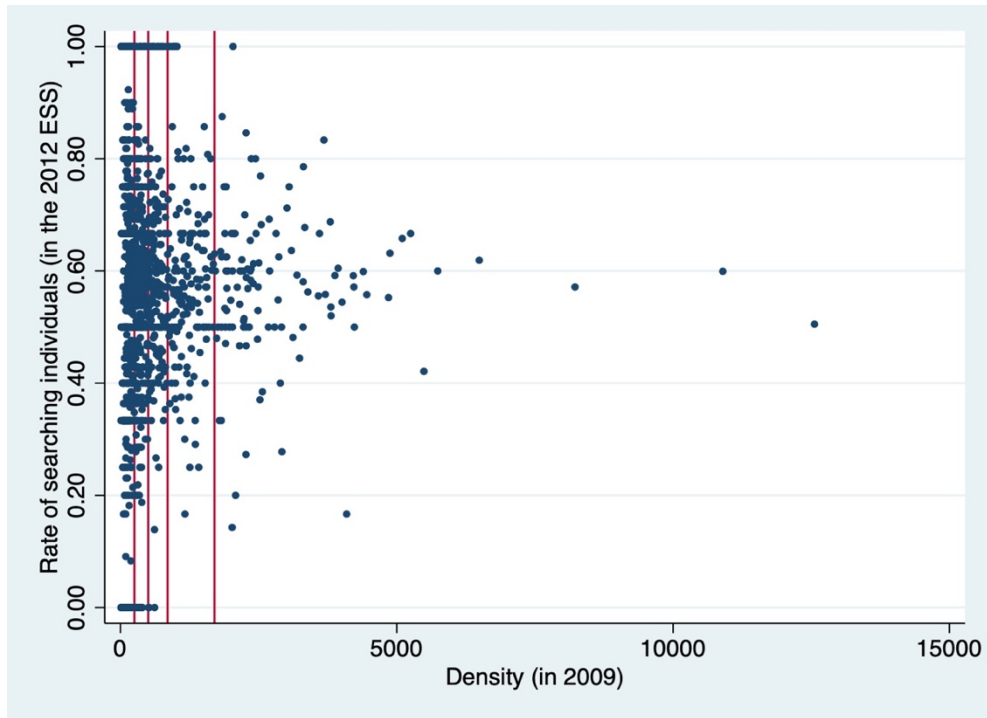
Figure 4: Rates of non-working females searching for jobs by agglomeration levels



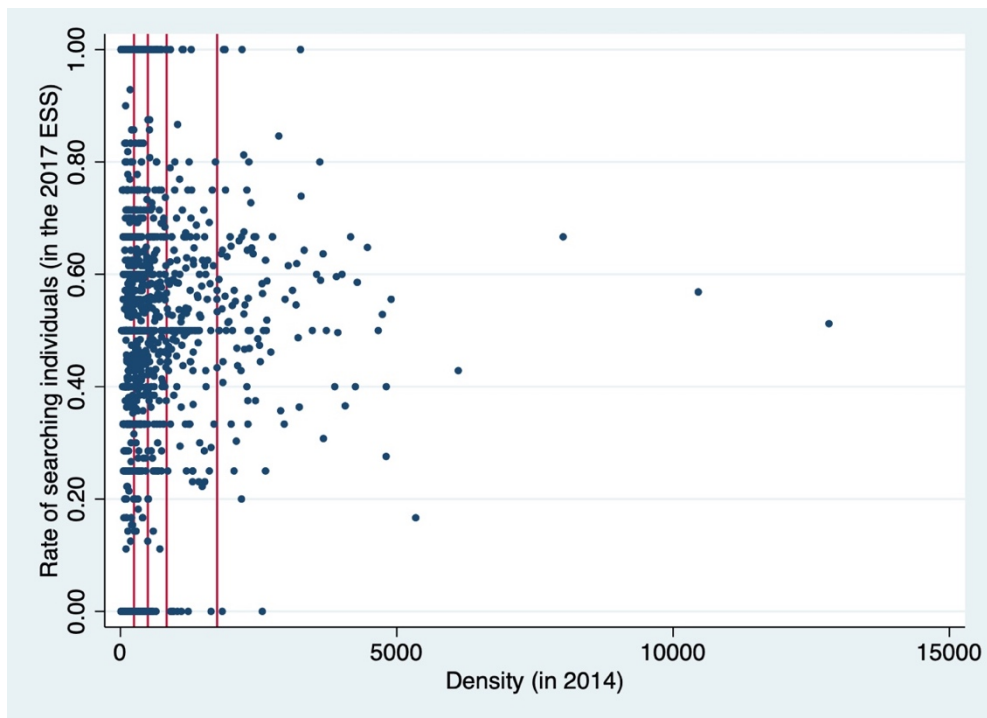
Notes: Error bars represent 95 percent confidence interval. The sample includes females who are not searching for jobs because of childbearing or childcare.

Figure A1: Rates of non-working individuals who are searching for jobs by municipalities

(a) 2012



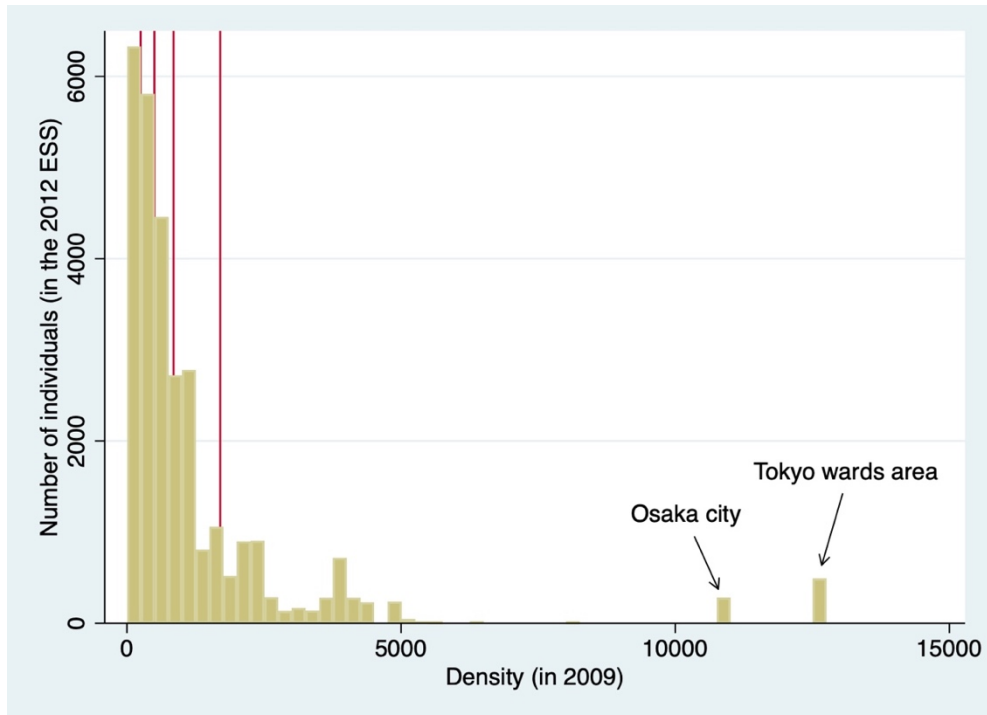
(b) 2017



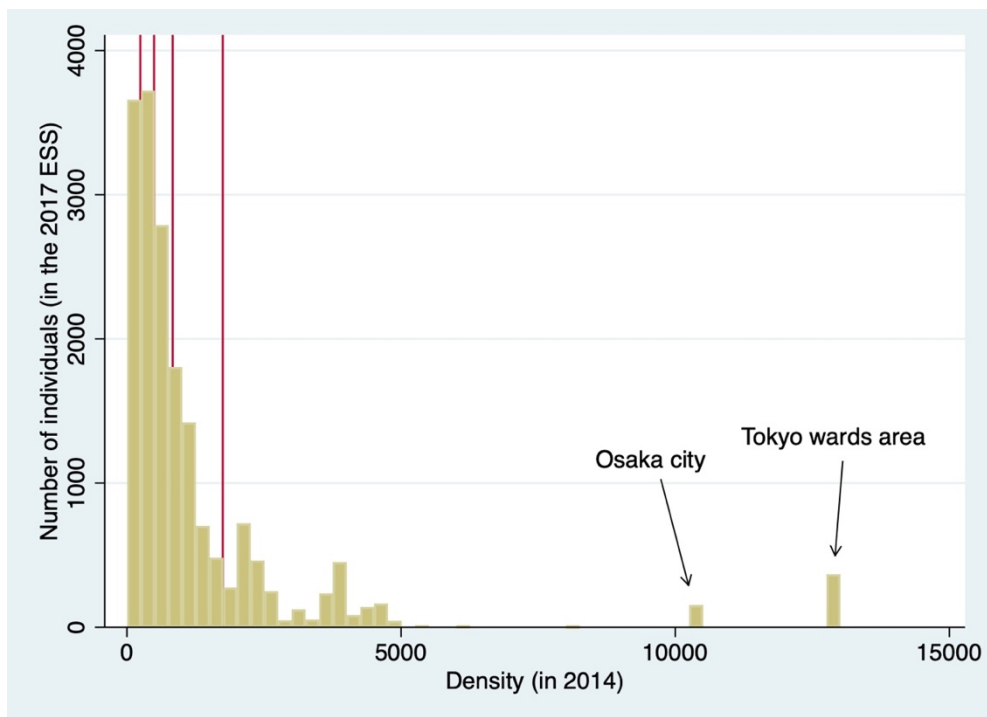
Note: Vertical lines are 20, 40, 60, and 80 percentiles of density of employees.

Figure A2: Sample sizes of our dataset by density of the number of employees

(a) 2012



(b) 2017



Note: Vertical lines are 20, 40, 60, and 80 percentiles of density of employees.