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Urbanization Effects on Job Search Decision*

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Abstract

This study examines the effect of urban agglomeration on a non-working individual's decision to search for a job using Japanese microdata. According to the results, urban agglomeration raises the probability of job search for less-educated men, suggesting that it raises the offer wages or decreases the out-of-pocket cost of job search. Urban agglomeration also encourages unmarried women to search for a job, whereas the effect is not significant for married women. It, however, discourages married women with children from searching, suggesting that life events, such as marriage and childbirth, raise women's value of household production, especially in urban areas.

Keywords: Local labor market; Agglomeration (dis)economies; Life event; Japan

JEL classification: J64; R11; R23

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1. Introduction

Urban agglomeration generates external economies that affect workers in urban areas. For example, it is well known that workers in larger local labor markets (i.e., urban areas) can, on average, receive higher wages than those in smaller local labor markets (i.e., rural areas). Although spatial sorting by workers' skills (i.e., workers in urban areas earn high wages because their ability is high) is not negligible as a source of such nature (Combes et al., 2008), the existing studies confirm that urban agglomeration causes the urban wage premium through some mechanisms.[1] One mechanism is that urban agglomeration fosters the accumulation of human capital (e.g., Glaeser and Maré, 2001; Gould, 2007; Heuermann et al., 2010; De La Roca and Puga, 2017). Other studies reveal that urban agglomeration affects the matching process between workers and firms. For example, it raises job seekers' likelihood of finding a job, suggesting that it improves matching efficiency in local labor markets (Di Addario, 2011).[2] In addition to job finding rates, urban agglomeration improves the quality of matching between workers and firms, leading to an increase in labor productivity, and thus an urban wage premium (e.g., Wheeler, 2006, 2008; Andersson et al., 2007; Bleakley and Lin, 2012; Abel and Deitz, 2015; Berlingieri, 2019; Dauth et al., 2022). Overall, through some mechanisms, we find agglomeration economies in labor markets.

Urban agglomeration also generates congestion, resulting in external diseconomies, such as longer commuting times. However, little is known about the

[1] Duranton and Puga (2004) offer a threefold theoretical classification of the sources of agglomeration economies: sharing, matching, and learning. These mechanisms can cause the urban wage premium (Heuermann et al., 2010).

[2] Petrongolo and Pissarides (2006) show that agglomeration does not affect the likelihood of finding a job, because agglomeration raises both firms' offer wages and job seekers' reservation wages, and they offset each other.

negative effects of urban agglomeration on the labor market. The aforementioned studies investigate the effects of urban agglomeration on wages and matching quality, which are observed only for employed workers. Moreover, job finding rates are observed only for job seekers who wish to work. The literature suggests that workers who already participate in the labor force experience the benefits of urban agglomeration that surpass its costs. Such workers seem to participate in the labor force because they find agglomeration economies. In other words, workers who find agglomeration diseconomies in labor markets may not decide to search for a job.

This study aims to examine two aspects of the effects of urbanization, namely, agglomeration economies and diseconomies. Specifically, this study explores the effect of urban agglomeration on the decision of a non-working individual to search for a job using Japanese microdata. We suppose that some workers find agglomeration economies, whereas others may find agglomeration diseconomies. To reveal the heterogeneity of urban agglomeration effects, this study focuses on some individual attributes that seem to determine how an individual responds to the level of urban agglomeration. Some studies confirm the heterogeneity of the agglomeration effect across individual attributes. Gould (2007), for example, shows that urban agglomeration does not raise wages of blue-collar workers but those of white-collar workers. Phimister (2005) reveals that women's probability of employment benefits from urban agglomeration, while the same does not hold for male workers. Andini et al. (2013) show that individuals of different ages and skills exhibit different magnitudes of agglomeration effects on job finding rates. In this study, we focus on gender, education, and family structure, such as marital status and the presence of preschool children. Gender and education are factors of human capital that directly affect labor productivity and wages. They may change the benefits of urban agglomeration, as the literature shows. Family structure is the socioeconomic status that affects the value of household production, a factor discouraging workers from participating in the labor force. On average, women perform housework and childcare more than men. Thus, if the value of household production varies across city sizes, it can generate heterogeneity in agglomeration effects on women's job search decisions.

This study contributes to the literature by providing implications for the employment policies of countries facing labor shortages. Some countries have recently been facing population decline, while others are predicted to do so in the near future. For example, the Japanese population has been declining and is projected to continue declining.[3] Two-thirds of the EU NUTS-3 regions are projected to face a population decline by 2050.[4] Amid this depopulation trend, labor shortages are expected to constitute a substantial issue for these countries. Indeed, many employers in Japan face labor shortages (Japan Institute for Labour Policy and Training, 2020). One solution lies in utilizing a potential labor force, namely, individuals who do not participate in the labor force but are able to work. To encourage such individuals to participate in the labor force, we must understand the factors leading them to decide to search for a job. Therefore, the investigation of job search decisions, that is, the step before individuals successfully find jobs and earn wages, is significant.

According to the estimation results, the agglomeration effects on job search decisions vary across individual attributes after controlling for observable individual characteristics and potential endogeneity stemming from the simultaneity of individual

[3] See the website of the National Institute of Population and Social Security Research of Japan (http://www.ipss.go.jp/pp-zenkoku/e/zenkoku_e2017/pp_zenkoku2017e.asp, accessed on August 22, 2022).

[4] See the website of the Eurostat (https://ec.europa.eu/eurostat/web/products-eurostat-news/-/ddn-20210430-2, accessed on August 22, 2022).

job search and residential location choice. The main findings of this study are twofold. First, agglomeration raises the probability of job search for less-educated men, while highly educated men tend to search regardless of the level of agglomeration, suggesting that agglomeration encourages less-educated men who potentially expect low offer wages to search for a job through an increase in the offer wages or a decrease in the out-of-pocket cost of job search. Second, life events such as marriage and childbirth change women's response of job search to agglomeration. The agglomeration effect on job search decisions is significantly positive for married women without children, while it is not statistically significant for unmarried women. Furthermore, for married women with children, the effect is significantly negative. These results suggest that life events increase women's value of leisure, that is, time spent on other than job search, including housework and childcare, especially in urban areas.

The remainder of this paper is organized as follows. Section 2 presents the empirical model to estimate the agglomeration effect on job search decisions. Section 3 presents the data. Section 4 presents the estimation results. Finally, Section 5 concludes the study.

2. Model

According to Mortensen (1986), non-working individuals face a decision problem of job search. If an individual finds that the present value of the search is sufficiently large, he/she decides to search for a job, that is, to participate in the labor force as an unemployed searching worker. In this case, the benefit of job search is larger than the out-of-pocket cost of job search. This benefit increases when an individual finds a higher offer wage or a higher offer arrival rate, but decreases when an individual encounters a higher value of leisure. Here, the value of "leisure" represents the value of time other than that spent on searching for a job, implying that it contains the value of household production (e.g., housework and childcare) as well as leisure activities. Hereafter, we label this value as the "value of leisure/household production."

Based on this framework, we consider the effects of urban agglomeration on job search decisions and individual attributes. First, urban agglomeration is assumed to increase the offer arrival rate because individuals can meet potential vacancies more often, resulting in a higher benefit of job search. Thus, in more agglomerated areas, individuals can receive more offers by paying a certain fixed search cost, resulting in a lower out-of-pocket cost of job search.[5] Consequently, urban agglomeration encourages individuals to search for a job through the offer arrival rate and the out-of-pocket cost of job search.

Next, in the benefit of job search, the offer wage can be assumed to increase with the level of urban agglomeration, as many studies show the urban wage premium. Furthermore, a wage gap arises among individual attributes of human capital, which can directly affect labor productivity. For example, highly educated individuals earn more than the less educated, and men earn more than women do. The value of leisure, the factor that decreases the benefit of job search, can be assumed to increase with the level of urban agglomeration because the value of leisure/household production seems high in urban areas. This assumption reflects how the market prices of services concerning household production (e.g., housekeeping services and childcare facilities) can be high. Additionally, longer commuting times in urban areas can cause a larger value of leisure/household production. We focus on individual socioeconomic status, such as family structure, as the

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[5] Wheeler (2001) develops the firm's search model assuming that urban agglomeration determines a firm's search cost. We consider that this assumption can be applied directly to a worker's job search.

individual attribute determining this value. Suppose that, as a consequence of a division of labor in the household, a wife will engage in household production, while a husband will perform paid work in the labor market after they marry. When a woman experiences marriage and childbirth, her value of leisure/household production increases because she spends her time doing housework and childcare.

Overall, we find that urban agglomeration can both increase and decrease the benefit of job search because it consists of the offer wage and the value of leisure/household production. Whether urban agglomeration increases or decreases the benefit of job search may depend on individual attributes, implying that the urban agglomeration effect on the benefit of job search is heterogeneous across individual attributes. Consequently, how urban agglomeration affects job search decisions is also heterogeneous across individual attributes, such as gender, education, marital status, and the presence of children.

Based on this conjecture, we present an empirical specification to estimate the effects of urban agglomeration on job search decisions. The source of individual microdata for the empirical analyses is a pooled cross-sectional survey; therefore, we cannot directly observe the process of job search decisions from the data. Instead, we examine the relationship between a non-working individual's job search status and the level of urban agglomeration where he/she resides. Therefore, the empirical model estimates the probability of searching for a job after controlling for the observable individual and household characteristics.

Let s_i denote the job search status taking one if a non-working individual i is searching for a job and zero otherwise. Owing to this binary outcome, the empirical specification is a probit model given by

$$\mathrm{P}(s_i = 1) = \Phi\big(\alpha + \beta \ln A_{r(i),t(i)} + X_i\gamma + Y_{r(i)}\delta + Z_{t(i)}\eta\big), \tag{1}$$

where $A_{r(i),t(i)}$, a measure of the level of urban agglomeration, is the employment density in region r, where individual i in survey year t resides; X_i is a vector of the individual and household characteristics; $Y_{r(i)}$ is a vector of regional block dummies; $Z_{t(i)}$ is a vector of survey year dummies; α is a constant; β, γ, δ, and η are the vectors of the parameters; finally, $\Phi(\cdot)$ is the normal cumulative distribution function.

Our interest parameter β establishes a distinction among the individual types concerning the relationship between urban agglomeration and job search decisions. To identify the heterogeneity of the urban agglomeration effects across individual attributes, the model is estimated by subsample based on three dimensions: gender, educational background (i.e., less than a university degree and a university degree or higher), and life events (i.e., marital status and the presence of preschool children under six years old). Focusing on these attributes is useful not only for verifying the conjecture but also for detecting policy targets to utilize the potential labor force. If the estimate is significantly positive, the level of urban agglomeration increases the probability of searching for a job. This suggests that the individuals in the subsample find agglomeration economies in their job search decisions. In contrast, if the estimate is significantly negative, agglomeration discourages individuals in the subsample from searching for a job. Individuals find agglomeration diseconomies. Lastly, if the estimate is not significantly different from zero, the individual is unlikely to fall under either category. In this case, we interpret that the individuals in the sample tend to exhibit one of the two types: individuals always search or never search, independent of the level of urban agglomeration. There is also another possibility that the sample contains two types of individuals, that is, agglomeration encourages some individuals to search, while discouraging others from searching, resulting in a statistically insignificant estimate.

A concern about the estimation of equation (1) is that the level of urban agglomeration (i.e., the log of employment density) might be endogenous because the individual job search and residential location choice exhibit simultaneity; therefore, the estimate may be biased. Combes et al. (2011) and Combes and Gobillon (2015) point out that endogeneity occurs at both regional and individual levels. First, if the agglomerated areas attract workers owing to, for example, high wages or a high likelihood of matching jobs, the local labor markets become denser. In this case, the unobservable regional factors are correlated with the level of urban agglomeration. Second, individuals with a high intention to work, determined by their unobservable factors, might choose to live in denser areas to obtain more opportunities to match jobs. This case induces a correlation between the unobservable individual factors and the level of urban agglomeration.

To cope with this endogenous problem, the existing literature investigating agglomeration effects has used long-lagged values of agglomeration variables as an instrument since Ciccone and Hall (1996). The literature related to this study on agglomeration effects on job search behavior and matching also uses such instruments (e.g., Di Addario, 2011; Bleakley and Lin, 2012; Andini et al., 2013; Abel and Deitz, 2015; Berlingieri, 2019). Following previous studies, we adopt the log of population density in 1920 as the instrument from the Population Census that was first conducted in Japan. Using this, we run instrumental variable (IV) probit estimations in addition to probit estimations. Such long-lagged values of agglomeration are considered valid instruments for the following reasons (Combes et al., 2011; Combes and Gobillon, 2015). The instrument satisfies the relevance because the stock of facilities, such as housing, office buildings, factories, and infrastructure, lasts over time, resulting in persistence in regional patterns of agglomeration. Furthermore, it satisfies the exclusion restriction because individuals' job search behaviors in the present should be quite different from the past owing to changes in the industrial structure and job search method.

3. Data

We construct a dataset for the estimations by combining individual-level microdata and regional-level agglomeration data from Japan. First, individual microdata is obtained from the Employment Status Survey (ESS), conducted every five years by the Ministry of Internal Affairs and Communications (MIC). We use a pooled cross-sectional dataset from eight waves of ESS between 1982 and 2017. Each wave covers approximately one million members aged 15 years and over in 500,000 households, which were collected through a stratified two-stage sampling method. They were asked about their employment status as of October 1 of the survey year. The ESS reports individuals' places of residence at the municipality level, a minimum administrative district in Japan, which allows one to merge this data with the regional-level agglomeration data. The study sample contains individuals who answered not working. Their records report whether they were searching for a job. Individuals who answered that they were preparing to open a business instead of searching for a job are omitted. The sample is restricted to working age (i.e., 15–64 years) and students are omitted.

Second, to create the variable of employment density as a measure of the level of urban agglomeration, we take the number of employees at the municipality level from six waves between 1981 and 2006 of the Establishment and Enterprise Census (EEC), conducted every five years, and two waves in 2009 and 2014 of the Economic Census for Business Frame (ECBF), a successor to the former EEC. These censuses were conducted in all establishments in Japan through the MIC. As a measure of the level of urban agglomeration, we calculate employment density, namely, the number of employees working at establishments in the region per square kilometer of inhabitable area.[6]

Here, the municipality, the available minimum regional unit from the study's data, may not be valid as the regional unit for the estimations, because it is not considered to correspond to the local labor market, but an administrative unit. Indeed, many workers commute beyond the boundaries of municipalities in Japan, implying that local labor markets have widened.[7] To deal with this problem, the regional unit for this study follows the Urban Employment Area (UEA) proposed by Kanemoto and Tokuoka (2002), which is defined by commuting rates across municipalities in Japan. Each UEA consists of core and outlying municipalities. The former is determined by the size of the densely inhabitable district population and the latter is defined by the rates of employed workers commuting to the core.[8] We thus consider that the UEAs represent a good proxy for the Japanese local labor markets. The number of UEAs is 222. Finally, we create a dataset for the estimations by merging each wave of the ESS with its immediately preceding year of EEC or ECBF, based on the individuals' residential UEAs.[9]

Table 1 shows the summary statistics of job search status and the variables to

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[6] Table A1 shows the summary statistics of the urban agglomeration variables at the UEA level.

[7] According to the 2015 Population Census, 44 percent of employed persons work in municipalities other than the ones where they reside.

[8] Based on municipal population and commuting rates across municipalities from the Population Census conducted every five years, the definition of UEA is revised after the census by the Center for Spatial Information Science (CSIS) of the University of Tokyo. To keep consistency of the regional unit and to deal with municipal mergers (see Appendix A for details), we adopt the 2015 standards of UEA unit, which is the latest during the study's sample periods. The UEA list is available through the website of the CSIS (http://www.csis.u-tokyo.ac.jp/UEA/index.htm, accessed on August 19, 2020).

[9] See Appendix A for how to construct the dataset in detail.

control for the individual and household characteristics by the subsample for the estimations, defined by gender, educational background (i.e., less than a university degree and a university degree or higher), and life events (i.e., marital status and the presence of preschool children under six years old). In addition to the variables in this table, the estimation models control for cohort group dummies as individual characteristics.[10] In the sample, individuals who lack one or more necessary variables are omitted.

[Table 1 about here]

The proportion of non-working individuals searching for a job is quite different across the subsamples. To consider this gap by understanding the characteristics of non-working individuals in the sample, Table 2 presents the proportion of non-working individuals to the whole population, as well as the proportion of searchers to non-working individuals by subsample. Panel A for men shows that, for both educational backgrounds, the proportion of non-working individuals to the whole population and the proportion of searchers to non-working individuals for married men with no children are lower than those for the unmarried men. This tendency indicates that married men tend to engage in paid work because of the division of labor in the household. Many men finally seem to engage in paid work after their spouse has children because the proportion of non-working individuals to the whole population and the proportion of searchers to non-working individuals for married men with children are the smallest and largest, respectively.

Panel B for women shows that, unlike men, the proportion of non-working individuals to the whole population is the smallest for unmarried women, followed in order by married women with no children and married women with children, for both

[10] See Table A2 for the cohort group dummies in detail.

educational backgrounds. In the reverse order, the proportion searchers to non-working individuals is the largest for unmarried women and the smallest for married women with children. Each order of the proportions is consistent, suggesting that life events such as marriage and childbirth discourage women from participating in the labor force.

[Table 2 about here]

Altogether, life events may indeed raise women's value of leisure/household production, whereas they have little effect on or decrease men's one. The following section investigates whether such heterogeneous effects of life events lead to heterogeneous effects of urban agglomeration on job search decisions of non-working individuals.

4. Results

4.1. Probit estimations

This section presents the estimation results of the empirical model (equation (1)) that examines the effect of urban agglomeration on the probability of non-working individuals' job search. Table 3 presents the probit model estimation results. All the models in this table control for observable individual and household characteristics. First, we consider the results for men, shown in panel A. Columns (1) to (3) for less than a university degree holders show that the marginal effect of the log of employment density on job search decisions is positive and significant at the 10 percent level, regardless of marital status and the presence of children. This result suggests that urban agglomeration can trigger a less-educated man's decision to search for a job. However, when the significance level is set at 1 percent, the effect for the unmarried group is not statistically significant. In addition, the magnitudes of the marginal effect for married men without children (0.0254) and with children (0.0209) are larger than that for unmarried men (0.0049). These results suggest that marriage and childcare encourage less-educated men in urban areas to work in labor markets because of the comparative advantage in their households; that is, husbands and wives tend to specialize in paid work in the labor market and household production (e.g., housework and childcare), respectively. This division of labor in the household may encourage husbands in more urban areas to decide to search for a job because they can expect to benefit from agglomeration, such as the urban wage premium as well as the lower out-of-pocket cost of job search.

[Table 3 about here]

The estimation results for men with a university degree or higher, shown in columns (4) to (6) of panel A, are similar to those for less-educated men. The agglomeration effect for the unmarried men is not statistically significant (column (4)), while those for married men both without and with children are significantly positive (columns (5) and (6)).

Next, panel B of Table 3 presents the estimation results for women. For less than a university degree holders in columns (1) to (3), the results show a significant gap in the agglomeration effect on job search decisions among the three groups with different marital statuses and the presence of children. For unmarried women, the agglomeration effect is significantly positive (column (1)), but not statistically significant for married women without children (column (2)). Finally, for married women with children, the agglomeration effect becomes negative and significant (column (3)). With regard to the magnitude of the effect, a 10 percent increase in employment density raises the likelihood of searching for a job by 0.14 percentage points for the unmarried. By contrast, it decreases the likelihood by 0.07 percentage points for married women with children.

These results suggest that life events, such as, marriage and childbirth, change the less-educated women's response of job search decisions to agglomeration. First, non-working unmarried women in urban areas tend to search for jobs because they find a lower out-of-pocket cost of job search there and higher benefits of job search, such as the urban wage premium. After they marry, but do not yet have children, based on the comparative advantage in the household, married couples allocate more of the female spouse's time to housework and the male spouse's time to paid work in the labor market. This household decision increases the women's value of leisure/household production, leading to a higher opportunity cost of job search. Their offer wages are supposed to remain unchanged, as marriage could not affect human capital.

Finally, if couples have children, the burden of childcare further increases women's value of leisure and household production. This tendency is large enough to surpass the offer wages, especially in urban areas, suggesting that childcare costs are higher in urban areas. Indeed, the labor force participation rates of married women with children in Japan are lower in urban areas than in others (Abe, 2013, 2018). The factors leading to this regional disparity could be longer commuting times in urban areas (Black et al., 2014; Kawabata and Abe, 2018) and supply shortages of childcare facilities in urban areas (Hashimoto and Miyagawa, 2008). Consequently, these features of urban areas can generate agglomeration diseconomies in job search decisions for married women with children.

Columns (4) to (6) of panel B present the estimation results for women with a university degree or higher. Unlike less-educated women, the agglomeration effect is not significant for unmarried women and married women with children (columns (4) and (6)), but is significantly positive for married women without children (column (5)). Highly educated unmarried women may search for jobs, regardless of the level of urban agglomeration, because their offer wages are high. Two possibilities are considered to be the factors causing the insignificant agglomeration effect for married women with children. First, even if the highly educated women's value of leisure/household production increases owing to marriage and childcare, their offer wages may be still high enough. They thus search for jobs regardless of the level of urban agglomeration. Second, highly educated women tend to marry highly educated men who earn high wages; therefore, wives may specialize in household production more. They thus do not search for jobs regardless of the level of urban agglomeration. The latter might be more reasonable because, regardless of the presence of children, the proportion of married women with a university degree or higher who are searching for a job is lower than that of less than a university degree holders, as shown in Table 2. However, it remains difficult to interpret the significant agglomeration effect for married women without children.

4.2. IV probit estimations

The simple probit models in the previous subsection may induce biased estimates because of the simultaneity of individual job search and residential location choice. To address this problem, we consider the estimation results using the 1920 population density as the instrument. Table 4 presents the marginal effects of the IV probit estimation. The instrument accurately predicts the agglomeration variable because the coefficient of the instrument in the first stage is significantly positive and the partial R-squared is approximately 0.5 for all models. Thus, the instrument is considered to satisfy the relevance.

[Table 4 about here]

For men with less than a university degree, columns (1) to (3) of panel A show similar results to the probit estimations in Table 3; that is, there are significant positive agglomeration effects on job search decisions regardless of marital status and the presence of children. In this case, we consider the endogenous bias to be a minor problem.

For men with a university degree or higher, column (4) shows that the agglomeration effect for unmarried men is not statistically significant, as in the probit estimation. For married men without children in column (5), the effect is significant only when the statistically significant level is set at the 10 percent level. Column (6) for married men with children does not indicate a statistically significant effect, unlike in the probit estimation. Probit estimation without the instrument may have been contaminated by simultaneous bias. In other words, men with a high search intensity may move to urban areas to search for jobs after they marry. The results after coping with this bias suggest that agglomeration does not change the job search decisions of highly educated men, regardless of marital status and the presence of children. We thus consider that highly educated non-working men search for jobs regardless of the agglomeration level because they expect to receive high offer wages.

Next, we consider the results for women in panel B. Columns (1) to (3) for women with less than a university degree confirm results similar to those in Table 3; that is, agglomeration encourages less-educated women to search for jobs when they are unmarried. The agglomeration effect becomes insignificant when they marry and becomes significantly negative when they have children. Consequently, even after coping with the endogeneity of agglomeration, the agglomeration effect on the job search decisions of less-educated women depends on their life events, such as marriage and childbirth.

For women with a university degree or higher, as shown in columns (4) to (6), the agglomeration effect is not statistically significant for all groups with different marital statuses and the presence of children. The significantly positive effect for married women with children confirmed by the probit estimations without the instrument in Table 3 may capture the simultaneity of their job search and residential location choice after marriage. After coping with this simultaneity, the job search decisions of highly educated women are confirmed not to depend on agglomeration, regardless of their marital status and the presence of children. These results reinforce the interpretation provided in the previous subsection for probit estimations without the instrument; that is, highly educated women do not change their job search decisions based on agglomeration, because they can expect high offer wages that offset the value of leisure/household production. Another possibility is that they do not search for a job after they marry because they tend to marry highly educated men who earn high wages, resulting in more specialized household production.

Overall, these estimations suggest that life events, such as marriage and childbirth, increase women's value of leisure/household production sufficiently enough to change the agglomeration effect on job search decisions. Ultimately, married women with children in urban areas do not decide to search for jobs.

5. Conclusion

This study examined the effect of urban agglomeration on the decision of a non-working individual to search for a job, a step before job matching and earning wages, using Japanese microdata. It also focused on the differences in this effect across individual attributes, such as gender, education, marital status, and the presence of children.

The estimation results showed that the agglomeration effect differs across individual attributes, even after coping with potential endogeneity stemming from the simultaneity of individuals' job search and residential location choice. The main findings were twofold. First, urban agglomeration encourages less-educated men to search for a job, suggesting that they find the benefit of agglomeration, such as higher offer wages. The effect of urban agglomeration is not significant for highly educated men, indicating that they search for jobs regardless of agglomeration because they can potentially expect high offer wages.

Second, life events, such as marriage and childbirth, remarkably change the job search decision responses of less-educated women to agglomeration. For unmarried women, the agglomeration effect on job search decisions is significantly positive, but becomes insignificant after marriage. This result suggests that the burden of housework increases the value of leisure/household production. When married women have children, the agglomeration effect becomes significantly negative, suggesting that childcare further increases the value of leisure/household production, especially in urban areas. A significant agglomeration effect was not confirmed for highly educated women, indicating that their high offer wages enable them to search for a job, or that marriage with highly educated men reduces their likelihood of searching for a job, regardless of agglomeration.

Finally, the results lead to the following implications for employment policy to utilize the potential labor force. To utilize inactive men, especially those who are less educated, it seems helpful to decrease the out-of-pocket cost of job search in rural areas by policies inducing high offer arrival rates, such as reinforcement of public employment referral, because those who reside in non-urban areas do not tend to search for a job.

Vocational training for male workers in rural areas might also be helpful because human capital accumulation is expected to increase offer wages, which leads to more job searching. To utilize inactive women, especially those who are married, the gender wage gap should be decreased, as comparatively lower wages may discourage wives from searching for jobs. In addition, to utilize inactive married women with children who encounter negative agglomeration effects, policymakers should support them in urban areas by solving the long commuting times or the shortages of childcare facilities in order to reduce these women's value of leisure/household production.

Appendix A. Construction of the dataset

First, some municipal mergers occurred in Japan during the sample period (1981–2017). To construct a consistent regional unit over the sample periods, we arranged the municipality unit as of October 1, 2015, when the latest Population Census was conducted during the sample periods. After this period, no municipal mergers occurred. Then, we converted the municipality unit to the 2015 standards of the UEA unit, which is defined based on the municipal population and commuting rates across municipalities from the Population Census. Exceptionally, Kamikuishiki-mura separated into two areas: one merged with Kofu-shi and the other merged with Fujikawaguchiko-machi on March 1, 2006. Furthermore, these two municipalities are situated in different UEAs. Then, individuals who resided in Kamikuishiki-mura from the ESS between 1982 and 2002 were dropped from the sample because their residential UEAs could not be identified. Regarding the agglomeration data, the number of employees from the EEC between 1981 and 2001 was distributed based on the areas after this separation.[11] The population

[11] To calculate the areas after the separation, we used the Municipality Map Maker for

density in 1920 for the instrument was calculated in the same manner.[12] Although some municipalities are classified into wards (*ku*) in ordinance-designated cities (*seirei-shitei toshi*) separated during the sample periods, these separations are not problematic for regional unit arrangements because the UEAs containing such municipalities cover all wards. Table A1 shows the summary statistics of the urban agglomeration variables (i.e., the log of employment density and log of population density in 1920) at the UEA level.

Second, the regional block of a UEA was determined based on the prefecture to which the core municipalities belong. The 11 regional blocks are as follows (prefectures are in parentheses): Hokkaido (Hokkaido), Tohoku (Aomori, Iwate, Miyagi, Akita, Yamagata, and Fukushima), Minami-Kanto (Saitama, Chiba, Tokyo, and Kanagawa), Kita-Kanto/Koshin (Ibaraki, Tochigi, Gumma, Yamanashi, and Nagano), Hokuriku (Niigata, Toyama, Ishikawa, and Fukui), Tokai (Gifu, Shizuoka, Aichi, and Mie), Kinki (Shiga, Kyoto, Osaka, Hyogo, Nara, and Wakayama), Chugoku (Tottori, Shimane, Okayama, Hiroshima, and Yamaguchi), Shikoku (Tokushima, Kagawa, Ehime, and Kochi), Kyushu (Fukuoka, Saga, Nagasaki, Kumamoto, Oita, Miyazaki, and Kagoshima), and Okinawa (Okinawa).

Third, the cohort group dummies for the estimations were constructed based on the age of individuals in each wave of the ESS, as shown in Table A2.

[Tables A1 and A2]

Web (http://www.tkirimura.com/mmm/, accessed on March 11, 2021), developed by Kirimura et al. (2011).

[12] We obtained the population data at the municipality level of the 1920 Population Census from a CD-ROM attached to Sinfonica and JSA (2005).

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Table 1: Summary statistics of non-working individual and household characteristics

	Less than university degree						University degree or higher					
	Unmarried		Married				Unmarried		Married			
			No children		With children				No children		With children	
	(1)		(2)		(3)		(4)		(5)		(6)	
Variable	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.
Panel A: Men												
Searching for a job	0.380	0.485	0.341	0.474	0.422	0.494	0.518	0.500	0.289	0.453	0.580	0.494
Age	38.034	15.396	58.477	6.902	51.622	13.405	38.207	13.301	58.719	7.051	44.162	12.908
Household head	0.358	0.479	0.948	0.222	0.838	0.369	0.294	0.455	0.945	0.227	0.838	0.369
Working a year ago	0.196	0.397	0.304	0.460	0.392	0.488	0.259	0.438	0.345	0.475	0.575	0.495
Previous job experience	0.644	0.479	0.962	0.191	0.960	0.197	0.736	0.441	0.982	0.134	0.961	0.193
Number of household members aged 15 or over	1.747	1.455	1.793	1.002	2.640	1.163	1.818	1.335	1.720	0.957	1.937	1.219
Number of children aged 0–5	0.028	0.209	0.000	0.000	1.396	0.571	0.013	0.145	0.000	0.000	1.311	0.513
Number of children aged 6–14	0.084	0.356	0.154	0.523	0.492	0.748	0.019	0.169	0.097	0.410	0.368	0.651
Household yearly income (JPY in millions)												
Less than 1	0.230	0.421	0.073	0.261	0.080	0.271	0.148	0.355	0.059	0.235	0.131	0.338
1–1.99	0.180	0.385	0.154	0.361	0.099	0.299	0.129	0.335	0.092	0.289	0.104	0.306
2–2.99	0.139	0.346	0.230	0.421	0.122	0.327	0.150	0.358	0.170	0.375	0.147	0.354
3–3.99	0.105	0.307	0.171	0.377	0.124	0.329	0.125	0.331	0.175	0.380	0.107	0.309
4–4.99	0.077	0.267	0.119	0.324	0.125	0.331	0.087	0.281	0.132	0.338	0.113	0.317
5–6.99	0.109	0.312	0.143	0.350	0.211	0.408	0.126	0.332	0.178	0.382	0.148	0.355
7–9.99	0.094	0.292	0.083	0.276	0.175	0.380	0.117	0.321	0.129	0.335	0.130	0.336
10–14.99	0.049	0.217	0.024	0.153	0.056	0.230	0.085	0.278	0.053	0.225	0.091	0.288
15 or higher	0.015	0.122	0.003	0.058	0.008	0.090	0.034	0.180	0.013	0.114	0.030	0.169
Observations	82,754		69,293		8,350		13,071		11,928		778	

Notes: Pooled data across eight waves of the ESS between 1982 and 2017.

Table 1 (continued)

	Less than university degree						University degree or higher					
	Unmarried		Married				Unmarried		Married			
			No children		With children				No children		With children	
	(1)		(2)		(3)		(4)		(5)		(6)	
Variable	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.
Panel B: Women												
Searching for a job	0.304	0.460	0.170	0.376	0.127	0.333	0.431	0.495	0.135	0.342	0.094	0.291
Age	44.304	16.053	50.110	10.438	34.648	9.852	36.894	13.568	46.579	10.441	33.559	4.778
Household head	0.432	0.495	0.023	0.148	0.008	0.088	0.259	0.438	0.033	0.177	0.009	0.093
Working a year ago	0.205	0.404	0.110	0.312	0.094	0.292	0.329	0.470	0.122	0.327	0.082	0.275
Previous job experience	0.674	0.469	0.710	0.454	0.858	0.349	0.747	0.435	0.808	0.394	0.908	0.289
Number of household members aged 15 or over	1.623	1.393	1.853	1.025	1.662	1.097	1.947	1.324	1.650	0.939	1.236	0.715
Number of children aged 0–5	0.116	0.413	0.000	0.000	1.397	0.560	0.040	0.248	0.000	0.000	1.376	0.549
Number of children aged 6–14	0.199	0.562	0.423	0.800	0.457	0.704	0.048	0.268	0.535	0.858	0.384	0.641
Household yearly income (JPY in millions)												
Less than 1	0.186	0.389	0.021	0.142	0.008	0.090	0.101	0.302	0.012	0.110	0.006	0.077
1–1.99	0.190	0.392	0.059	0.236	0.039	0.194	0.101	0.302	0.016	0.126	0.009	0.094
2–2.99	0.145	0.352	0.128	0.334	0.133	0.339	0.128	0.334	0.048	0.213	0.049	0.217
3–3.99	0.116	0.320	0.141	0.348	0.193	0.395	0.110	0.312	0.077	0.266	0.128	0.334
4–4.99	0.093	0.290	0.134	0.340	0.187	0.390	0.098	0.297	0.097	0.295	0.172	0.378
5–6.99	0.125	0.331	0.211	0.408	0.237	0.425	0.131	0.337	0.196	0.397	0.313	0.464
7–9.99	0.091	0.288	0.187	0.390	0.137	0.344	0.147	0.354	0.261	0.439	0.211	0.408
10–14.99	0.042	0.201	0.093	0.290	0.052	0.222	0.114	0.318	0.201	0.401	0.082	0.275
15 or higher	0.013	0.114	0.027	0.163	0.014	0.117	0.069	0.254	0.093	0.290	0.030	0.170
Observations	124,134		448,214		188,121		7,777		30,283		20,174	

Notes: Pooled data across eight waves of the ESS between 1982 and 2017.

Table 2: Fractions of non-working individuals and those who are searching

	Less than university degree			University degree or higher		
	Unmarried	Married		Unmarried	Married	
		No children	With children		No children	With children
Variable	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Men						
Non-working/Whole population	0.162	0.073	0.031	0.087	0.040	0.007
Searching/Non-working	0.380	0.341	0.422	0.518	0.289	0.580
Panel B: Women						
Non-working/Whole population	0.213	0.355	0.541	0.099	0.330	0.486
Searching/Non-working	0.304	0.170	0.127	0.431	0.135	0.094

Note: Pooled data across eight waves of the ESS between 1982 and 2017. Sample of the working individuals is restricted to those who have no missing values of the same variables, which are used for the estimations for the non-working individuals.

Table 3: Probit marginal effects of agglomeration on job search decision

	Less than university degree			University degree or higher		
	Unmarried	Married		Unmarried	Married	
		No children	With children		No children	With children
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Men						
ln(Employment density)	0.0049*	0.0254***	0.0209***	0.0003	0.0184***	0.0541***
	(0.0030)	(0.0040)	(0.0067)	(0.0068)	(0.0070)	(0.0172)
Observations	82754	69293	8350	13071	11928	778
Log pseudo likelihood	-42841.29	-36350.46	-3919.27	-7239.34	-5471.87	-322.29
Pseudo R2	0.220	0.182	0.311	0.200	0.237	0.391
Panel B: Women						
ln(Employment density)	0.0141***	0.0014	-0.0074***	0.0071	0.0107***	-0.0006
	(0.0026)	(0.0018)	(0.0018)	(0.0085)	(0.0036)	(0.0042)
Observations	124134	448214	188121	7777	30283	20174
Log pseudo likelihood	-57844.24	-177329.05	-68044.23	-4182.89	-10456.54	-6004.36
Pseudo R2	0.241	0.132	0.051	0.213	0.129	0.042

Notes: Standard errors clustered at the regional level are in parentheses. ***, **, and * represent statistical significance at 1%, 5%, and 10% level, respectively. All models contain a constant, individual and household characteristics, cohort group dummies, regional block dummies, and the survey year dummies.

Table 4: IV Probit marginal effects of agglomeration on job search decision

	Less than university degree			University degree or higher		
	Unmarried	Married		Unmarried	Married	
		No children	With children		No children	With children
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Men						
ln(Employment density)	0.0094**	0.0287***	0.0367***	0.0077	0.0204*	0.0246
	(0.0044)	(0.0059)	(0.0097)	(0.0092)	(0.0108)	(0.0280)
First stage results						
ln(Population density in 1920)	1.3053***	1.3230***	1.3496***	1.3788***	1.4080***	1.4616***
	(0.1102)	(0.1108)	(0.0985)	(0.1218)	(0.1213)	(0.1218)
Observations	82754	69293	8350	13071	11928	778
Log pseudo likelihood	-82657.48	-68816.88	-7451.38	-12930.73	-10230.27	-656.29
Partial R2	0.495	0.514	0.543	0.474	0.504	0.519
Wald test of exogeneity (chi2)	2.083	0.865	6.216	1.051	0.082	2.323
(p-value)	0.149	0.352	0.013	0.305	0.775	0.127
Panel B: Women						
ln(Employment density)	0.0135***	0.0005	-0.0059**	0.0094	0.0077	-0.0061
	(0.0037)	(0.0023)	(0.0027)	(0.0125)	(0.0049)	(0.0053)
First stage results						
ln(Population density in 1920)	1.3440***	1.3675***	1.3737***	1.4116***	1.4245***	1.4106***
	(0.1126)	(0.1137)	(0.1051)	(0.1369)	(0.1381)	(0.1281)
Observations	124134	448214	188121	7777	30283	20174
Log pseudo likelihood	-116927.38	-369116.86	-144527.55	-7317.31	-19282.89	-12256.61
Partial R2	0.507	0.528	0.549	0.478	0.503	0.521
Wald test of exogeneity (chi2)	0.064	0.241	0.736	0.049	0.722	1.667
(p-value)	0.800	0.624	0.391	0.824	0.395	0.197

Notes: Standard errors clustered at the regional level are in parentheses. ***, **, and * represent statistical significance at 1%, 5%, and 10% level, respectively. All models contain a constant, individual and household characteristics, cohort group dummies, regional block dummies, and the survey year dummies.

Table A1: Summary statistics of urban agglomeration variables

Variable	Mean	Std. dev.	Min	Max
ln(Employment density)	5.496	0.753	3.112	7.734
ln(Population density in 1920)	6.021	0.647	3.692	7.287

Notes: Numbers of observations are 1776 (= 222 UEAs * 8 waves) and 222 for the log of employment density and the log of population density in 1920, respectively. Employment and population density are calculated by the number of the employees and population per square kilometer of inhabitable area, respectively.

Table A2: Cohort groups for dummy variables for the estimations

ESS wave	Aged 15–20	Aged 20–25	Aged 25–30	Aged 30–35	Aged 35–40	Aged 40–45	Aged 45–50	Aged 50–55	Aged 55–60	Aged 60–65
1982	10	9	8	7	6	5	4	3	2	1
1987	11	10	9	8	7	6	5	4	3	2
1992	12	11	10	9	8	7	6	5	4	3
1997	13	12	11	10	9	8	7	6	5	4
2002	14	13	12	11	10	9	8	7	6	5
2007	15	14	13	12	11	10	9	8	7	6
2012	16	15	14	13	12	11	10	9	8	7
2017	17	16	15	14	13	12	11	10	9	8

Notes: Numbers represent the cohort groups.