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Does Agglomeration Discourage Fertility? Evidence from the Japanese General Social Survey 2000-2010*

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Abstract

This study employs Japanese household-level data to quantify the extent to which congestion diseconomy in large cities affects married couples' fertility behavior. The theoretical model of this study emphasizes the importance of controlling for preference heterogeneity in the demand for children. The baseline quantification shows that, all else equal, a 10-fold difference in city size generates a spatial variation of -22.13% in the average number of children born to couples aged 30 and a spatial variation of -6.07% at age 49. The narrowing of the gap suggests that young married couples in larger cities delay childbearing.

Keywords: Fertility, Agglomeration, Social survey, Migration
JEL classification: J10, J13, R23

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1 Introduction

Recent literature in economic geography has emphasized the benefits of agglomeration economies, including higher productivity and faster human capital accumulation in more densely populated areas (e.g., Combes et al., 2012; Combes and Gobillon, 2015; Glaeser and Maré, 2001; Glaeser and Resseger, 2010; de la Roca and Puga, 2017). Although economists and policymakers considers the economics of agglomeration when designing growth policies, less attention is devoted to the *diseconomies* brought about by agglomeration. This study aims to shed light on the fact that not only benefits but also congestion costs arising from agglomeration affect socioeconomic behavior.

In most developed counties, demographic issues are central to the current policy agendas. These counties have experienced rapid declines in total fertility rates (TFR) with economic growth, and raising fertility rates has become a policy priority in several countries. For example, France, Germany, the United Kingdom (UK), and the United States (US) have exhibited sharp declines in their TFRs since the 1960s, as have Italy and Japan after the 1970s. Although recent TFRs have remained at approximately 2 in France, the UK, and the US, they are less in Germany, Italy, and Japan (approximately 1.4). The low fertility rate has led to an acceleration in the aging of the population. Since an unbalanced demographic structure distorts social security systems, governments seek effective policies to recover fertility rates (e.g., Grant et al., 2004). In addition, Krugman (2014) points out that slow population growth precedes reduced demand for new investment and may contribute to secular stagnation.

This study attempts to theoretically and empirically clarify how agglomeration discourages fertility behavior. In particular, this study emphasizes spatial rather than temporal views of national fertility. The theoretical model of this study clarifies possible channels through which both agglomeration economies and diseconomies affect the demand for children. For example, Panels (a) and (b) of Figure 1 illustrate fertility rates and population density for Japanese municipalities, respectively. They clearly exhibit a negative relationship, as shown in Panel (c).

[Figure 1]

There are many possible factors that could explain this negative relationship. For example, Sato (2007) constructs a theoretical model, in which an agglomerated region attracts workers, intensifying the population density and wage rates while reducing fertility rates through agglomeration diseconomies. As empirically studied by Schultz (1986), Sato and Yamamoto (2005), Aiura and Sato (2014), Morita and Yamamoto (2014), and Goto and Minamimura (2015) theoretically examine the mechanics through which rising real wages in more densely populated areas increase the opportunity cost of childrearing while attracting workers, further elevating the population density and the opportunity cost. This circularity engenders lower fertility rates in more densely populated areas.[1]

Although these theoretical studies clarify possible channels through which agglomeration affects the demand for children, it remains unclear how agglomeration affects married couples' decisions to bear children at different ages. Figure 2 presents geographical distributions of fertility rates by age cohort and shows regional heterogeneity among age groups. The fertility rates among couples aged 35–39 are relatively high in more densely populated areas, especially in Greater Tokyo and Osaka, although they are lower among couples aged 25–29. The data depicted in Figure 2 imply that individuals residing in large cities postpone parenthood.

[Figure 2]

Using household-level microdata, this study aims to quantify the extent to which congestion costs in large cities discourage married couples from bearing children per parental age cohort. As explained in the theoretical model, this study emphasizes that preference heterogeneity in the demand for children leads to the bias when researchers estimate the *ex post* effect of agglomeration on the demand for children. For example, the spatial sorting of individuals with weak preferences for the demand for children is a possible source of bias.[2] To control for preference heterogeneity and self-selected migration, this study employs the Japanese General Social Survey (JGSS) dataset.

This study advances the economic geography literature by offering new evidence concerning childbearing by married couples in large cities. Controlling for economic and social factors, this study finds that congestion costs in large cities discourage fertility among married couples, with the magnitude of this effect shrinking as couples age. The baseline estimates reveal that, holding other factors equal, a 10-fold increase in population density (in general, the difference between central cities in Japanese rural prefectures and metropolitan areas in Tokyo) reduces fertility by 22% for couples age 30 but by only 6% for couples age 49. Further analyses show that young married

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[1] Another explanation for the negative relationship between TFR and city size is the spatial sorting of high-skilled people, who earn higher wages in larger cities. Maruyama and Yamamoto (2010) also provide insightful views on endogenous fertility decisions focusing on the variety expansion effects in large cities. In this literature, Becker (1960) develops the economic analysis of fertility. As Becker and Lewis (1973) explain, the interaction between the quantity and quality of children is important in economic models of fertility. Willis (1973) extends the fertility model to incorporate the opportunity costs of rearing children versus earning wages from working. See Becker (1992), Browning (1992), and Hotz et al. (1997) for details of fertility analysis.

[2] Large cities attract high-skilled workers, who tend to have fewer children. Therefore, the negative relationship between TFR and city size may not be explained by *ex post* effects of agglomeration, such as high opportunity costs of rearing children and congestion costs. This spatial sorting can be viewed as an *ex ante* effect of agglomeration.

couples in large cities postpone having their first child by an average of 5 months in the case of a 10-fold increase in population density.

Concerning existing studies in Japan, Sasai (2007) finds that the regional gap in completed fertility shrinks after controlling for social and economic factors, and mentions a possibility that married couples have children later in life. Therefore, my study contributes to the literature by providing supportive evidence for this aspect. In addition, Yamauchi (2016) points out that completed fertility in the Tokyo Metropolitan Area is still lower than that in other areas. Note that my study is consistent with findings in both Sasai (2007) and Yamauchi (2016). Using a more general quantitative analysis by population density, this study reveals that married couples in large cities have children later in life, which decreases the regional gap in completed fertility. However, a slight gap in completed fertility exists.[3]

This study also extends the literature concerning fertility and housing prices. Simon and Tamura (2009) investigate the effects of housing rents on age at first marriage, age at birth of the first child, and number of children. They find that higher rents delay marriage and childbirth and reduce the number of children per household. Given that rents are higher in more densely populated areas, this study complements their findings. In addition, Lovenheim and Mumford (2013) and Dettling and Kearney (2014) show that the effects of housing prices on fertility differ for homeowners and renters owing to differences in the importance of housing's wealth and price effects. By contrast, this study does not specify each factor of congestions, such as housing and land. This study emphasizes that housing and land are not the only factors that delay the timing of childbearing. For example, high uncertainty of accessibility to nursery schools is another factor, and this factor is highly correlated with city size in Japan. High educational costs in large cities also affect the timing of childbearing. Married couples may wait to have their first child until they have saved enough money. There are also numerous potential costs in large cities that researchers cannot observe directly. Therefore, this study attempts to capture wide-ranging aggregate congestion costs arising from agglomeration by population density.

[3]There are other existing studies related to this paper. Dekle (1990) finds that an increase in the husband's income tends to increase completed fertility, whereas an increase in women's real earnings tends to decrease it. His finding is consistent with mine. Koike (2009) shows that rural-to-urban migrants have fewer children than those who stay in urban or rural areas. In the existing literature, some of them discuss city size effects on the number of children, although these studies generally use dummies of region or city size (e.g., Dekle, 1990; Sasai, 2007; Koike, 2009; Yamauchi, 2016). One exception is Kitamura and Miyazaki (2005), who discuss potential sources that generate a negative correlation between TFR and population density using regional data. However, their main focus is on the relationship between marriage experience and childbearing. Unlike the traditional approach, this study uses a continuous variable for city size, specifically population density.

The remainder of this paper is organized as follows. Section 2 explains a theoretical model. Section 3 describes the empirical framework. Section 4 presents the dataset. Section 5 discusses the estimation results and a robustness check. Section 6 presents the conclusions.

2 Theoretical Explanation

This study aims to quantify the extent to which congestion costs arising from agglomeration discourage fertility behavior. Using a simple theoretical model, this study clarifies possible channels through which both agglomeration economies and diseconomies affect the demand for children.

Following Becker (1992), Willis (1973), and Sato (2007), this study describes households' fertility decisions, in which both the number and quality (e.g., the education level) of children are assumed. For simplicity, this study employs a Cobb–Douglas utility function in which all goods are normal, as follows:[4]

$$u(x_r, y_r, q_r) = x_r^{1-\mu-\xi} y_r^{\mu} q_r^{\xi}, \quad 0 < \mu + \xi < 1, \quad 0 < \mu < 1, \quad 0 < \xi < 1,$$

where x_r, y_r, and q_r represent consumption of a composite good, the number of children, and the quality per child, respectively. This study assumes that each household is endowed with one unit of time allocated between working and childrearing. Households must spend a quantity of time by_r, where b is a positive constant tied to the time requirement of rearing one child. Thus, the budget constraint is given as follows:[5]

$$p_{xr}(n_r)x_r + p_{qr}(n_r)q_r y_r = I_r(n_r) + w_r(n_r)(1 - by_r) - c_r(n_r),$$

where n_r is the city size variable (e.g., the population density or population size) in region r, $p_{xr}(n_r)$ is the price of composite goods in region r, $p_{qr}(n_r)$ is the price related to the quality of children (e.g., education, training, health), $I_r(n_r)$ is the household's non-labor income or the income of a full-time worker in the household (e.g., the husband's income or the income of a household member who has little time for childrearing) in region r, $w_r(n_r)$ is the wage rate for a household member who

[4]This study constructs a simple model based on the Cobb–Douglas utility function. Despite some strong assumptions that the Cobb–Douglas utility function imposes (e.g., there is no cross price elasticity of demand), a specific functional form allows for a more intuitive understanding of the theoretical results. In particular, the Cobb–Douglas specification allows for discussion of the mechanism of spatial sorting in terms of preference heterogeneity in the utility function.

[5]This type of simple formulation can be found in Sato (2007). By contrast, Aiura and Sato (2014) consider land/housing consumption in the utility function. The high land/housing price plays a similar role in the congestion costs of agglomeration, but consumers can simultaneously reduce their land/housing consumption. This simple formulation, like that of Sato (2007), omits the latter channel.

takes care of children (e.g., the wife's wage) in region r, and $c_r(n_r)$ is the congestion cost arising from agglomeration in region r. It is assumed that prices, income, wages, and congestion costs depend on the city size.

In the budget constraint, $bw_r(n_r) + p_{qr}(n_r)q_r$ denotes the marginal cost of rearing children, in which $bw_r(n_r)$ captures the opportunity cost of rearing a child relative to working (i.e., the loss of earnings). Importantly, an increase in the wife's wage rate $w_r(n_r)$ leads to higher opportunity costs of rearing a child.

In addition, agglomeration economies and diseconomies are assumed as follows:

$$\frac{\mathrm{d}p_{xr}(n_r)}{\mathrm{d}n_r} \gtreqless 0, \quad \frac{\mathrm{d}p_{qr}(n_r)}{\mathrm{d}n_r} > 0, \quad \frac{\mathrm{d}I_r(n_r)}{\mathrm{d}n_r} > 0, \quad \frac{\mathrm{d}w_r(n_r)}{\mathrm{d}n_r} > 0, \quad \text{and} \quad \frac{\mathrm{d}c_r(n_r)}{\mathrm{d}n_r} > 0, \tag{1}$$

where the price index, $p_{xr}(n_r)$, may increase in n_r, whereas if x_r also includes differentiated goods, $p_{xr}(n_r)$ may decrease in n_r (e.g., Ottaviano et al., 2002; Handbury and Weinstein, 2015). As discussed in the Online Appendix, the price related to the quality of children, $p_{qr}(n_r)$, might be higher in large cities. As studies in urban economics have established, income and wage rates in more densely populated regions tend to be higher (e.g., Combes and Gobillon, 2015). The congestion costs of agglomeration $c_r(n_r)$ (e.g., commuting) increase in n_r.

Households' utility maximization yields respective demand functions for consumption goods, children, and the quality of children, as follows:

$$\begin{aligned} x_r\Big(I_r(n_r), w_r(n_r), c_r(n_r), p_{xr}(n_r)\Big) &= (1-\mu-\xi)\frac{I_r(n_r)+w_r(n_r)-c_r(n_r)}{p_{xr}(n_r)}, \\ y_r\Big(I_r(n_r), w_r(n_r), c_r(n_r)\Big) &= (\mu-\xi)\frac{I_r(n_r)+w_r(n_r)-c_r(n_r)}{bw_r(n_r)}, \\ q_r\Big(w_r(n_r), p_{qr}(n_r)\Big) &= \frac{\xi}{\mu-\xi}\frac{bw_r(n_r)}{p_{qr}(n_r)}, \end{aligned} \tag{2}$$

where $\mu - \xi > 0$ and $I_r(n_r) + w_r(n_r) - c_r(n_r) > 0$ are assumed to satisfy positive demands. The comparative statics regarding the demand for children y_r yields the the following relationships:

$$\frac{\partial y_r}{\partial I_r(n_r)} > 0, \quad \frac{\partial y_r}{\partial w_{yr}(n_r)} \lesseqgtr 0 \quad \text{if} \quad I_r(n_r) - c_r(n_r) \gtreqless 0, \quad \text{and} \quad \frac{\partial y_r}{\partial c_r(n_r)} < 0, \tag{3}$$

which clarify that an increase in the husband's income $I_r(n_r)$ raises the demand for children per household. An increase in the wife's wage $w_r(n_r)$ has both positive and negative effects depending on the husband's income and congestion costs. When $I_r(n_r) - c_r(n_r) > 0$, which may hold in many cases, an increase in the wife's wage reduces the demand for children through the high opportunity costs of rearing children. An increase in the congestion costs of agglomeration $c_r(n_r)$ reduces the demand for children.[6]

To connect the theoretical predictions with the empirical analysis, this study discusses these key channels through which agglomeration economies and diseconomies affect the demand for children. Matching the agglomeration economies in Equation (1) with the comparative statics in Equation (3), I find that agglomeration economies have both positive and negative effects on the number of children through income effects and the high opportunity costs of rearing children. By contrast, agglomeration diseconomies have negative effects on the number of children through high congestion costs. In addition, the details of the comparative statics for total effects of agglomeration on demand for children are discussed in the Online Appendix.

Another key prediction is that preference heterogeneity in parameters μ and ξ affects the spatial distribution of the number of children. From the demand functions in Equation (2), the following relationships can be derived:

$$\frac{\mathrm{d}y_r}{\mathrm{d}\mu} > 0, \quad \frac{\mathrm{d}q_r}{\mathrm{d}\mu} < 0, \quad \frac{\mathrm{d}y_r}{\mathrm{d}\xi} < 0, \quad \text{and} \quad \frac{\mathrm{d}q_r}{\mathrm{d}\xi} > 0,$$

which mean (i) that consumers with strong preferences for the quantity of children have more children and decrease expenditures on their quality and (ii) that consumers with strong preference for the quality of children have fewer children and increase expenditures on their quality.

Importantly, this preference heterogeneity leads to a bias in the empirical analysis when researchers estimate the *ex post* effects of agglomeration on the demand for children. For example, suppose that consumers with *weak* preferences for the quantity of children tend to migrate into large cities because the large variety of goods and services available in large cities increases these consumers' utility compared to having children. This relationship can be written as $\mu_s < \mu_r$ when $n_s > n_r$, which generates the negative correlation between the number of children and city size. Therefore, in the empirical analysis, it is important to control for consumers' preference heterogeneity and their endogenous migration choice.

Although the theoretical model uncovers how agglomeration affects fertility behavior in terms of its channels, the total effects of agglomeration on the demand for children become highly com-

[6]In addition, an interesting theoretical prediction is that an increase in the wife's wage rate reduces the number of children per household when $I_r(n_r) - c_r(n_r) > 0$ and *simultaneously* increases expenditures toward the quality of children. In other words, a shift from quantity to quality occurs in the demand for children.

plicated. In the empirical analysis, this study uncovers how additional controls for economic and social factors change the aggregate impacts of agglomeration.[7]

3 Empirical Framework

3.1 Estimating Agglomeration Effects on Fertility

This study estimates the demand function for children, y_{ir}, among married couples i in which the wife is of childbearing age (15–49 years old, as per the definition of TFR). A standard approach is to linearly regress the number of children on population density and other control variables. However, an empirical issue is that the dependent variable takes a discrete value. In that case, a Poisson regression is more appropriate. Therefore, the regression model to be estimated is given by

$$\begin{aligned} \Pr(Y_{ir} = y_{ir}) &= \frac{\exp\Big(-\lambda_{ir}(\boldsymbol{\theta})\Big)\Big(\lambda_{ir}(\boldsymbol{\theta})\Big)^{y_{ir}}}{y_{ir}!}, \quad y_{ir} = 0, 1, 2, \ldots, \\ \lambda_{ir}(\boldsymbol{\theta}) &\equiv \exp\Big(\alpha \log(\mathrm{Dens}_{r(i)t}) + \gamma M_i + \boldsymbol{X}_i\boldsymbol{\beta} + \tilde{\boldsymbol{X}}_i\boldsymbol{\delta} + \boldsymbol{D}^{\mathrm{Reg}}_{r(i)}\boldsymbol{\eta} + \boldsymbol{D}^{\mathrm{Year}}_{t}\boldsymbol{\psi}\Big), \end{aligned} \tag{4}$$

where y_{ir} is the number of children in household i residing in region r; $\mathrm{Dens}_{r(i)}$ is the population density of region r where couple i lives during the study period; α is our parameter of interest, which captures the density elasticity of the number of children and is expected to be negative; M_i is a dummy that takes the value of 1 if either spouse in couple i has emigrated and 0 otherwise; $\boldsymbol{X}_i$ is a vector of variables denoting household characteristics (age, gender, cohort dummies, employment status, health condition, education, years of working experience, and the husband's and wife's incomes), $\tilde{\boldsymbol{X}}_i$ is a vector of variables for household social characteristics that affect fertility decisions; $\boldsymbol{D}^{\mathrm{Reg}}_{r}$ is a vector of regional dummies; $\boldsymbol{D}^{\mathrm{Year}}_{t}$ is a vector of year dummies; and $\boldsymbol{\theta}$ is a vector of parameters $(\alpha, \gamma, \boldsymbol{\beta}', \boldsymbol{\delta}', \boldsymbol{\eta}', \boldsymbol{\psi}')'$. Thus, the parameter vector that maximizes the log-likelihood function $\ell(\boldsymbol{y}, \boldsymbol{\theta})$ is estimated as follows:

$$\ell(\boldsymbol{y}, \boldsymbol{\theta}) = \sum_{i=1}^{N}\Big(-\lambda_{ir}(\boldsymbol{\theta}) + y_{ir}\log\Big(\lambda_{ir}(\boldsymbol{\theta})\Big) - \log(y_{ir}!)\Big),$$

where N is the number of observations.

A key feature of the Poisson regression model is that $\lambda_{ir}(\boldsymbol{\theta})$ can be seen as a predicted average number of children per household. Therefore, α can be interpreted as an elasticity that captures

[7] A limitation of this theoretical model is that the dynamic process of fertility behavior is not explicitly considered. This study empirically addresses this issue.

spatial variations in the number of children born to households in terms of city size. This study quantifies, holding other factors constant, the extent to which differences in city size affect the number of children per married couple.

The regression includes customarily unobservable household characteristics $\tilde{\boldsymbol{X}}_i$. The use of a social survey dataset mitigates estimation bias arising from spatial sorting driven by heterogeneity in households' preference. Migration influences the decisions to bear children through its higher financial and non-financial costs. For example, non-migrants residing near their parents have advantages in rearing children. In addition, large cities offer numerous job opportunities and may attract people who are more intent on careers than parenthood. Thus, migrants are expected to have fewer children than non-migrants. Furthermore, it needs to be considered that this migration choice is endogenously determined.

The next question is whether agglomeration affects completed fertility. Focusing on married couples for which the wife is age 50 or older (i.e., the outer age for childbearing), I estimate the Poisson regression model as follows:

$$\lambda_{ir}(\boldsymbol{\theta}) \equiv \exp\Big(\alpha \log(\mathrm{Dens}^{50}_{r(i)t}) + \gamma M_i + \boldsymbol{Z}_i\boldsymbol{\varphi} + \tilde{\boldsymbol{X}}_i\boldsymbol{\delta} + \boldsymbol{D}^{\mathrm{Reg}}_{r(i)}\boldsymbol{\eta} + \boldsymbol{D}^{\mathrm{Year}}_{t}\boldsymbol{\psi}\Big), \tag{5}$$

where $\mathrm{Dens}^{50}_{r(i)t}$ denotes the population density of the city where the married couple lived when the wife was age 50, and $\boldsymbol{Z}_i$ is limited to the vector of variables capturing husbands' and wives' university education because the dataset includes no historical information on income, work experience, or health status.[8]

The interpretations of parameter α in models (4) and (5) may be ambiguous when the sample includes migrants, even if migration status is controlled for. If possible, it is ideal to control for all of the cities in which migrants have ever resided. Another related issue is that migration itself is highly related to the fertility decision, presenting self-selection bias. Although the method proposed by Dahl (2002) is more appropriate, because of data limitations, the robustness check is based on a classical approach to the selection bias by an endogenous binary-variable model. See Section 5.5 for details of the robustness check.

[8]For migrants, I calculate the population densities of cities where couples in which the wife is 50 or older lived during the survey year.

3.2 Testing the Catch-Up Process in Large Cities

This section examines the observation that married couples residing in more densely populated areas bear children later in life, as shown in Figure 2. To measure the catch-up process in the regression framework, this study introduces a cross term of population density and wife's age into the Poisson regression model (4) as follows:

$$\lambda_{ir}(\boldsymbol{\theta}) \equiv \exp\Big(\alpha \log(\mathrm{Dens}_{r(i)t}) + \phi \log(\mathrm{Dens}_{r(i)t}) \times \mathrm{Age}_i^{\mathrm{wife}} + \boldsymbol{X}_i\boldsymbol{\beta} + \tilde{\boldsymbol{X}}_i\boldsymbol{\delta} + \boldsymbol{D}_{r(i)}^{\mathrm{Reg}}\boldsymbol{\eta} + \boldsymbol{D}_t^{\mathrm{Year}}\boldsymbol{\psi}\Big), \tag{6}$$

where $\mathrm{Age}_i^{\mathrm{wife}}$ denotes the wife's age for married couple i and ϕ measures the catch-up process on fertility decisions. A positive value of ϕ suggests that married couples residing in more densely populated areas delay having children and have children when they are older. This regression is estimated using the sample of non-migrants aged 50 or younger to control for households' dynamic location choice. This baseline model considers a linear dynamic fertility decision process. In the Online Appendix, this study additionally considers two specifications of the dynamic catch-up process on fertility decisions that include nonlinear and discrete effects of age.

To quantify the extent to which congestion costs arising from population concentration discourage households' fertility behavior, this study emphasizes that a dynamic fertility process should be considered. For example, it is inappropriate to quantify the magnitude of congestion costs simply by comparing married couples across cities at a point in time. The fact that young married couples in large cities tend to have children later in life causes spatial variation in the number of children to be overestimated. Therefore, this study proposes a method of quantifying spatial variations in the number of children per parental age cohort using the estimates of α and ϕ in regression (6).

Another aspect of the catch-up process is whether agglomeration affects the timing of marriage and the birth of the first child (e.g., Simon and Tamura, 2009). These agglomeration effects are estimated by the following linear regression:

$$\mathrm{Age}_{ir,k}^{\mathrm{wife}} = \alpha_k \log\Big(\mathrm{Dens}_{r(i)t}^{\mathrm{All}}\Big) + \gamma_k M_i + \boldsymbol{Z}_i\boldsymbol{\varphi}_k + \tilde{\boldsymbol{X}}_i\boldsymbol{\delta}_k + \boldsymbol{D}_{r(i)}^{\mathrm{Reg}}\boldsymbol{\eta}_k + \boldsymbol{D}_t^{\mathrm{Year}}\boldsymbol{\psi}_k + u_{i,k}, \tag{7}$$

where $\mathrm{Age}_{ir,k}^{\mathrm{wife}}$ denotes the wife's age for married couple i at the the time of marriage ($k = 1$) and birth of the first child ($k = 2$), respectively; $\mathrm{Dens}_{r(i)t}^{\mathrm{All}}$ denotes the population density and takes the value of $\mathrm{Dens}_{r(i)t}$ if married couple i is aged 50 or younger and the value of $\mathrm{Dens}_{r(i)t}^{50}$ if the wife in couple i is age 50 or older; and $u_{i,k}$ is the error term. In this regression, the sample is not divided by the wife's age. Parameter α_k captures the congestion diseconomy effects on the timing of marriage and the birth of the first child.

3.3 Quantifying Spatial Variation in Fertility

The quantification of the spatial variation in the number of children per married couple uses the estimates of α and ϕ (i.e., the density elasticity of the number of children) of model (6). Holding other factors equal, the percentage change in the average number of children per household between two cities s and r can be estimated as

$$\frac{\lambda_s - \lambda_r}{\lambda_r} = \left(\frac{\text{Dens}_s}{\text{Dens}_r}\right)^{\hat{\alpha}+\hat{\phi}\times\text{Age}} - 1.$$

Note that this spatial variation in the average number of children per household is measured at a relative level, not an absolute level. For example, consider the case where there are two cities s and r. City s has twice the population of city r. The density elasticity of the number of children is -0.04 at a certain age. In this case, the percentage change is calculated as -2.73% ($\approx 2^{-0.04} - 1$). If households in city r have 2 children on average, then households in city s on average have 1.95 children. Similarly, if city s has 10 times the population of city r, the percentage change in average number of children becomes -8.80% ($\approx 10^{-0.04} - 1$). If households in city r have 2 children on average, then households in city s on average have 1.824 children.

Similarly, this study examines how long the congestion diseconomy in large cities delays marriage and the birth of the first child for married couples from model (7). Holding other factors equal, differences in a wife's age between cities s and r can be estimated as

$$\text{Age}^{\text{wife}}_{s,k} - \text{Age}^{\text{wife}}_{r,k} = \hat{\alpha}_k \log\left(\frac{\text{Dens}_s}{\text{Dens}_r}\right),$$

where $\hat{\alpha}_k$ is the estimate of the parameter in model (7). Note that the spatial variation in wife's age is measured at the absolute level. For example, consider the case where city s has twice the population of city r and $\hat{\alpha}_2 = 0.2$. In this case, married couples in large cities postpone having their first child by an average of 1.6 ($= 12 \times 0.2 \times \log(2)$) months.

4 Data

This study uses the cumulative dataset (i.e., a pooled cross section) of the Japan General Social Surveys (JGSS), which covers the years 2000, 2001, 2002, 2005, 2006, 2008, and 2010.[9] The sample is limited to married couples (i.e., unmarried persons are excluded).

Table 1 presents descriptive statistics of the variables. Detailed definitions of the variables used in this study, such as population density, migration, and income, are explained in the Online Appendix. The average number of children per household in the sample with wife's age < 50 is 1.810, whereas the average number of children per household in the sample with wife's age ≥ 50 is 2.204.[10]

Figure 3 presents differences in the numbers of children between large and small cities in the JGSS dataset. Note that the sample with wife's age < 50 is used, and migrants are excluded from the sample. Panel (a) of Figure 3 shows that households residing in large cities have fewer children than those residing in small cities. Panel (b) of Figure 3 presents the average number of children per married couple by parental age cohort. An interesting trend is that households with ages averaging from 20–24 in more densely populated areas (exceeding the 75th percentile of population density of 4,176 persons/km^2) have half as many children as households in less dense areas do. The gap between the two narrows, but a slight gap remains.

Figure 4 presents regional variations in the number of children per married couple in the JGSS dataset. I aggregated individual microdata for the geographical unit used in this study. Panel (a) of Figure 4 presents a similar trend to that in Figure 1. Although the JGSS sample size is quite small, it adequately captures the characteristics of the entire country. Panel (b) of Figure 4 presents the spatial variation in completed fertility. The spatial variation in completed fertility becomes small, suggesting that agglomeration affects the timing of childbearing.

Figure 5 presents regional variations in the wife's age at marriage and at the birth of the first

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[9] This study discarded the JGSS 2003 dataset because it omits questions about the number of siblings. Its surveyed population consists of men and women ages 20 to 89 as of September 1st of the particular survey year, and the survey subjects are selected by a stratified two-stage sampling method. In the first step, stratification is conducted among six regional blocks (Hokkaido/Tohoku, Kanto, Chubu, Kinki, Chugoku/Shikoku, and Kyushu). Then, cities and districts in each block are classified into three groups of the largest cities, other cities, and towns/villages. This study constructs regional variables based on three groups of cities in each prefecture by taking the averages of the corresponding municipalities. The sample sizes of valid response vary from 2,023 (in 2005) to 5,003 (in 2010). Detailed information about the JGSS sampling design is available from the web-site (URL: `http://jgss.daishodai.ac.jp/english/index.html`).

[10] Heterogeneity in having children across generations exists between couples with ages over and under 50. Importantly, the number of brothers and sisters captures the completed fertility of an individual's parents. In Table 1, the average number of siblings for people younger than 50 is 1.715, whereas that for individuals older than 50 is 3.225. This study controls for these generation heterogeneities using cohort dummies.

child in the JGSS dataset. Panels (a) and (b) of Figure 5 present positive correlations between wife's age at marriage and at birth of first child and city size, suggesting that agglomeration affects the timing of marriage and childbearing. To examine whether agglomeration indeed leads to this relationship, regression analyses are undertaken.

To control for preference heterogeneity in the demand for children, this study makes use of three variables on social factors. The first variable relates to the motive of security in old age, which predicts that such households have more children.[11] The second variable directly captures the household's preference for children. The JGSS asks a question about households' opinions of whether children are necessary in a marriage. A dummy variable based on this question takes the value of 1 for households that agree or somewhat agree children are unnecessary and 0 otherwise. The third variable is the number of siblings because couples that have relatively many siblings may have more children.

[Table 1 and Figures 3–5]

5 Estimation Results

5.1 Agglomeration Discourages the Fertility Behavior of Young Married Couples

Table 2 presents the baseline estimation results of Poisson regression model (4).[12] Column (1) shows the aggregate impacts of agglomeration diseconomies on the number of children. The density elasticity of the number of children is significantly negative at the 1% level and its value is -0.075. To decompose channels through which agglomeration affects the demand for children, economic and social factors are controlled for in Columns (2)–(7) of Table 2.

The estimation results in Table 2 show that including migration and education variables reduces the density elasticity of the number of children. After controlling for migration, the density elasticity becomes -0.069 in Column (2), whereas after controlling for university education, the density elasticity becomes -0.061 in Column (3). These results mean that migrants with university education, who tend to have fewer children, are concentrated in large cities, which leads to an overestimation

[11]For example, city dwellers might hold different opinions about parenthood than rural residents or the desire for security during old age may motivate having children, particularly in rural areas (Nugent and Gillaspy, 1983; Nugent, 1985; Rendall and Bahchieva, 1998).

[12]IV Poisson estimation results are provided in the Online Appendix. In some situations, a negative binominal model may be more appropriate than a Poisson model. As shown in Figure 3, the mode of the number of children is 2, and thus, the number of children per married couple is not bounded below by 0. In fact, the Poisson and negative binominal estimation results are almost identical.

of the impacts of agglomeration diseconomies. By contrast, the inclusion of incomes increases the magnitude of the coefficient on population density. These results mean that individuals with high income, who tend to have more children due to income effects, are concentrated in large cities, which leads to underestimation of the impact of agglomeration diseconomies. In Column (6), the inclusion of the social factor variables slightly decreases the magnitude of the effect, which may imply that the spatial sorting of preference heterogeneity is not relevant for this study.

These results in Column (7) imply that, holding other factors equal, a 10-fold difference in city size on average generates spatial variation in the per-household number of children by 14.31% ($\approx 10^{-0.067} - 1$). Consider the case where city s is 10 times the population of city r. If the average number of children in city r is 2, the average in city s is 1.714. The spatial gap shows approximately 286 children per 1,000 households.[13] Therefore, the results show that congestion costs in large cities discourage fertility behavior.

An interesting finding is that that husbands' and wives' incomes, which relate highly to city size, have significant positive and negative signs, respectively. This finding can be explained by the simple theoretical model of this study. Agglomeration economies increase income and wages, which have both positive and negative effects on the demand for children through income effects and the opportunity cost of rearing children, respectively.

Concerning preference heterogeneity in the demand for children, the dummy denoting that children are unnecessary in a marriage significantly decreases the number of children at the 1% level. In addition, when either the husband or wife has more siblings, they tend to have more children. Indeed, the inclusion of these social characteristics tends to reduce the magnitude of the dummy for wife's university education, implying that female workers with high earnings simultaneously tend to have the opinion that children are unnecessary in a marriage. These results emphasize the importance for controlling for preference heterogeneity among individuals.

In addition, the migration dummy is significantly negative at the 5% level. Households in which either spouse has migration experience tend to have fewer children than those in which neither has migration experience. The negative sign may derive from both a causal relationship and from a reverse causality. That is, migration itself may impose substantial costs on having children, but having fewer children may enable households to easily migrate. The robustness check for self-selected migration is carried out in Section 5.5.

[13] Here is another numerical example. Holding other factors equal, doubling the difference in city size on average generates spatial variation in the per-household number of children by 4.54% ($\approx 2^{-0.067} - 1$).

[Table 2]

5.2 Completed Fertility and Agglomeration

Table 3 presents estimation results for couples whose childbearing years have ended because the wife is age 50 or older. This estimation intends to examine whether congestion costs in large cities discourage completed fertility.

Column (1) of Table 3 shows the impact of wide-ranging aggregate congestion costs arising from agglomeration on completed fertility. The density elasticity of the number of children is −0.035, whereas the density elasticity for the sample with wife's age < 50 is −0.074, as shown in Table 2.

This relationship remains negative after controlling for economic and social household characteristics and migration status, but the density elasticity declines to −0.029 in Column (5). The estimation results suggest that the costs associated with agglomeration discourage completed fertility and, holding other factors equal, a 10-fold difference in city size on average generates a spatial variation of 6.40% ($\approx 10^{-0.029} - 1$) in number of children per household. Consider a case where the population of city s is 10 times larger than that of city r. If the average number of children in city r is 2, the average in city s becomes 1.872. The spatial gap shows approximately 128 children per 1,000 households.[14]

More importantly, the density elasticity of the number of children decreases between Tables 2 and 3. This finding suggests that costs associated with agglomeration affect the timing of childbirth. The two numerical examples above also imply that the regional gap in the average number of children decreases as couples age.

Another interesting finding is that the effect of higher education on completed fertility is not significant at the 10% level. Combined with the estimation results in Table 2, this finding suggests that higher education discourages childbearing among young married couples but does not affect completed fertility. These results also imply that, holding other factors equal, university graduates postpone having children.

Concerning preference heterogeneity in the demand for children, the dummy variable denoting that children are unnecessary in a marriage has a significant negative effect on completed fertility. In addition, the number of siblings exerts a significantly positive effect on completed fertility. Seeking security in old age shows no significant relationship with completed fertility.

[14] Holding other factors equal, doubling the difference in city size on average generates spatial variation in the number of children per household by 1.97% ($\approx 2^{-0.029} - 1$).

The migration dummy also shows negative effects on completed fertility, but it is significant at 10% level. A robustness check for self-selected migration is carried out in Section 5.5.

[Table 3]

5.3 Catch-Up Process of Fertility in More Densely Populated Areas

Table 4 presents the estimation results of Poisson regression model (6), which considers the dynamic process of fertility behavior across different city sizes. This study quantifies spatial variations in average number of children by parents' ages estimating the cross-term of population density and wife's age. Note that samples used in Table 4 do not include migrants.

Overall, the Poisson estimation results in Columns (1)–(6) show that the estimated coefficients for the cross-term of population density and wife's age are significantly positive, which means that young married couples in large cities postpone having children. The results are robust for additional controls for economic and social factors. In Column (6), the coefficient on population density captures the effects of the congestion costs in large cities on the demand for children. An important finding is that the gap in the number of children between large and small cities is large early in life, but it shrinks gradually as couples age.

Figure 6 illustrates estimated spatial variations in the average number of children using estimates in Column (6) of Table 4. Panel (a) of Figure 6 shows the density elasticity of the number of children at different ages. This density elasticity is large for couples in their 20s (e.g., -0.113 at age 29) but declines to -0.027 at age 49.

Panel (b) of Figure 6 quantifies spatial variations in number of children by wife's age, showing what percentage change in the average number of children is generated by the difference in city size, holding other variables equal. Among couples age 30, the estimated percentage change in the number of children between a city and a city with 10 times more people is -22.13% ($\approx 10^{-0.237+0.004\times 30} - 1$). If households in the baseline city have 1.5 children at age 30 on average, households in a city with 10 times more people have 1.168 children on average. The spatial gap shows approximately 332 ($= 1,500 - 1,168$) children per 1,000 households. However, the estimated percentage change in the number of children between those cities for couples at age 49 is -6.07% ($\approx 10^{-0.237+0.004\times 49} - 1$). If the average number of children per household at age 49 in the baseline city is 2.2, the average in a city with 10 times more people is 2.066. The spatial gap shows approximately 134 ($= 2,200 - 2066$) children per 1,000 households.[15] Although slight spatial variation in the

[15]Here is another numerical example. Among couples age 30, the estimated percentage change in the number of

average number of children between large and small cities remains, the important finding is that couples residing in larger cities have children relatively late in life, which reduces the spatial gap in the number of children around age 50.

Thus far, the estimation results suggest that congestion costs in large cities discourage younger couples from bearing children, but the gap in completed fertility shrinks between large and small cities as couples age. To offer supportive evidence on this finding, this study examines whether agglomeration affects the timing of childbirth in the next subsection.

[Table 4 and Figure 6]

5.4 Agglomeration Delays the Birth of the First Child

Table 5 presents estimation results concerning how agglomeration affects the wife's age at marriage. Importantly, in Column (3), the inclusion of dummies for university education decreases the coefficient on population density, which means that the spatial sorting of highly educated people, who tend to have children later in life, leads to an upward bias when the impact of congestion costs on fertility behavior is estimated.

Although the estimated coefficients on population density are positive in Columns (1)–(5), they are not significant at even the 10% level. It is not evident that agglomeration discourages the timing of marriage. Higher education, specifically for females, markedly delays age at marriage at the 1% level. In the baseline estimation, Column (5) shows that couples in which both spouses have a university education marry about 26 months later than those in which both have a non-university education.

Table 6 provides evidence on whether congestion costs in large cities delay the birth of the first child. As noted earlier, the inclusion of dummies for university education decreases the coefficient on population density in Column (3). However, the coefficient on population density remains significant. In the baseline estimation, Column (5) shows that couples in which both spouses have a university education bear their first child about 22 months later than those in which both have a non-university education.

Unlike the estimation results for marriage, the estimated coefficients for population density are significantly positive at the 5% level in Columns (1)–(5). In Column (5), the density semi-elasticity of the number of children is 0.180. Using this value, the quantification shows that, holding other

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children between one city and a city with twice as many people is -7.25% ($\approx 2^{-0.237+0.004\times30} - 1$). However, among couples age 49, the estimated percentage change in the number of children between those cities is -1.87% ($\approx 2^{-0.237+0.004\times49} - 1$).

variables equal, couples residing in a city that is 10 times more populous delay childbirth by an average of approximately 5 ($\approx 0.180 \times \log(10)$) months.[16]

In sum, congestion costs strongly defer childbirth decisions among younger couples, but married couples in more densely populated areas generally have children later in life, whereas couples in less dense areas have children early and stop after approximately two or three children. As a result, spatial variation in the number of children per household diminishes as couples age, although a statistically significant slight gap remains.

[Tables 5–6]

5.5 Robustness Check for Self-Selected Migration

As discussed in Section 2, the endogenous migration choices of individuals with preference heterogeneity in the demand for children lead to biases in two ways. First, the magnitude of the effect of agglomeration on the number of children is overestimated when individuals with weak preferences for the quantity of children and with strong preferences for the quality of children migrate into large cities. This bias derives from the spatial sorting of individuals with preference heterogeneity. Second, the coefficient on the migration dummy γ is biased due to this self-selection.

This study applies a classical approach to the selectivity bias correction (Heckman, 1979; Maddala, 1986), which is known as an endogenous binary-variable model.[17] This study estimates the following regression model:

$$y_{ir} = \alpha \log(\text{Dens}_{r(i)t}) + \gamma M_i + \boldsymbol{X}_i\boldsymbol{\beta} + \tilde{\boldsymbol{X}}_i\boldsymbol{\delta} + \boldsymbol{D}^{\text{Reg}}_{r(i)}\boldsymbol{\eta} + \boldsymbol{D}^{\text{Year}}_{t}\boldsymbol{\psi} + u_{ir},$$

$$M_i = \begin{cases} 1, & \text{if} \quad \boldsymbol{W}_i\boldsymbol{\pi} + \tilde{\boldsymbol{X}}_i\boldsymbol{\delta} + \boldsymbol{D}^{\text{Pref15}}_{r(i)}\boldsymbol{\eta} + \boldsymbol{D}^{\text{Year}}_{t}\boldsymbol{\psi} + v_{ir} > 0, \\ 0, & \text{otherwise,} \end{cases}$$

where it is assumed that the error terms u_{ir} and v_{ir} follow bivariate normal distribution with mean 0 and covariance matrix

$$\begin{pmatrix} \sigma_u^2 & \rho\sigma_u \\ \rho\sigma_u & 1 \end{pmatrix}.$$

[16] Here is another numerical example. Holding other factors equal, couples residing in a city that is twice as populous delay childbirth by an average of approximately 2 ($\approx 0.181 \times \log(2)$) months. The detailed numerical simulation results are provided in the Online Appendix.

[17] The method proposed by Dahl (2002) may be appropriate to address the selectivity issue when individuals face multiple choices. However, data limitations of the JGSS (i.e., a small sample for interregional migration flows) makes the gravity estimation of migration flows difficult. Greene (2012, Chap. 19.6.1) provides a detailed explanation for an endogenous binary-variable model.

The determinants of migration choice include a vector of household's characteristics $\boldsymbol{W}_i$ (dummies for whether parents of the married couples are university graduates and the variables included in $\boldsymbol{Z}_i$) and a vector of prefecture dummies at age 15 $\boldsymbol{D}_{r(i)}^{\text{Pref15}}$, and v_{ir} is an error term. Note that a linear rather than a Poisson model is estimated. Therefore, the parameter α is not directly comparable with the corresponding parameter in the Poisson estimates. In the same manner, the wife's age at marriage and at the birth of the first child is also estimated by this framework.

Table 7 presents the estimation results of the endogenous binary-variable model. More importantly, the coefficients on the population density essentially do not change even after controlling for self-selected migration. However, the coefficients on migration drastically change after controlling for self-selection. Comparing Columns (3) and (4), completed fertility is highly affected by the migration experience, implying that migration costs have larger impacts on the demand for children in the long-term.

In Columns (5)–(8), this robustness check is applied to estimate whether congestion costs in large cities delay marriage and the timing of the birth of the first child, and this study finds that migration costs greatly delay marriage and the birth of the first child. Interestingly, the self-selection model reveals new channels on fertility behavior. Highly educated men tend to migrate, which delays marriage and the birth of the first child. On the other hand, highly educated women directly delay marriage and the birth of the first child regardless of migration costs. In addition, the dummy variable for the non-necessity of children in marriage increases the migration probability, which delays marriage and the birth of the first child.

[Table 7]

6 Conclusion

This study has examined how agglomeration economies and diseconomies affect married couples' decisions to bear children at different life stages. By employing a Japanese social survey dataset that inquires into households' fertility decisions, this study has been able to control for economic factors alongside preference heterogeneity in the demand for children. In addition, this study has proposed a method to quantify spatial variations in the average number of children born to households per parental age cohort.

This study has found that, although congestion costs in large cities significantly discourage couples' fertility decisions, the magnitude declines as couples age: in the baseline quantification, holding other things equal, a 10-hold difference in city size generates a spatial variation of −22.13% in the average number of children among couples at age 30 and a variation of −6.07% among married couples at age 49, suggesting that young married couples in larger cities bear children later in life. The results show that congestion costs in large cities delay the birth of the first child by an average of about five months among couples living in cities that are 10 times larger than the baseline cities.

Despite the acknowledged economic benefits of agglomeration economies (e.g., Combes and Gobillon, 2015), my findings present the important conclusion that agglomeration hampers fertility rates through higher congestion costs. In short, agglomeration-oriented growth policies may accelerate the graying of the population that policymakers struggle to reverse. Policymakers in graying societies need to set effective policies considering differences in the dynamic fertility behaviors of married couples across cities.

This study has some limitations. Although the empirical results emphasize the importance of different dynamic fertility behaviors across cities, theoretical studies have not been explored sufficiently in this literature. A dynamic theory that includes space, such as Goto and Minamimura (2015), is required when considering the conditions of effective fertility policies. This study focuses on married couples, but the decision to marry affects national fertility rates. Thus, it should be noted that low fertility rates in more densely populated areas also originate from their high proportions of unmarried people. Following Baudin et al. (2015), childlessness should be studied in detail. Furthermore, self-selected migration also needs to be studied using a large-sized panel dataset with information on migration history. More densely populated areas are likely to attract single people who will work long term and will displace married couples with children because of the high cost of living. Households' endogenous location choices will feature prominently in spatial variations in fertility rates. Distinguishing congestion diseconomy from self-selected migration is an important topic, and clarifying these mechanisms remains for future research.

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Table 1: Descriptive Statistics of Variables for Regression Analysis

	Sample with Wife's Age < 50					Sample with Wife's Age ≥ 50				
Variables	Obs.	Mean	S.D.	Min	Max	Obs.	Mean	S.D.	Min	Max
Number of Children	2339	1.810	0.964	0	6	1995	2.204	0.865	0	8
Ideal Number of Children	2085	2.617	0.604	0	10	1804	2.774	0.610	0	9
Gap in Number of Children	2085	−0.805	0.987	−8	4	1804	−0.579	0.978	−7	4
Log(Population Density) in Survey Year	2339	7.431	1.077	4.646	9.628					
Log(Population Density) at Age 50						1995	7.359	1.065	4.694	9.597
Log(Population Density) in 1930	2339	6.732	1.257	3.374	9.492	1995	6.698	1.308	3.374	9.492
D(1=Migration)	2339	0.239	0.427	0	1	1995	0.282	0.450	0	1
D(1=University or Higher for Husband)	2339	0.354	0.478	0	1	1995	0.209	0.406	0	1
D(1=University or Higher for Wife)	2339	0.239	0.426	0	1	1995	0.114	0.318	0	1
Husband's Income (Unit: Million Yen)	2339	5.510	2.823	0	27.600	1995	3.950	3.954	0	27.600
Wife's Income (Unit: Million Yen)	2339	1.731	1.850	0	20.363	1995	1.410	1.972	0	17.130
Hours Worked Last Week for Husband (Unit: 10 Hours)	2339	4.810	1.143	0	8.000	1995	3.350	2.110	0	8.200
Hours Worked Last Week for Wife (Unit: 10 Hours)	2339	2.828	1.544	0	6.500	1995	2.318	1.846	0	6.500
D(1=Non-Labor Force for Husband)	2339	0.007	0.082	0	1	1995	0.203	0.402	0	1
D(1=Non-Labor Force for Wife)	2339	0.091	0.288	0	1	1995	0.258	0.437	0	1
D(1=Not Healthy)	2339	0.139	0.346	0	1	1995	0.155	0.362	0	1
Old-Age Security Index	2339	4.583	1.880	2	10	1995	4.719	2.098	2	10
D(1=Non-Necessity of Children in a Marriage)	2339	0.432	0.495	0	1	1995	0.283	0.450	0	1
Number of Siblings	2339	1.715	0.955	0	8	1995	3.225	1.575	0	15
Husband's Age	2339	42.253	7.828	20	66	1995	62.804	8.063	33	91
Wife's Age	2339	39.520	6.684	20	49	1995	60.275	7.563	51	90
Wife's Age at Marriage	1034	24.653	3.351	16	45	624	23.962	3.338	16	51
Wife's Age at Birth of First Child	2019	26.568	3.710	16	41	1861	25.722	3.727	16	50
D(1=University or Higher for Father)	2339	0.100	0.300	0	1	1995	0.044	0.204	0	1
D(1=University or Higher for Mother)	2339	0.040	0.195	0	1	1995	0.006	0.077	0	1

Note: The household who has the maximum number of children and the uppermost 1 percentile of the distribution of hours worked for husband and wife are excluded from the full sample as extreme outliers. Population density is expressed in persons/km^2.

Table 2: Poisson Regression Estimation Results for Fertility Decision and City Size

	Dependent Variable: Number of Children						
	Sample with Wife's Age < 50						
Explanatory Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Log(Population Density)	−0.074***	−0.069***	−0.061***	−0.080***	−0.082***	−0.071***	−0.067***
	(0.015)	(0.015)	(0.014)	(0.015)	(0.016)	(0.016)	(0.015)
Husband's Age	0.090***	0.089***	0.092***	0.085***	0.086***	0.088***	0.080***
	(0.029)	(0.028)	(0.028)	(0.028)	(0.028)	(0.028)	(0.027)
Husband's Age Squared (×1/100)	−0.098***	−0.096***	−0.100***	−0.093***	−0.094***	−0.096***	−0.088***
	(0.031)	(0.031)	(0.030)	(0.030)	(0.030)	(0.030)	(0.029)
Wife's Age	0.166***	0.167***	0.168***	0.162***	0.163***	0.166***	0.163***
	(0.029)	(0.029)	(0.028)	(0.029)	(0.029)	(0.028)	(0.028)
Wife's Age Squared (×1/100)	−0.190***	−0.192***	−0.192***	−0.184***	−0.188***	−0.192***	−0.187***
	(0.034)	(0.034)	(0.033)	(0.035)	(0.035)	(0.033)	(0.033)
D(1=Migration)		−0.073**					−0.063**
		(0.028)					(0.028)
D(1=University Graduate for Husband)			−0.122***				−0.121***
			(0.026)				(0.023)
D(1=University Graduate for Wife)			−0.094***				−0.085***
			(0.020)				(0.021)
Husband's Income				0.010***			0.015***
				(0.003)			(0.003)
Wife's Income				−0.034***			−0.017***
				(0.007)			(0.006)
Hours Worked Last Week for Husband					0.009		0.006
					(0.011)		(0.010)
Hours Worked Last Week for Wife					−0.045***		−0.032***
					(0.011)		(0.011)
D(1=Non-Labor Force for Husband)					−0.136		−0.092
					(0.178)		(0.170)
D(1=Non-Labor Force for Wife)					−0.109**		−0.098*
					(0.054)		(0.056)
D(1=Not Healthy)						−0.056**	−0.064**
						(0.028)	(0.028)
Old-Age Security Motive Score						0.009	0.009
						(0.006)	(0.006)
D(1=Non-Necessity of Children)						−0.077***	−0.079***
						(0.019)	(0.018)
Number of Siblings						0.036***	0.025**
						(0.011)	(0.011)
Cohort Groups, Region, and Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	2339	2339	2339	2339	2339	2339	2339
Log Likelihood	−3331.608	−3329.873	−3318.649	−3322.692	−3324.573	−3324.556	−3300.614
AIC	6711.216	6709.745	6689.298	6697.384	6705.145	6705.111	6675.229

Note: Heteroskedasticity-consistent standard errors clustered by cohort year are in parentheses. Constant is not reported.
* denotes statistical significance at the 10% level, ** at the 5% level, and *** at the 1% level.

Table 3: Poisson Regression Estimation Results for Completed Fertility Decision and City Size

	Dependent Variable: Number of Children				
	Sample with Wife's Age ≥ 50				
Explanatory Variables	(1)	(2)	(3)	(4)	(5)
Log(Population Density) at Age 50	−0.035***	−0.032**	−0.036***	−0.031**	−0.029**
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
D(1=Migration)		−0.033*			−0.031*
		(0.017)			(0.018)
D(1=University Graduate for Husband)			−0.013		−0.005
			(0.025)		(0.026)
D(1=University Graduate for Wife)			0.046		0.049
			(0.033)		(0.031)
D(1=Not Healthy)				−0.026	−0.024
				(0.029)	(0.029)
Old-Age Security Motive Score				−0.000	−0.001
				(0.005)	(0.005)
D(1=Non-Necessity of Children)				−0.088***	−0.087***
				(0.020)	(0.020)
Number of Siblings				0.016***	0.017**
				(0.006)	(0.007)
Cohort Groups, Region, and Year Dummies	Yes	Yes	Yes	Yes	Yes
Number of Observations	1995	1995	1995	1995	1995
Log Likelihood	−2977.043	−2976.656	−2976.691	−2972.469	−2971.705
AIC	5990.087	5991.312	5993.382	5988.939	5993.409

Note: Heteroskedasticity-consistent standard errors clustered by cohort year are in parentheses. Constant is not reported. * denotes statistical significance at the 10% level, ** at the 5% level, and *** at the 1% level.

Table 4: Poisson Regression Estimation Results for Dynamic Fertility Decision and City Size with Linear Effects of Age

	Dependent Variable: Number of Children					
	Sample with Wife's Age < 50, Non-Migrants					
Explanatory Variables	(1)	(2)	(3)	(4)	(5)	(6)
Log(Population Density)	−0.245***	−0.244***	−0.233***	−0.246***	−0.247***	−0.237***
	(0.079)	(0.080)	(0.079)	(0.076)	(0.078)	(0.076)
Log(Population Density) × Wife's Age	0.004**	0.005**	0.004**	0.004**	0.005**	0.004**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Husband's Age	0.070**	0.071**	0.065**	0.067**	0.066**	0.059**
	(0.029)	(0.029)	(0.029)	(0.029)	(0.029)	(0.028)
Husband's Age Squared (×1/100)	−0.074**	−0.074**	−0.069**	−0.070**	−0.070**	−0.062**
	(0.032)	(0.031)	(0.032)	(0.031)	(0.032)	(0.031)
Wife's Age	0.124***	0.125***	0.124***	0.125***	0.125***	0.127***
	(0.035)	(0.034)	(0.035)	(0.034)	(0.034)	(0.034)
Wife's Age Squared (×1/100)	−0.186***	−0.189***	−0.180***	−0.186***	−0.190***	−0.188***
	(0.041)	(0.041)	(0.041)	(0.041)	(0.040)	(0.040)
D(1=University Graduate for Husband)		−0.111***				−0.116***
		(0.025)				(0.024)
D(1=University Graduate for Wife)		−0.108***				−0.096***
		(0.027)				(0.029)
Husband's Income			0.010***			0.015***
			(0.004)			(0.004)
Wife's Income			−0.031***			−0.014**
			(0.008)			(0.007)
Hours Worked Last Week for Husband				0.010		0.006
				(0.011)		(0.012)
Hours Worked Last Week for Wife				−0.038***		−0.025**
				(0.013)		(0.012)
D(1=Non-Labor Force for Husband)				0.025		0.048
				(0.145)		(0.144)
D(1=Non-Labor Force for Wife)				−0.057		−0.046
				(0.057)		(0.055)
D(1=Not Healthy)					−0.081***	−0.094***
					(0.025)	(0.025)
Old-Age Security Motive Score					0.005	0.007
					(0.007)	(0.006)
D(1=Non-Necessity of Children)					−0.076***	−0.077***
					(0.025)	(0.024)
Number of Siblings					0.044***	0.034***
					(0.011)	(0.012)
Cohort Groups, Region, and Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	1779	1779	1779	1779	1779	1779
Log Likelihood	−2536.763	−2527.288	−2531.063	−2532.827	−2530.365	−2515.435
AIC	5123.527	5108.576	5116.127	5123.654	5118.729	5104.871

Note: Heteroskedasticity-consistent standard errors clustered by cohort year are in parentheses. Constant is not reported. * denotes statistical significance at the 10% level, ** at the 5% level, and *** at the 1% level.

Table 5: Wife's Ages at Marriage, City Size, and Migration

	Dependent Variable: Wife's Age at Marriage				
	Full Sample				
Explanatory Variables	(1)	(2)	(3)	(4)	(5)
Log(Population Density)	0.130	0.119	0.077	0.125	0.079
	(0.116)	(0.116)	(0.120)	(0.118)	(0.118)
D(1=Migration)		0.115			−0.021
		(0.181)			(0.179)
D(1=University Graduate for Husband)			0.709***		0.699***
			(0.175)		(0.178)
D(1=University Graduate for Wife)			1.478***		1.467***
			(0.274)		(0.268)
D(1=Not Healthy)				−0.245	−0.158
				(0.215)	(0.201)
Old-Age Security Motive Score				−0.041	−0.041
				(0.037)	(0.037)
D(1=Non-Necessity of Children)				−0.091	−0.139
				(0.166)	(0.170)
Number of Siblings				−0.104**	−0.032
				(0.045)	(0.041)
Cohort Groups, Region, and Year Dummies	Yes	Yes	Yes	Yes	Yes
Number of Observations	1658	1658	1658	1658	1658
Adjusted R^2	0.045	0.044	0.078	0.046	0.076

Note: Heteroskedasticity-consistent standard errors clustered by cohort year are in parentheses. Constant is not reported. * denotes statistical significance at the 10% level, ** at the 5% level, and *** at the 1% level.

Table 6: Wife's Ages at Birth of First Child, City Size, and Migration

	Dependent Variable: Wife's Ages at Birth of First Child				
	Full Sample				
Explanatory Variables	(1)	(2)	(3)	(4)	(5)
Log(Population Density)	0.290***	0.257***	0.205***	0.281***	0.180**
	(0.072)	(0.074)	(0.071)	(0.071)	(0.073)
D(1=Migration)		0.356**			0.242
		(0.168)			(0.168)
D(1=University Graduate for Husband)			0.844***		0.813***
			(0.152)		(0.154)
D(1=University Graduate for Wife)			1.090***		1.086***
			(0.190)		(0.190)
D(1=Not Healthy)				0.034	0.110
				(0.189)	(0.190)
Old-Age Security Motive Score				−0.030	−0.037
				(0.031)	(0.030)
D(1=Non-Necessity of Children)				0.006	−0.009
				(0.129)	(0.128)
Number of Siblings				−0.121**	−0.045
				(0.054)	(0.054)
Cohort Groups, Region, and Year Dummies	Yes	Yes	Yes	Yes	Yes
Number of Observations	3880	3880	3880	3880	3880
Adjusted R^2	0.044	0.045	0.072	0.045	0.072

Note: Heteroskedasticity-consistent standard errors clustered by cohort year are in parentheses. Constant is not reported. * denotes statistical significance at the 10% level, ** at the 5% level, and *** at the 1% level.

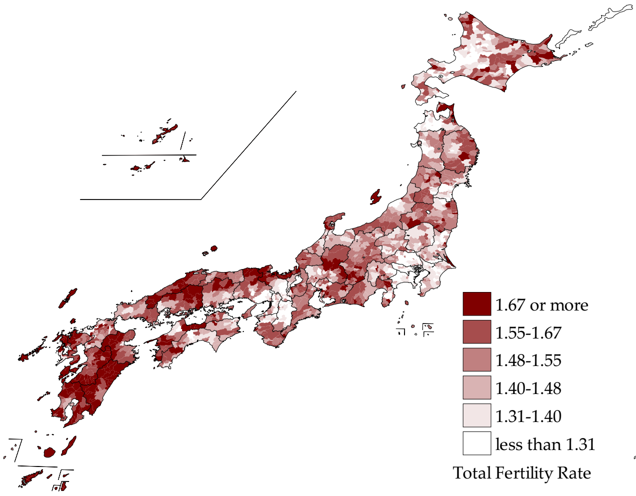
Table 7: Estimation Results for Fertility Decision and Self-Selected Migration Choice

	Dependent Variable: Number of Children				Dependent Variable: Wife's Age at Marriage		Dependent Variable: Wife's Age at Birth of First Child	
	Sample with Wife's Age < 50		Sample with Wife's Age ≥ 50		Full Sample		Full Sample	
Explanatory Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log(Population Density)	−0.113***	−0.115***	−0.062**	−0.062**	0.079	0.012	0.180**	0.170**
	(0.024)	(0.024)	(0.028)	(0.028)	(0.118)	(0.123)	(0.073)	(0.075)
D(1=Migration)	−0.116**	0.171	−0.068*	−0.823***	−0.021	3.970***	0.242	4.830***
	(0.049)	(0.213)	(0.038)	(0.230)	(0.179)	(0.606)	(0.168)	(0.373)
D(1=University Graduate for Husband)	−0.207***	−0.239***	−0.011	0.119	0.699***	0.210	0.813***	0.208
	(0.033)	(0.046)	(0.057)	(0.081)	(0.178)	(0.237)	(0.154)	(0.190)
D(1=University Graduate for Wife)	−0.140***	−0.154***	0.107	0.076	1.467***	1.197***	1.086***	0.998***
	(0.036)	(0.035)	(0.070)	(0.068)	(0.268)	(0.292)	(0.190)	(0.180)
Husband's Income	0.031***	0.030***						
	(0.007)	(0.007)						
Wife's Income	−0.030***	−0.030***						
	(0.010)	(0.010)						
Hours Worked Last Week for Husband	0.013	0.013						
	(0.018)	(0.018)						
Hours Worked Last Week for Wife	−0.054***	−0.054***						
	(0.019)	(0.019)						
D(1=Non-Labor Force for Husband)	−0.069	−0.076						
	(0.244)	(0.246)						
D(1=Non-Labor Force for Wife)	−0.188*	−0.187**						
	(0.097)	(0.095)						
D(1=Not Healthy)	−0.117**	−0.126**	−0.053	−0.074	−0.158	−0.186	0.110	0.088
	(0.051)	(0.051)	(0.064)	(0.065)	(0.201)	(0.267)	(0.190)	(0.238)
Old-Age Security Motive Score	0.014	0.017	−0.001	−0.003	−0.041	0.015	−0.037	−0.026
	(0.011)	(0.011)	(0.011)	(0.011)	(0.037)	(0.045)	(0.030)	(0.033)
D(1=Non-Necessity of Children)	−0.142***	−0.157***	−0.186***	−0.125***	−0.139	−0.355**	−0.009	−0.280*
	(0.031)	(0.034)	(0.042)	(0.043)	(0.170)	(0.174)	(0.128)	(0.146)
Number of Siblings	0.051**	0.046**	0.038**	0.043**	−0.032	−0.102*	−0.045	−0.088
	(0.022)	(0.022)	(0.015)	(0.018)	(0.041)	(0.055)	(0.054)	(0.062)
Age, Cohort Groups, Region, and Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control for Endogenous Migration Choice	No	Yes	No	Yes	No	Yes	No	Yes

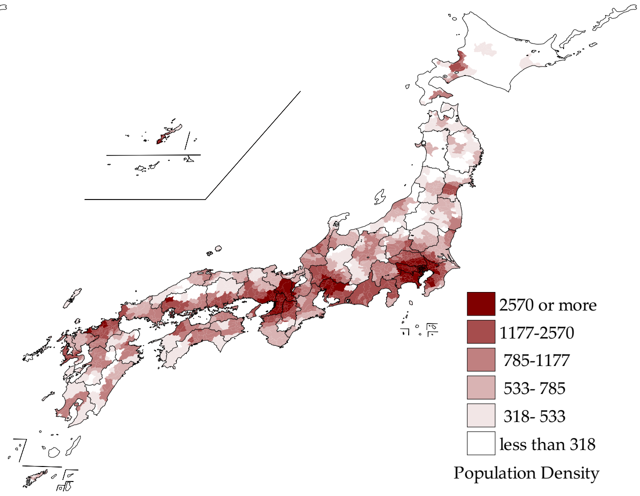
(Continued on next page)

	Treatment Variable: D(1=Migration)							
Explanatory Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
D(1=University Graduate for Father)		0.225**		0.241**		0.135		0.280***
		(0.107)		(0.098)		(0.112)		(0.070)
D(1=University Graduate for Mother)		−0.109		−0.014		−0.146		−0.006
		(0.150)		(0.331)		(0.269)		(0.135)
D(1=University Graduate for Husband)		0.350***		0.454***		0.375***		0.374***
		(0.066)		(0.101)		(0.081)		(0.062)
D(1=University Graduate for Wife)		0.149*		−0.137		0.130		0.020
		(0.081)		(0.085)		(0.113)		(0.056)
D(1=Not Healthy)		0.129		−0.139		−0.003		−0.002
		(0.094)		(0.102)		(0.103)		(0.075)
Old-Age Security Motive Score		−0.026*		−0.007		−0.040***		−0.007
		(0.014)		(0.015)		(0.014)		(0.010)
D(1=Non-Necessity of Children)		0.151***		0.241***		0.154***		0.154***
		(0.057)		(0.065)		(0.058)		(0.045)
Number of Siblings		0.053		0.033		0.063**		0.026
		(0.038)		(0.023)		(0.027)		(0.020)
Husband's Age		−0.011		−0.122		0.040		0.028
		(0.049)		(0.080)		(0.046)		(0.031)
Husband's Age Squared (×1/100)		0.033		0.082		−0.091**		−0.060**
		(0.057)		(0.064)		(0.043)		(0.028)
Wife's Age		0.062		0.219**		0.140**		0.039
		(0.063)		(0.091)		(0.063)		(0.035)
Wife's Age Squared (×1/100)		−0.062		−0.163**		−0.050		0.012
		(0.081)		(0.074)		(0.053)		(0.033)
ρ		−0.209		0.523***		−0.674***		−0.690***
		(0.158)		(0.127)		(0.080)		(0.048)
σ_u		0.831***		0.909***		3.624***		4.080***
		(0.016)		(0.049)		(0.179)		(0.113)
Cohort Groups, Region, and Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	2339	2339	1995	1995	1658	1658	3880	3880
Adjusted R^2	0.260		0.031		0.076		0.072	

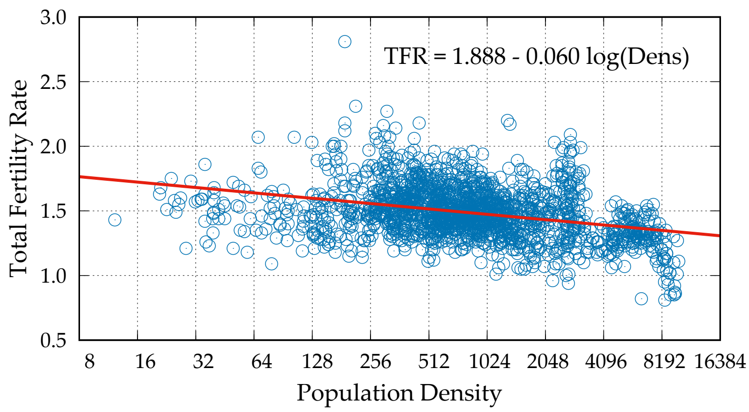
Note: Heteroskedasticity-consistent standard errors clustered by cohort year are in parentheses. Constant is not reported. * denotes statistical significance at the 10% level, ** at the 5% level, and *** at the 1% level.



(a) Total Fertility Rate, 2008–2012



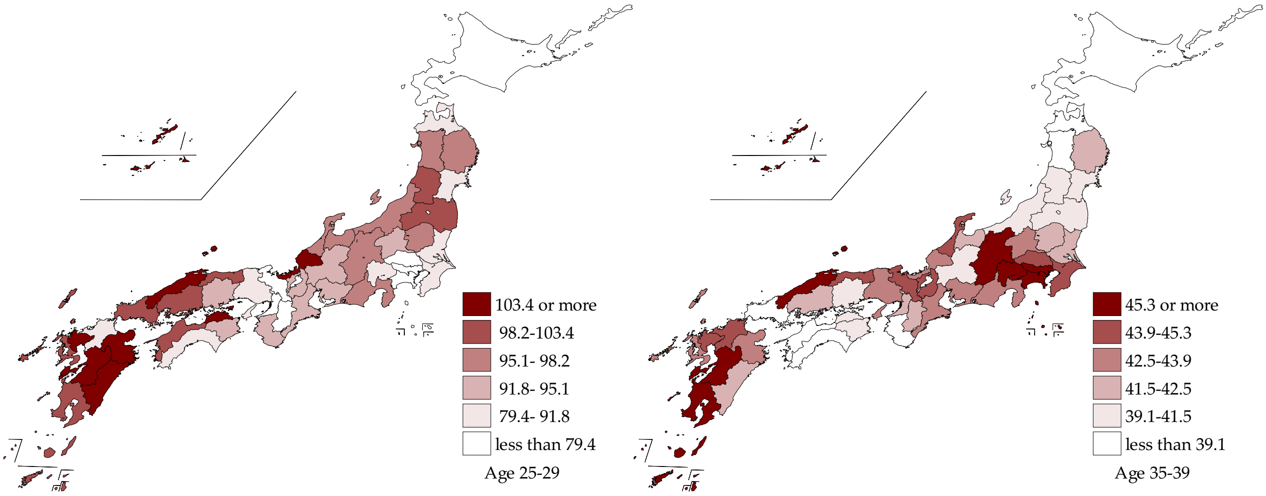
(b) Population Density, 2010



(c) Relationship between Total Fertility Rate and Population Density

Figure 1: Geographical Distribution of Total Fertility Rate and Population Density

Note: Created by author based on Vital Statistics by Health Center and Municipality in 2008–2012 and 2010 Population Census. Municipalities are categorized into six quantiles. Population densities are calculated as total population divided by inhabitable area. Spatially smoothed population densities are calculated by including neighboring municipalities that lie within the circle of 30 km radius from the centroid of municipality. Several municipalities lacking data are classified into the lowest group.

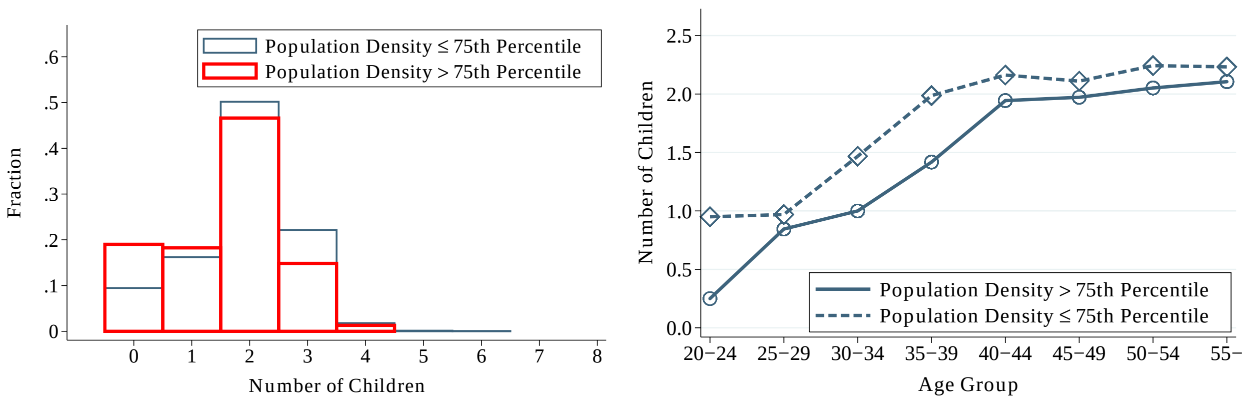


(a) Age Group 25–29

(b) Age Group 35–39

Figure 2: Fertility Rate by Age Group (Births per 1,000 Women)

Note: Created by author based on Specified Report of Vital Statistics in FY2010. Prefectures are categorized into six quantiles.



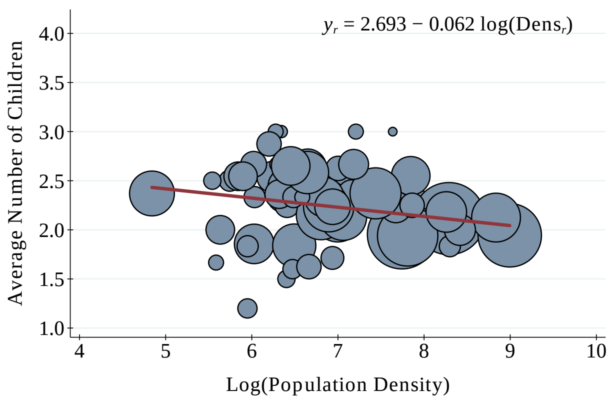
(a) Histogram of Number of Children

(b) Average Number of Children by Age Group

Figure 3: Number of Children per Married Couple between Large and Small Cities

Note: Author's calculation from Japanese General Social Surveys Cumulative Data 2000–2010. Sample of wife's age < 50 is used. Migrants are excluded from the sample. The 75th percentile of population density is calculated from the distribution in the JGSS dataset.

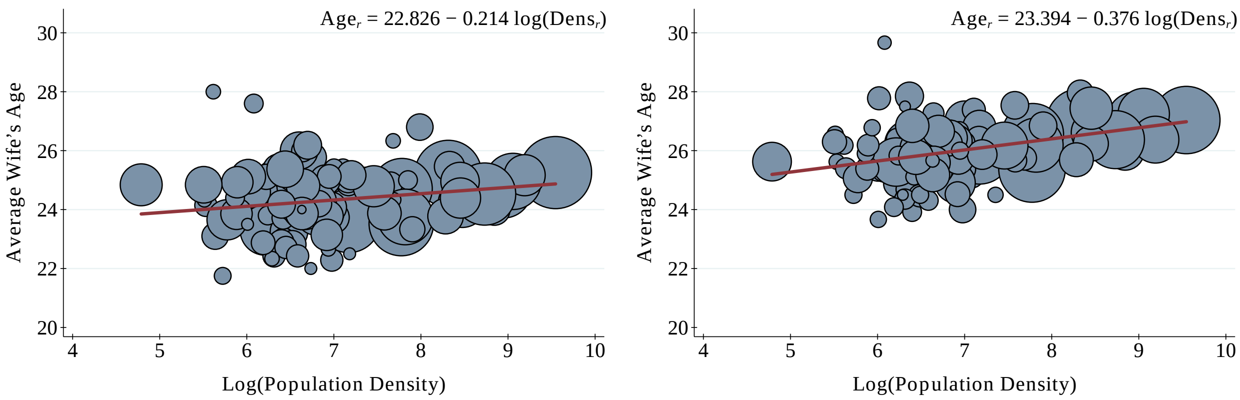
(a) Sample of Wife's Age < 50



(b) Sample of Wife's Age ≥ 50

Figure 4: Average Number of Children per Married Couple and City Size in JGSS Cumulative Data 2000–2010

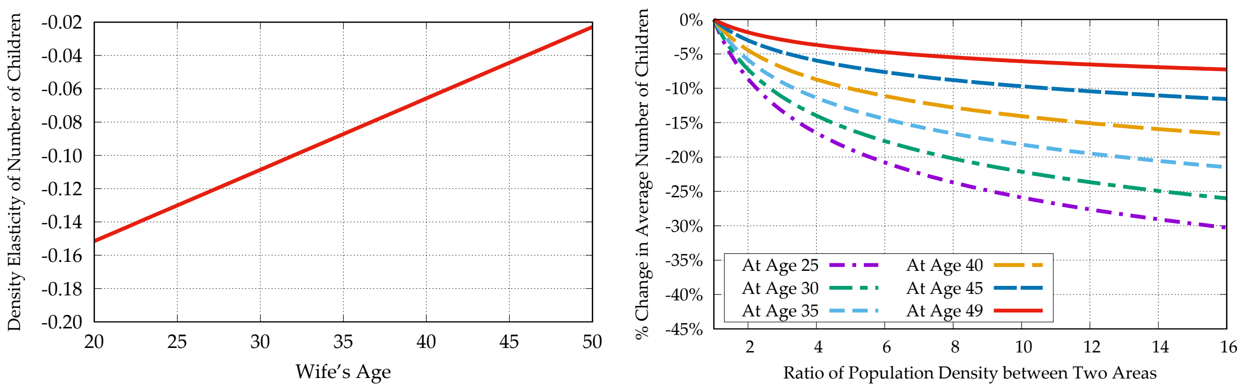
Note: Author's calculation from Japanese General Social Surveys Cumulative Data 2000–2010. The circle size represents the sample size in each geographical unit.



(a) Wife's Age at Marriage (b) Wife's Age at Birth of First Child

Figure 5: Average Wife's Age and City Size in JGSS Cumulative Data 2000–2010

Note: Author's calculation from Japanese General Social Surveys Cumulative Data 2000–2010. The circle size represents the sample size in each geographical unit.



(a) Density Elasticity of Number of Children

(b) Spatial Variation in Average Number of Children

Figure 6: Percentage Change in the Average Number of Children by City Size Simulated from Poisson Estimates

Note: The density elasticity of the number of children in Panel (a) is calculated as $\hat{\alpha} + \hat{\phi} \times \text{Age}$ using the estimates in Columns (4) of Table 4. The percentage change in the average number of children in Panel (b) is calculated as $[\lambda_s(\hat{\boldsymbol{\theta}}) - \lambda_r(\hat{\boldsymbol{\theta}})]/\lambda_r(\hat{\boldsymbol{\theta}}) = \text{Ratio}_{sr}^{\hat{\alpha}+\hat{\phi}\times\text{Age}} - 1$, where Ratio_{sr} is the population density ratio between cities s and r, and households' characteristics are assumed to be identical. This numerical simulation uses the estimates $\hat{\boldsymbol{\theta}}$ in Columns (4) of Table 4. The Online Appendix provides two specifications of the dynamic catch-up process on fertility decisions that include nonlinear and discrete effects of age.

Online Appendix for

Does Agglomeration Discourage Fertility? Evidence from the Japanese General Social Survey 2000–2010

This online appendix provides supplementary information on the paper.

§ Low Japanese Fertility Rates and Costs Associated with Agglomeration

In most developed counties, demographic issues are central to current policy agendas. These counties have experienced rapid declines in total fertility rates (TFR) with economic growth, and raising fertility rates has become a policy priority in several countries. As shown in Figure OA.1, France, Germany, the United Kingdom (UK), and the United States (US) have exhibited sharp declines in total fertility rates since the 1960s, as have Italy and Japan after the 1970s. Although recent total fertility rates have remained at approximately two in France, the UK, and the US, they are less in Germany, Italy, and Japan (approximately 1.4).

[Figure OA.1]

Japan's National Institute of Population and Social Security Research (2012) regularly surveys fertility rates. As Figure OA.2(a) shows, the high costs of rearing and educating children are major reasons why households do not have ideal numbers of children. Figure OA.2(b) shows that both reasons decrease the planned number of children relative to the ideal number of children. Thus, higher costs of rearing children drive lower fertility rates.

To identify regions with higher childrearing costs, we employ surveys by Japan's Ministry of Education, Culture, Sports, Science and Technology (2009). Panel (a) of Figure OA.3 shows the annual costs of extramural activities for public school students by city size. Clearly, households in larger cities pay more for extramural activities. Two possibilities arise from these data: (1) the prices of extramural activities are higher in larger cities and (2) households with students in such cities consume more such services. Focusing on these prices, Panel (b) of Figure OA.3 shows regional differences in indices of tutorial fees. A stylized fact is that the price indices of educational services in more densely populated areas exceed those in less dense areas. Thus, even if the consumption of educational services is identical across areas, educational costs differ regionally.

[Figures OA.2–OA.3]

§ Comparative Statics and Empirical Evidence

From the Cobb–Douglas utility function, the demand for children is given as follows:

$$y_r\Big(I_r(n_r), w_r(n_r), c_r(n_r)\Big) = (\mu - \xi)\frac{I_r(n_r) + w_r(n_r) - c_r(n_r)}{bw_r(n_r)}.$$

The comparative statics clarify how agglomeration affects the demand for children. Differentiating the demand for children with respect to city size n_r, we have the following equation:

$$\frac{\mathrm{d}y_r\Big(I_r(n_r), w_r(n_r), c_r(n_r)\Big)}{\mathrm{d}n_r} = \underbrace{\frac{\partial y_r}{\partial I_r(n_r)}}_{\text{Income effects}}\frac{\mathrm{d}I_r(n_r)}{\mathrm{d}n_r} + \underbrace{\frac{\partial y_r}{\partial w_r(n_r)}}_{\substack{\text{Income effects or}\\ \text{opportunity}\\ \text{costs of rearing}\\ \text{children}}}\frac{\mathrm{d}w_r(n_r)}{\mathrm{d}n_r} + \underbrace{\frac{\partial y_r}{\partial c_r(n_r)}}_{\substack{\text{Congestion}\\ \text{costs}}}\frac{\mathrm{d}c_r(n_r)}{\mathrm{d}n_r},$$

where the three terms on the right-hand side capture income effects, the opportunity costs of rearing children, and congestion costs. The calculation result is given below:

$$\frac{\mathrm{d}y_r\Big(I_r(n_r), w_r(n_r), c_r(n_r)\Big)}{\mathrm{d}n_r} = (\mu - \xi)\frac{w_r(n_r)\frac{\mathrm{d}I_r(n_r)}{\mathrm{d}n_r} - [I_r(n_r) - c_r(n_r)]\frac{\mathrm{d}w_r(n_r)}{\mathrm{d}n_r} - w_r(n_r)\frac{\mathrm{d}c_r(n_r)}{\mathrm{d}n_r}}{bw_r^2(n_r)}, \tag{OA.1}$$

or equivalently

$$\frac{\mathrm{d}y_r\Big(I_r(n_r), w_r(n_r), c_r(n_r)\Big)}{\mathrm{d}n_r} = (\mu - \xi)\frac{\left[\frac{\mathrm{d}I_r(n_r)}{\mathrm{d}n_r} - \frac{\mathrm{d}c_r(n_r)}{\mathrm{d}n_r}\right]w_r(n_r) - [I_r(n_r) - c_r(n_r)]\frac{\mathrm{d}w_r(n_r)}{\mathrm{d}n_r}}{bw_r^2(n_r)}. \tag{OA.2}$$

The discussion in the main text is based on the first equation (OA.1). The second term in the numerator captures the opportunity costs of rearing children, which means that the negative sign of $\partial y_r/\partial w_r(n_r)$ holds if $I_r(n_r) - c_r(n_r) > 0$.

It is important to discuss conditions regarding the total effects of agglomeration on the demand for children.[1] From the second equation (OA.2), the sufficient condition for $\mathrm{d}y_r/\mathrm{d}n_r > 0$ is

$$\frac{\mathrm{d}[I_r(n_r) - c_r(n_r)]/\mathrm{d}n_r}{[I_r(n_r) - c_r(n_r)]} > \frac{\mathrm{d}w_r(n_r)/\mathrm{d}n_r}{w_r(n_r)}, \tag{OA.3}$$

which means that the percentage change in net husband's income (husband's income minus congestion costs) arising from agglomeration is higher than that in wife's income. Otherwise, the total effect of agglomeration becomes negative. Since $[I_r(n_r) - c_r(n_r)] > 0$ holds in most cases, if $\mathrm{d}y_r/\mathrm{d}n_r > 0$ is empirically observed, the following condition must be satisfied:

$$\frac{\mathrm{d}I_r(n_r)}{\mathrm{d}n_r} > \frac{\mathrm{d}c_r(n_r)}{\mathrm{d}n_r}, \tag{OA.4}$$

which means that the marginal benefits of agglomeration economies for husband's income $\mathrm{d}I_r(n_r)/\mathrm{d}n_r$ are larger than the marginal costs of agglomeration diseconomies $\mathrm{d}c_r(n_r)/\mathrm{d}n_r$.

In the empirical analysis, we examine the prediction of the comparative statics controlling for the channels of the income effect $\partial y_r/\partial I_r(n_r) > 0$ and the opportunity costs of rearing children $\partial y_r/\partial w_r(n_r) < 0$ to capture the channel of agglomeration diseconomies $\partial y_r/\partial c_r(n_r) < 0$. This study also empirically shows that $\mathrm{d}y_r/\mathrm{d}n_r < 0$.

This study uses spatial variation at the same time as an identification strategy for "agglomeration" effects. In other words, our empirical approach is based on spatial differences in city size between city s and city r. This empirical approach is also emphasized by Combes and Gobillon (2015). On the other hand, one might want to examine the predictions of comparative statics using temporal variation, which means the temporal difference between $n_{r,t}$ and $n_{r,t-1}$ in the same city r. Importantly, the predictions of comparative statics hold in the case of both spatial and temporal variation in city size. However, the identification strategy using temporal variation does not necessarily capture the effect of "agglomeration." In other words, the information on "city size" is not included in temporal variation. Temporal variation captures the *growth effect* of city size, regardless of the level of city size (i.e., small cities can have high population growth, whereas large cities can have low population growth.). When it comes to the effects of agglomeration, spatial variations must be used.

In the Online Appendix, this study complements the discussions about the temporal variation in TFR across prefectures focusing on the case of $\mathrm{d}y_r/\mathrm{d}n_r > 0$. Figure OA.4 shows interesting relationships regarding the predictions of the comparative statics. Panel (a) of Figure OA.4 shows

[1] I appreciate the valuable comments of an anonymous reviewer for total effects of agglomeration.

the negative relationship between the percentage change in TFR and population growth in the period 1990–1995. On the other hand, Panel (b) of Figure OA.4 shows the positive relationship between the two variables in the period 2005–2010, meaning that $\mathrm{d}y_r/\mathrm{d}n_r > 0$ holds in the recent Japanese economy. Based on the comparative statics in this study, it is suggested that the sufficient condition (OA.3) holds in recent years. In turns, it can be said that the marginal costs of population growth were larger than the marginal benefits of population growth in the period 1990–1995. Since the cities with higher population growth are the same as the large cities in the period 2005–2010, as shown in Panel (d), it can be said that the marginal benefits of agglomeration are larger than the marginal congestion costs of agglomeration.

[Figure OA.4]

Although the demand for child quality is not empirically examined due to data limitations, the comparative statics offer an insightful theoretical prediction. From the Cobb–Douglas utility function, the demand for child quality is given as follows:

$$q_r\Big(w_r(n_r), p_{qr}(n_r)\Big) = \frac{\xi}{\mu - \xi}\frac{bw_r(n_r)}{p_{qr}(n_r)}.$$

Differentiating the demand for child quality with respect to city size n_r, we have the following equation:

$$\frac{\mathrm{d}q_r\Big(w_r(n_r), p_{qr}(n_r)\Big)}{\mathrm{d}n_r} = \underbrace{\frac{\partial q_r}{\partial w_r(n_r)}}_{\text{Income effects}}\frac{\mathrm{d}w_r(n_r)}{\mathrm{d}n_r} + \underbrace{\frac{\partial q_r}{\partial p_{qr}(n_r)}}_{\text{Price effects}}\frac{\mathrm{d}p_{qr}(n_r)}{\mathrm{d}n_r},$$

where the two terms on the right-hand side capture income and price effects regarding agglomeration. The calculation result is given below:

$$\frac{\mathrm{d}q_r\Big(w_r(n_r), p_{qr}(n_r)\Big)}{\mathrm{d}n_r} = \frac{b\xi}{\mu - \xi}\frac{p_{qr}(n_r)\frac{\mathrm{d}w_r(n_r)}{\mathrm{d}n_r} - w_r(n_r)\frac{\mathrm{d}p_{qr}(n_r)}{\mathrm{d}n_r}}{p_{qr}^2(n_r)},$$

where an increase in the wife's income has a positive effect on the demand for child quality, and an increase in the prices of goods and services for child quality reduces the demand for child quality. Under the assumption of $\mathrm{d}w_r(n_r)/\mathrm{d}n_r > 0$ and $\mathrm{d}p_{qr}(n_r)/\mathrm{d}n_r > 0$, the sufficient condition for $\mathrm{d}q_r/\mathrm{d}n_r > 0$ is

$$\frac{\mathrm{d}w_r(n_r)/\mathrm{d}n_r}{w_r(n_r)} > \frac{\mathrm{d}p_{qr}(n_r)/\mathrm{d}n_r}{p_{qr}(n_r)},$$

which means that the percentage change in the wife's income arising from agglomeration is higher than the percentage change of price in the goods and services for child quality arising from agglomeration.

§ Additional Estimation Results

➤ Table OA.1

Table OA.1 presents the descriptive statistics for full sample (both the sample in which wife's age < 50 and that in which wife's age ≥ 50).

➤ Tables OA.2–OA.6

Tables OA.2–OA.6 present results of the IV Poisson estimation. An estimation issue for the demand function for children relates to the fact that number of children has a positive impact on population density unless children born to households in that city migrate to other cities. Although our aim is to measure the extent to which the costs associated with agglomeration discourage married couples from bearing children, this magnitude may be underestimated owing to the opposite force.

To address this endogeneity issue in the literature of agglomeration economies, the method of IV estimation is proposed. A possible instrumental variable candidate is a long-lagged population density, as used by Ciccone and Hall (1996). A long-lagged population density is highly correlated with current city size. In this study, the correlation coefficient between the logarithm of population density and the logarithm of population density in 1930 is 0.746 (See OA.5). On the correlation between the error term and population density, the validity of using a historical lag as an instrumental variable relies on the hypothesis that the population agglomeration in the past is not related to couples' current fertility decisions. This study uses the logarithm of population density in 1930 and its squared term as instruments and estimates the demand function for children by the IV Poisson method assuming an additive error term.

In general, the magnitudes of the IV Poisson estimates are larger than those of the Poisson estimates, which slightly changes the quantified impacts of agglomeration economies. However, our qualitative results are identical between the simple Poisson and IV Poisson estimations.

➤ Tables OA.7–OA.9

The baseline model considers a linear process of the dynamic fertility decision. In the Online Appendix, two additional specifications are considered.[2]

The first specification considers nonlinear effects of age by including the cross-term of population density and the wife's age squared as follows:

$$\begin{aligned}\lambda_{ir}(\boldsymbol{\theta}) \equiv \exp\Big(&\alpha \log(\mathrm{Dens}_{r(i)t}) + \phi_1 \log(\mathrm{Dens}_{r(i)t}) \times \mathrm{Age}_i^{\mathrm{wife}} + \phi_2 \log(\mathrm{Dens}_{r(i)t}) \times (\mathrm{Age}_i^{\mathrm{wife}})^2 \\ &+ \boldsymbol{X}_i\boldsymbol{\beta} + \tilde{\boldsymbol{X}}_i\boldsymbol{\delta} + \boldsymbol{D}_{r(i)}^{\mathrm{Reg}}\boldsymbol{\eta} + \boldsymbol{D}_t^{\mathrm{Year}}\boldsymbol{\psi}\Big),\end{aligned} \tag{OA.5}$$

where parameters ϕ_1 and ϕ_2 capture different nonlinear effects of the dynamic fertility decision across cities. Note that the squared variables on husband's and wife's age are dropped owing to a high collinearity with the cross-term of population density and wife's age squared. The quantification of the spatial variation in the number of children per married couple is extended as follows:

$$\frac{\lambda_s - \lambda_r}{\lambda_r} = \left(\frac{\mathrm{Dens}_s}{\mathrm{Dens}_r}\right)^{\hat{\alpha}+\hat{\phi}_1\times\mathrm{Age}+\hat{\phi}_2\times\mathrm{Age}^2} - 1.$$

Tables OA.7–OA.8 present the estimation results of the standard and IV Poisson regression models (OA.5), respectively. Figures OA.10–OA.11 show the quantification results of the spatial variation in the number of children in terms of city size and wife's age.

The second specification considers the discrete effects of age by including the cross-term of population density and dummy variables of age groups as follows:

$$\lambda_{ir}(\boldsymbol{\theta}) \equiv \exp\left(\alpha \log(\mathrm{Dens}_{r(i)t}) + \sum_{g=1}^{5} \phi_g \log(\mathrm{Dens}_{r(i)t}) \times D_g(\mathrm{Age}_{\mathrm{i}}^{\mathrm{wife}}) + \boldsymbol{X}_i\boldsymbol{\beta} + \tilde{\boldsymbol{X}}_i\boldsymbol{\delta} + \boldsymbol{D}_{r(i)}^{\mathrm{Reg}}\boldsymbol{\eta} + \boldsymbol{D}_t^{\mathrm{Year}}\boldsymbol{\psi}\right), \tag{OA.6}$$

where $D_g(\mathrm{Age}_{\mathrm{i}}^{\mathrm{wife}})$ is a dummy variable for wife's age based on five categories (g = 1: 25–29, g = 2: 30–34, g = 3: 35–39, g = 4: 40–44, g = 5: 45–49) and the the baseline age group is 20–24. The quantification of the spatial variation in the number of children per married couple is extended as follows:

$$\frac{\lambda_s - \lambda_r}{\lambda_r} = \left(\frac{\mathrm{Dens}_s}{\mathrm{Dens}_r}\right)^{\hat{\alpha}+\sum_{g=1}^{5}\hat{\phi}_g D_g(\mathrm{Age})} - 1.$$

Table OA.9 presents the estimation results of Poisson regression model (OA.6). Figure OA.12 shows the quantification results of the spatial variation in the number of children in terms of city size and wife's age.

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[2] I appreciate the valuable comments of an anonymous reviewer for the dynamic process of fertility behavior.

➤ Table OA.10

As a robustness check, Table OA.10 presents Poisson estimation results including the dynamic process of fertility behavior for the sample in which the wife's age ≥ 50. Importantly, the coefficient on the cross-term of population density and wife's age is not significant, suggesting that the density elasticity of the number of children does not change after the childbearing age.

➤ Tables OA.11–OA.12

Tables OA.11 and OA.12 present Poisson estimation results in which the *ideal number of children* is used as a dependent variable. As shown in Figure OA.7, households residing in larger cities, on average, represent a smaller ideal number of children. The density elasticity of the ideal number of children is −0.021 in Column (7) of Table OA.11. However, when we estimate the dynamic change in the ideal number of children using the sample without migrants, the density elasticity of ideal number of children is not significant.

➤ Table OA.13

Table OA.13 presents estimation results for income effects and opportunity costs by including husband's and wife's incomes separately. The estimation results suggest that a high husband's income leads to income effects, whereas a high wife's income leads to opportunity costs of rearing children.

Since agglomeration increases husband's income, the congestion costs arising from agglomeration can be *under*-estimated by the income effect if the husband's income is not controlled for. In other words, controlling for "Husband's Income" increases the magnitude of congestion costs. In turn, since agglomeration increases the wife's income, the congestion costs arising from agglomeration can be *over*-estimated by the opportunity costs of rearing children if the wife's income is not controlled for. In other words, controlling for "Wife's Income" decreases the magnitude of congestion costs. Indeed, Columns (4)–(6) of Table OA.13 support this explanation, but these economic effects are not so large.

➤ Table OA.14

This study cannot investigate how preference heterogeneity for child quality affects the number of children per married couple owing to data limitations. However, only the 2006 JGSS asks a question about the preference for child quality, which is "Generally speaking, how important do you think the following are for children?: Taking lessons after-school." Therefore, in the Online Appendix, this study conducts an additional analysis using the dummy variable D(1=Importance of Taking Lessons After-School), which takes the value of 1 if individuals answer very important or important for the question, and 0 otherwise.

Table OA.14 presents Poisson estimation results including the dummy variable for child quality. To keep the sample size large, variables on household characteristics are excluded from the regressions. The estimation results show that, as predicted in the theoretical model, married couples with strong preferences for child quality have fewer children since the coefficient on the dummy is negative and significant at the 10% level. The inclusion of this dummy variable does not largely affect the coefficient of population density, implying that preference for child quality is not strongly spatially sorted.

➤ Tables OA.15–OA.16

Tables OA.15 and OA.16 present the estimation results of zero-inflated Poisson regression models as a robustness check. Tables OA.15 and OA.16 correspond to Tables 2 and 4 in the main text, respectively. The variables included in the inflation equation are limited to wife's age, a dummy variable for whether the wife is a university graduate, and a dummy variable for the non-necessity of children in a marriage due to the stability of numerical optimization (i.e., convergence is not achieved in some cases if many variables are included in inflation equation.).

➤ Figure OA.5

Figure OA.5 presents the correlation between the population density in recent decades and the population density in 1930. In this study, population density in 1930 is used as an instrumental variable for the population density. The vertical axis represents the population density in the survey year for sample with the wife's age < 50 and population density at age 50 for sample with the wife's age ≥ 50.

➤ Figure OA.6

Figure OA.6 presents the kernel density estimation of the wife's age at marriage and at the birth of the first child. Clearly, the distributions for large cities are right-shifted. However, there are other possible factors that explain this right-shift, such as education and migration experience. To examine whether agglomeration indeed leads to this right-shift of the distribution, this study conducts regression analyses. The estimation results are shown in Tables 5–7 in the main text and Tables OA.5–OA.6 in the Online Appendix.

➤ Figure OA.7

Figure OA.7 presents histograms of the ideal number of children and of the gap in the number of children (i.e., the difference between the actual and ideal number of children) between large and small cities in the JGSS cumulative data from 2000–2010. Panel (a) shows that the average of the ideal number of children in large cities is slightly smaller than that in small cities. Panel (b) shows that the gap between the actual and ideal number of children is slightly larger for households residing in larger cities. The regression results are shown in Tables OA.11–OA.12.

➤ Figure OA.8

Figure OA.8 presents numerical simulation results for spatial variations in the wife's age at marriage and at the birth of the first child using the estimation results in Columns (5)–(8) of Table 7 of the main text, Column (5) of Table OA.5, and Column (5) of Table OA.6. Panels (a) and (b) of Figure OA.8 quantify, holding other factors equal, for how long the difference in city size leads to the delay in the marriage and the birth of first child, respectively.

➤ Figure OA.9

Figure OA.9 illustrates the estimated spatial variations in the average number of children using the estimates in Column (6) of Table OA.4. Note that this quantification is based on the IV Poisson estimation results. Panel (a) shows the density elasticity of the number of children at different ages. The spatial variation in the number of children is greater for couples in their 20s (e.g., -0.146 at age 29) but declines to -0.044 at age 49.

Panel (b) of Figure OA.9 quantifies the spatial variations in number of children by couples' ages, showing what percent change in the average number of children per married couple is generated by the difference in city size, holding other factors equal. Among couples age 30, the estimated percentage change in the number of children between one city and a city with 10 times more people is -27.71% ($\approx 10^{-0.295+0.005\times 30} - 1$). If households in the baseline city on average have 1.5 children at age 30, households in a city with 10 times more people have 1.084 children on average. The spatial gap shows approximately 416 ($= 1,500 - 1,084$) children per 1,000 households. However, the estimated percentage change in the number of children between those cities for couples at age

49 is −9.56% ($\approx 10^{-0.295+0.005\times 49} - 1$). If the average number of children per household at age 49 in the baseline city is 2.2, the average in a city with 10 times more people is 1.990. The spatial gap shows approximately 210 ($= 2,200 - 1,990$) children per 1,000 households.

➤ Figure OA.10

Figure OA.10 illustrates the estimated spatial variations in the average number of children using the estimates in Column (6) of Table OA.7. Note that, unlike the linear process in the baseline analysis, this density elasticity shows a nonlinear process as wife's age increases. Panel (a) of Figure OA.10 shows the density elasticity of the number of children at different ages.

Panel (b) of Figure OA.10 quantifies the spatial variations in the number of children by the wife's age, showing what percentage change in the average number of children is generated by the difference in city size, holding other things equal. The estimation results with nonlinear effects of age show that there is no spatial variation in the number of children when wives are in their 40s.

➤ Figure OA.11

Figure OA.11 illustrates estimated the spatial variations in the average number of children using the estimates in Column (6) of Table OA.8. Note that, unlike the linear process in the baseline analysis, this density elasticity shows a nonlinear process as the wife's age increases. Panel (a) of Figure OA.11 shows the density elasticity of the number of children at different ages. Compared to Figure OA.10, the IV Poisson estimation results show a downward shift in the density elasticities of the number of children.

Panel (b) of Figure OA.11 quantifies the spatial variations in the number of children by wife's age, showing what percentage change in the average number of children is generated by the difference in city size, holding other things equal. Similar to Figure OA.11, the estimation results with nonlinear effects of age show that there is no spatial variation in the number of children when wives are in their 40s.

➤ Figure OA.12

Figure OA.12 illustrates the estimated spatial variations in the average number of children using the estimates in Column (6) of Table OA.9. Note that, unlike the linear process in the baseline analysis, this density elasticity shows a discrete process for each age group. Panel (a) of Figure OA.12 shows the density elasticity of the number of children at different ages.

Panel (b) of Figure OA.12 quantifies the spatial variations in the number of children by wife's age, showing what percentage change in the average number of children is generated by the difference in city size, holding other factors equal. The estimation results show that the spatial variation in number of children does not change substantially after age 35.

§ Definitions of Variables

Number of Children The total number of children (including deceased) that married couples had by the date of survey.

Population Density The total population divided by inhabitable area (in km^2). The municipal panel dataset was constructed from 1980, 1985, 1990, 1995, 2000, 2005, and 2010 population censuses. The reference date for geographical information is April 1, 2011, when Japan had 1,747 municipalities (excluding the Northern Territories). Tokyo's 23 wards are counted individually. Ordinance-designated cities (*Seirei Shitei Toshi*) are counted as cities (*shi*), rather than subcategories *ku*. The corresponding cities are Sapporo-shi, Sendai-shi, Saitama-shi, Chiba-shi, Yokohama-shi, Kawasaki-shi, Sagamihara-shi, Niigata-shi, Shizuoka-shi, Hamamatsu-shi, Nagoya-shi, Kyoto-shi, Osaka-shi, Sakai-shi, Kobe-shi, Okayama-shi, Hiroshima-shi, Kitakyushu-shi, and Fukuoka-shi. Since some municipalities merged between 1980 and 2011, their populations are re-aggregated from relevant information. Linear interpolation is implemented between the census years.

The JGSS offers geographical information on 47 prefectures using a three-tiered category of municipalities (1: 23 wards of Tokyo and ordinance-designated city, 2: city, and 3: town/village). The geographical unit in the analysis is based on this category. There were 109 ($= 15 \times 3 + 32 \times 2$) geographical units in 2010 since only 15 prefectures actually have the first category of municipality. In 2005, there were 105 ($= 11 \times 3 + 36 \times 2$) geographical units. The arithmetic mean of the municipal population density corresponding to the geographical unit of the JGSS dataset is calculated, and then, the logarithm of the average population density is taken.

The Population densities when the wife is age 50 ($\mathrm{Dens}^{50}_{r(i)}$) are replaced by those in 1980 for wives who reached age 50 before 1980. The instrumental variables for the population density are constructed from the 1930 population census based on administrative unit as of April 1, 2011, and then the average population density is calculated based on the geographical unit used in the JGSS dataset.

Migration Dummy Takes the value of if respondents' current residential prefecture differs from prefectures where either spouse lived at age 15 and 0 otherwise.

Old Age Security Score Ranges from 2 to 10, which is the sum of two questions about how households perceive the roles of government and family in providing security for the elderly (1: Governments, 5: Individuals and Families): (1) responsibility for livelihood of the elderly (2) responsibility for medical and nursing care of the elderly. Greater values indicate how households are responsible within the families in their old age.

Dummy for Non-Necessity of Children in a Marriage Takes the value of 1 for households that agree or somewhat agree children are unnecessary in a marriage and 0 otherwise.

Number of Siblings is calculated by merging spousal responses. If both answer, the average number of siblings is used; if one answers the question, the number that he or she provided is used.

Husband's and Wife's Incomes Class values (0, 35, 85, 115, 145, 200, 300, 400, 500, 600, 700, 800, 925, 1100, 1300, 1500, 1725, 2075, and 2300 in 10,000 JPY). The maximum class value is multiplied by 1.2. Income is deflated by the consumer price index (2010=100)

Working Hours Total weekly worked during the past week (in 10 hours).

Dummy for Non-Labor Force Takes the value of 1 if a respondent has never worked (i.e., a person who answered 0 years of work experience) and 0 otherwise.

Dummy for University Graduate Takes the value of 1 if a respondent graduated from university or graduate school and 0 otherwise.

Dummy for Not Healthy Takes the value of 1 if answers are 4 or 5 on a one-to-five scale (1=good, 5=bad).

Dummies for Cohort Groups Take the value of 1 if the wife in married couple i was born in 1944 and earlier, 1945–1949, 1950–1954, 1955–1959, 1960–1964, 1965–1969, 1970–1974, or 1975 and later, and 0 otherwise.

Dummies for Survey Years Take the value of 1 if married couple i answers the questionnaire either in the 2000, 2001, 2002, 2005, 2006, 2008, or 2010 survey and 0 otherwise.

Dummies for Regions Take the value of 1 if married couple i lives either in Hokkaido–Tohoku (Hokkaido, Aomori, Iwate, Miyagi, Akita, Yamagata, Fukushima), Kanto (Ibaraki, Tochigi, Gunma, Saitama, Chiba, Tokyo, and Kanagawa), Chubu (Niigata, Toyama, Ishikawa, Fukui, Yamanashi, Nagano, Gifu, Shizuoka, Aichi, and Mie), Kinki (Shiga, Kyoto, Osaka, Hyogo, Nara, and Wakayama), Chugoku–Shikoku (Tottori, Shimane, Okayama, Hiroshima, Yamaguchi, Tokushima, Kagawa, Ehime, and Kochi), or Kyushu (Fukuoka, Saga, Nagasaki, Kumamoto, Oita, Miyazaki, Kagoshima, Okinawa) and 0 otherwise.

Dummies for Prefectures at Age 15 Take the value of 1 if married couple i lived at age 15 either in Hokkaido, Aomori, Iwate, Miyagi, Akita, Yamagata, Fukushima, Ibaraki, Tochigi, Gunma, Saitama, Chiba, Tokyo, and Kanagawa, Niigata, Toyama, Ishikawa, Fukui, Yamanashi, Nagano, Gifu, Shizuoka, Aichi, and Mie, Shiga, Kyoto, Osaka, Hyogo, Nara, and Wakayama, Tottori, Shimane, Okayama, Hiroshima, Yamaguchi, Tokushima, Kagawa, Ehime, and Kochi, Fukuoka, Saga, Nagasaki, Kumamoto, Oita, Miyazaki, Kagoshima, or Okinawa, and 0 otherwise.

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Table OA.1: Descriptive Statistics for Full Sample

	Full Sample				
Variables	Obs.	Mean	S.D.	Min	Max
Number of Children	4334	1.991	0.941	0	8
Ideal Number of Children	3889	2.690	0.612	0	10
Gap in Number of Children	3889	−0.700	0.989	−8	4
Log(Population Density)	4334	7.397	1.072	4.646	9.628
Log(Population Density) in 1930	4334	6.716	1.281	3.374	9.492
D(1=Migration)	4334	0.259	0.438	0	1
D(1=University or Higher for Husband)	4334	0.287	0.453	0	1
D(1=University or Higher for Wife)	4334	0.181	0.385	0	1
Husband's Income (Unit: Million yen)	4334	4.792	3.478	0.000	27.600
Wife's Income (Unit: Million yen)	4334	1.583	1.914	0.000	20.363
Hours Worked Last Week for Husband (Unit: 10 Hours)	4334	4.138	1.812	0.000	8.200
Hours Worked Last Week for Wife (Unit: 10 Hours)	4334	2.593	1.708	0.000	6.500
D(1=Non-Labor Force for Husband)	4334	0.097	0.296	0	1
D(1=Non-Labor Force for Wife)	4334	0.168	0.374	0	1
D(1=Not Healthy)	4334	0.146	0.353	0	1
Old-Age Security Index	4334	4.646	1.984	2	10
D(1=Non-Necessity of Children in a Marriage)	4334	0.363	0.481	0	1
Number of Siblings	4334	2.410	1.483	0	15
Husband's Age	4334	51.713	12.958	20	91
Wife's Age	4334	49.074	12.548	20	90
Wife's Age at Marriage	1658	24.393	3.362	16	51
Wife's Age at Birth of First Child	3880	26.162	3.742	16	50
D(1=University or Higher for Father)	4334	0.074	0.262	0	1
D(1=University or Higher for Mother)	4334	0.024	0.154	0	1

Note: The household who has the maximum number of children and the uppermost 1 percentile of the distribution of hours worked for husband and wife are excluded from the full sample as extreme outliers. Population density is expressed in persons/km^2.

Table OA.2: IV Poisson Regression Estimation Results for Fertility Decision and City Size

	Dependent Variable: Number of Children						
	Sample with Wife's Age < 50						
Explanatory Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Log(Population Density)	−0.099***	−0.095***	−0.085***	−0.105***	−0.106***	−0.096***	−0.091***
	(0.018)	(0.018)	(0.018)	(0.018)	(0.019)	(0.019)	(0.018)
Husband's Age	0.101***	0.101***	0.105***	0.096***	0.097***	0.100***	0.096***
	(0.027)	(0.027)	(0.026)	(0.026)	(0.027)	(0.027)	(0.025)
Husband's Age Squared (×1/100)	−0.111***	−0.111***	−0.116***	−0.107***	−0.107***	−0.111***	−0.107***
	(0.029)	(0.029)	(0.028)	(0.028)	(0.028)	(0.029)	(0.027)
Wife's Age	0.161***	0.162***	0.159***	0.159***	0.159***	0.160***	0.154***
	(0.029)	(0.029)	(0.028)	(0.029)	(0.029)	(0.028)	(0.027)
Wife's Age Squared (×1/100)	−0.186***	−0.186***	−0.181***	−0.180***	−0.183***	−0.185***	−0.176***
	(0.034)	(0.034)	(0.033)	(0.034)	(0.035)	(0.033)	(0.032)
D(1=Migration)		−0.065**					−0.059**
		(0.029)					(0.028)
D(1=University Graduate for Husband)			−0.118***				−0.116***
			(0.026)				(0.022)
D(1=University Graduate for Wife)			−0.087***				−0.079***
			(0.019)				(0.020)
Husband's Income				0.012***			0.016***
				(0.003)			(0.003)
Wife's Income				−0.037***			−0.018***
				(0.007)			(0.006)
Hours Worked Last Week for Husband					0.012		0.007
					(0.010)		(0.010)
Hours Worked Last Week for Wife					−0.048***		−0.034***
					(0.011)		(0.011)
D(1=Non-Labor Force for Husband)					−0.128		−0.094
					(0.177)		(0.172)
D(1=Non-Labor Force for Wife)					−0.116**		−0.102*
					(0.053)		(0.054)
D(1=Not Healthy)						−0.044	−0.054**
						(0.027)	(0.027)
Old-Age Security Motive Score						0.006	0.006
						(0.006)	(0.006)
D(1=Non-Necessity of Children)						−0.075***	−0.075***
						(0.019)	(0.018)
Number of Siblings						0.038***	0.026**
						(0.011)	(0.011)
Cohort Groups, Region, and Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	2339	2339	2339	2339	2339	2339	2339
Overidentification (p-value)	0.058	0.055	0.047	0.114	0.087	0.047	0.071

Note: Heteroskedasticity-consistent standard errors clustered by cohort year are in parentheses. Instrumental variables for the population density are the logarithm of population density in 1930 and its squared variable. Constant is not reported. * denotes statistical significance at the 10% level, ** at the 5% level, and *** at the 1% level.

Table OA.3: IV Poisson Regression Estimation Results for Completed Fertility Decision and City Size

	Dependent Variable: Number of Children				
	Sample with Wife's Age ≥ 50				
Explanatory Variables	(1)	(2)	(3)	(4)	(5)
Log(Population Density) at Age 50	−0.045***	−0.043***	−0.046***	−0.041***	−0.039***
	(0.015)	(0.014)	(0.015)	(0.014)	(0.015)
D(1=Migration)		−0.030*			−0.029*
		(0.016)			(0.016)
D(1=University Graduate for Husband)			−0.014		−0.006
			(0.024)		(0.025)
D(1=University Graduate for Wife)			0.051		0.054*
			(0.032)		(0.030)
D(1=Not Healthy)				−0.027	−0.025
				(0.029)	(0.029)
Old-Age Security Motive Score				−0.000	−0.001
				(0.005)	(0.005)
D(1=Non-Necessity of Children)				−0.084***	−0.083***
				(0.019)	(0.019)
Number of Siblings				0.015**	0.017**
				(0.006)	(0.007)
Cohort Groups, Region, and Year Dummies	Yes	Yes	Yes	Yes	Yes
Number of Observations	1995	1995	1995	1995	1995
Overidentification (*p*-value)	0.636	0.651	0.638	0.540	0.567

Note: Heteroskedasticity-consistent standard errors clustered by cohort year are in parentheses. Instrumental variables for the population density are the logarithm of population density in 1930 and its squared variable. Constant is not reported. * denotes statistical significance at the 10% level, ** at the 5% level, and *** at the 1% level.

Table OA.4: IV Poisson Regression Estimation Results for Dynamic Fertility Decision and City Size with Linear Effects of Age

	Dependent Variable: Number of Children					
	Sample with Wife's Age < 50, Non-Migrants					
Explanatory Variables	(1)	(2)	(3)	(4)	(5)	(6)
Log(Population Density)	−0.273***	−0.288***	−0.262***	−0.280***	−0.295***	−0.294***
	(0.093)	(0.093)	(0.094)	(0.093)	(0.090)	(0.091)
Log(Population Density) × Wife's Age	0.004**	0.005**	0.004*	0.004**	0.005**	0.005**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Husband's Age	0.081***	0.083***	0.076***	0.076***	0.076***	0.068***
	(0.026)	(0.025)	(0.026)	(0.026)	(0.026)	(0.024)
Husband's Age Squared (×1/100)	−0.086***	−0.088***	−0.080***	−0.080***	−0.081***	−0.073***
	(0.028)	(0.027)	(0.028)	(0.028)	(0.028)	(0.026)
Wife's Age	0.117***	0.111***	0.118***	0.117***	0.116***	0.113***
	(0.039)	(0.038)	(0.040)	(0.039)	(0.038)	(0.038)
Wife's Age Squared (×1/100)	−0.178***	−0.176***	−0.173***	−0.177***	−0.183***	−0.178***
	(0.040)	(0.039)	(0.040)	(0.040)	(0.038)	(0.039)
D(1=University Graduate for Husband)		−0.105***				−0.111***
		(0.025)				(0.024)
D(1=University Graduate for Wife)		−0.121***				−0.107***
		(0.025)				(0.027)
Husband's Income			0.011***			0.016***
			(0.004)			(0.004)
Wife's Income			−0.036***			−0.014**
			(0.008)			(0.007)
Hours Worked Last Week for Husband				0.011		0.004
				(0.011)		(0.011)
Hours Worked Last Week for Wife				−0.045***		−0.029**
				(0.013)		(0.012)
D(1=Non-Labor Force for Husband)				0.020		0.034
				(0.142)		(0.142)
D(1=Non-Labor Force for Wife)				−0.060		−0.039
				(0.058)		(0.055)
D(1=Not Healthy)					−0.080***	−0.094***
					(0.024)	(0.023)
Old-Age Security Motive Score					0.004	0.005
					(0.006)	(0.006)
D(1=Non-Necessity of Children)					−0.072***	−0.072***
					(0.024)	(0.023)
Number of Siblings					0.047***	0.035***
					(0.011)	(0.012)
Cohort Groups, Region, and Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	1779	1779	1779	1779	1779	1779
Overidentification (*p*-value)	0.356	0.320	0.389	0.386	0.370	0.385

Note: Heteroskedasticity-consistent standard errors clustered by cohort year are in parentheses. Instrumental variables for the population density are the logarithm of population density in 1930, its squared variable, and cross-terms of these two variables and wife's age. Constant is not reported. * denotes statistical significance at the 10% level, ** at the 5% level, and *** at the 1% level.

Table OA.5: IV Estimation for Wife's Ages at Marriage, City Size, and Migration

	Dependent Variable: Wife's Age at Marriage				
Explanatory Variables	(1)	(2)	(3)	(4)	(5)
Log(Population Density)	0.263*	0.255*	0.211	0.259*	0.213
	(0.150)	(0.150)	(0.152)	(0.150)	(0.150)
D(1=Migration)		0.111			−0.027
		(0.160)			(0.163)
D(1=University Graduate for Husband)			0.650***		0.644***
			(0.174)		(0.176)
D(1=University Graduate for Wife)			1.488***		1.476***
			(0.270)		(0.265)
D(1=Not Healthy)				−0.232	−0.148
				(0.208)	(0.194)
Old-Age Security Motive Score				−0.043	−0.045
				(0.037)	(0.037)
D(1=Non-Necessity of Children)				−0.085	−0.123
				(0.163)	(0.167)
Number of Siblings				−0.098**	−0.027
				(0.044)	(0.039)
Cohort Groups, Region, and Year Dummies	Yes	Yes	Yes	Yes	Yes
Number of Observations	1658	1658	1658	1658	1658
Overidentification (*p*-value)	0.375	0.380	0.297	0.340	0.276

Note: Heteroskedasticity-consistent standard errors clustered by cohort year are in parentheses. Instrumental variables for the population density are the logarithm of population density in 1930 and its squared variable. Constant is not reported. * denotes statistical significance at the 10% level, ** at the 5% level, and *** at the 1% level.

Table OA.6: IV Estimation for Wife's Ages at Birth of First Child, City Size, and Migration

	Dependent Variable: Wife's Ages at Birth of First Child				
Explanatory Variables	(1)	(2)	(3)	(4)	(5)
Log(Population Density)	0.399***	0.378***	0.321***	0.389***	0.306***
	(0.094)	(0.096)	(0.090)	(0.092)	(0.089)
D(1=Migration)		0.308*			0.196
		(0.165)			(0.163)
D(1=University Graduate for Husband)			0.828***		0.800***
			(0.147)		(0.149)
D(1=University Graduate for Wife)			1.073***		1.069***
			(0.187)		(0.187)
D(1=Not Healthy)				0.033	0.107
				(0.181)	(0.180)
Old-Age Security Motive Score				−0.029	−0.036
				(0.030)	(0.029)
D(1=Non-Necessity of Children)				−0.003	−0.018
				(0.127)	(0.127)
Number of Siblings				−0.118**	−0.043
				(0.053)	(0.053)
Cohort Groups, Region, and Year Dummies	Yes	Yes	Yes	Yes	Yes
Number of Observations	3880	3880	3880	3880	3880
Overidentification (p-value)	0.973	0.967	0.993	0.973	0.991

Note: Heteroskedasticity-consistent standard errors clustered by cohort year are in parentheses. Instrumental variables for the population density are the logarithm of population density in 1930 and its squared variable. Constant is not reported. * denotes statistical significance at the 10% level, ** at the 5% level, and *** at the 1% level.

Table OA.7: Poisson Regression Estimation Results for Dynamic Fertility Decision and City Size with Nonlinear Effects of Age

	Dependent Variable: Number of Children					
	Sample with Wife's Age < 50, Non-Migrants					
Explanatory Variables	(1)	(2)	(3)	(4)	(5)	(6)
Log(Population Density)	−0.719***	−0.724***	−0.687***	−0.715***	−0.723***	−0.696***
	(0.126)	(0.128)	(0.123)	(0.124)	(0.121)	(0.119)
Log(Population Density) × Wife's Age	0.030***	0.030***	0.028***	0.029***	0.030***	0.029***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Log(Population Density) × Wife's Age Squared (×1/100)	−0.033***	−0.033***	−0.031***	−0.032***	−0.033***	−0.032***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Husband's Age	0.007	0.007	0.006	0.006	0.006	0.005
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Wife's Age	−0.018	−0.019	−0.013	−0.017	−0.020	−0.017
	(0.015)	(0.015)	(0.014)	(0.014)	(0.014)	(0.014)
D(1=University Graduate for Husband)		−0.112***				−0.118***
		(0.024)				(0.024)
D(1=University Graduate for Wife)		−0.105***				−0.093***
		(0.027)				(0.029)
Husband's Income			0.011***			0.016***
			(0.004)			(0.004)
Wife's Income			−0.032***			−0.014**
			(0.008)			(0.007)
Hours Worked Last Week for Husband				0.012		0.008
				(0.012)		(0.012)
Hours Worked Last Week for Wife				−0.039***		−0.026**
				(0.013)		(0.012)
D(1=Non-Labor Force for Husband)				0.025		0.050
				(0.141)		(0.140)
D(1=Non-Labor Force for Wife)				−0.058		−0.047
				(0.057)		(0.055)
D(1=Not Healthy)					−0.085***	−0.098***
					(0.024)	(0.024)
Old-Age Security Motive Score					0.005	0.006
					(0.007)	(0.006)
D(1=Non-Necessity of Children)					−0.079***	−0.081***
					(0.024)	(0.023)
Number of Siblings					0.043***	0.033***
					(0.011)	(0.012)
Cohort Groups, Region, and Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	1779	1779	1779	1779	1779	1779
Log Likelihood	−2538.892	−2529.526	−2532.939	−2534.760	−2532.294	−2517.018
AIC	5125.784	5111.052	5117.877	5125.520	5120.587	5106.036

Note: Heteroskedasticity-consistent standard errors clustered by cohort year are in parentheses. Constant is not reported. * denotes statistical significance at the 10% level, ** at the 5% level, and *** at the 1% level.

Table OA.8: IV Poisson Regression Estimation Results for Dynamic Fertility Decision and City Size with Nonlinear Effects of Age

	Dependent Variable: Number of Children					
	Sample with Wife's Age < 50, Non-Migrants					
Explanatory Variables	(1)	(2)	(3)	(4)	(5)	(6)
Log(Population Density)	−0.775***	−0.796***	−0.741***	−0.770***	−0.802***	−0.779***
	(0.119)	(0.118)	(0.117)	(0.118)	(0.112)	(0.110)
Log(Population Density) × Wife's Age	0.030***	0.031***	0.029***	0.030***	0.031***	0.030***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Log(Population Density) × Wife's Age Squared (×1/100)	−0.033***	−0.033***	−0.032***	−0.033***	−0.033***	−0.032***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Husband's Age	0.008**	0.008**	0.007*	0.007*	0.007*	0.006
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Wife's Age	−0.021	−0.026	−0.016	−0.020	−0.027*	−0.026
	(0.017)	(0.017)	(0.017)	(0.016)	(0.016)	(0.016)
D(1=University Graduate for Husband)		−0.107***				−0.113***
		(0.024)				(0.023)
D(1=University Graduate for Wife)		−0.118***				−0.106***
		(0.025)				(0.027)
Husband's Income			0.012***			0.017***
			(0.004)			(0.004)
Wife's Income			−0.036***			−0.014**
			(0.008)			(0.007)
Hours Worked Last Week for Husband				0.013		0.007
				(0.011)		(0.011)
Hours Worked Last Week for Wife				−0.045***		−0.030**
				(0.013)		(0.012)
D(1=Non-Labor Force for Husband)				0.011		0.033
				(0.140)		(0.139)
D(1=Non-Labor Force for Wife)				−0.062		−0.046
				(0.056)		(0.053)
D(1=Not Healthy)					−0.087***	−0.102***
					(0.023)	(0.022)
Old-Age Security Motive Score					0.004	0.004
					(0.006)	(0.006)
D(1=Non-Necessity of Children)					−0.075***	−0.075***
					(0.023)	(0.022)
Number of Siblings					0.046***	0.034***
					(0.011)	(0.011)
Cohort Groups, Region, and Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	1779	1779	1779	1779	1779	1779
Overidentification (*p*-value)	0.559	0.479	0.617	0.607	0.555	0.577

Note: Heteroskedasticity-consistent standard errors clustered by cohort year are in parentheses. Constant is not reported. * denotes statistical significance at the 10% level, ** at the 5% level, and *** at the 1% level. Instrumental variables for the population density and these cross-terms with wife's age and wife's age squared are the logarithm of population density in 1930, its squared variable, and these cross-terms with wife's age and wife's age squared.

Table OA.9: Poisson Regression Estimation Results for Dynamic Fertility Decision and City Size with Discrete Effects of Each Age Group

	Dependent Variable: Number of Children					
	Sample with Wife's Age < 50, Non-Migrants					
Explanatory Variables	(1)	(2)	(3)	(4)	(5)	(6)
Log(Population Density)	−0.130***	−0.126***	−0.134***	−0.139***	−0.130***	−0.135***
	(0.037)	(0.038)	(0.037)	(0.036)	(0.036)	(0.037)
Log(Population Density) × D(Wife's Age 25–29)	0.020	0.022	0.020	0.020	0.022	0.024
	(0.030)	(0.030)	(0.030)	(0.030)	(0.030)	(0.030)
Log(Population Density) × D(Wife's Age 30–34)	0.047	0.053	0.045	0.047	0.050	0.052*
	(0.033)	(0.033)	(0.033)	(0.032)	(0.032)	(0.032)
Log(Population Density) × D(Wife's Age 35–39)	0.070**	0.076**	0.067*	0.070**	0.072**	0.074**
	(0.035)	(0.035)	(0.034)	(0.034)	(0.034)	(0.034)
Log(Population Density) × D(Wife's Age 40–44)	0.074**	0.082**	0.071*	0.075**	0.078**	0.081**
	(0.037)	(0.037)	(0.036)	(0.036)	(0.036)	(0.035)
Log(Population Density) × D(Wife's Age 45–49)	0.058	0.067*	0.056	0.060	0.062	0.067*
	(0.040)	(0.040)	(0.039)	(0.039)	(0.039)	(0.038)
Husband's Age	0.007*	0.007*	0.006	0.006	0.006	0.005
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Wife's Age	0.006	0.005	0.007	0.005	0.004	0.004
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
D(1=University Graduate for Husband)		−0.113***				−0.120***
		(0.024)				(0.024)
D(1=University Graduate for Wife)		−0.100***				−0.089***
		(0.026)				(0.028)
Husband's Income			0.012***			0.016***
			(0.004)			(0.004)
Wife's Income			−0.032***			−0.014**
			(0.008)			(0.007)
Hours Worked Last Week for Husband				0.013		0.009
				(0.012)		(0.012)
Hours Worked Last Week for Wife				−0.039***		−0.026**
				(0.013)		(0.012)
D(1=Non-Labor Force for Husband)				0.024		0.049
				(0.142)		(0.143)
D(1=Non-Labor Force for Wife)				−0.058		−0.048
				(0.058)		(0.056)
D(1=Not Healthy)					−0.081***	−0.094***
					(0.024)	(0.024)
Old-Age Security Motive Score					0.005	0.006
					(0.007)	(0.006)
D(1=Non-Necessity of Children)					−0.079***	−0.081***
					(0.024)	(0.023)
Number of Siblings					0.042***	0.032***
					(0.011)	(0.012)
Cohort Groups, Region, and Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	1779	1779	1779	1779	1779	1779
Log Likelihood	−2541.392	−2532.266	−2535.290	−2537.193	−2535.055	−2519.666
AIC	5136.784	5122.531	5128.580	5136.386	5132.109	5117.332

Note: Heteroskedasticity-consistent standard errors clustered by cohort year are in parentheses. Constant is not reported. * denotes statistical significance at the 10% level, ** at the 5% level, and *** at the 1% level.

Table OA.10: Poisson Regression Estimation Results for Dynamic Fertility Decision and City Size for Sample with Wife's Age ≥ 50

	Dependent Variable: Number of Children			
	Sample with Wife's Age ≥ 50, Non-Migrants			
Explanatory Variables	(1)	(2)	(3)	(4)
Log(Population Density)	−0.053**	−0.057***	−0.043**	−0.047**
	(0.021)	(0.021)	(0.022)	(0.021)
Log(Population Density) × **Wife's Age**	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
D(1=University Graduate for Husband)		−0.005		−0.001
		(0.027)		(0.027)
D(1=University Graduate for Wife)		0.054		0.055
		(0.037)		(0.035)
D(1=Not Healthy)			−0.005	−0.003
			(0.030)	(0.030)
Old-Age Security Motive Score			−0.001	−0.001
			(0.005)	(0.005)
D(1=Non-Necessity of Children)			−0.085***	−0.084***
			(0.025)	(0.024)
Number of Siblings			0.012*	0.013*
			(0.007)	(0.007)
Cohort Groups, Region, and Year Dummies	Yes	Yes	Yes	Yes
Number of Observations	1432	1432	1432	1432
Log Likelihood	−2142.819	−2142.458	−2140.228	−2139.820
AIC	4319.638	4322.917	4322.457	4325.640

Note: Heteroskedasticity-consistent standard errors clustered by cohort year are in parentheses. Constant is not reported. * denotes statistical significance at the 10% level, ** at the 5% level, and *** at the 1% level.

Table OA.11: Poisson Regression Estimation Results for Ideal Number of Children and City Size

	Dependent Variable: Ideal Number of Children						
	Sample with Wife's Age < 50						
Explanatory Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Log(Population Density)	−0.022***	−0.022***	−0.020***	−0.023***	−0.022***	−0.022***	−0.021***
	(0.005)	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)
Husband's Age	0.021**	0.021**	0.022**	0.021**	0.020**	0.021**	0.019**
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Husband's Age Squared (×1/100)	−0.024**	−0.024**	−0.025**	−0.024**	−0.023**	−0.024**	−0.022**
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Wife's Age	−0.008	−0.008	−0.008	−0.009	−0.008	−0.007	−0.007
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.011)
Wife's Age Squared (×1/100)	0.013	0.012	0.012	0.013	0.012	0.010	0.010
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
D(1=Migration)		−0.006					−0.002
		(0.008)					(0.009)
D(1=University Graduate for Husband)			−0.042***				−0.041***
			(0.011)				(0.011)
D(1=University Graduate for Wife)			0.002				0.004
			(0.014)				(0.015)
Husband's Income				0.003*			0.004***
				(0.002)			(0.002)
Wife's Income				−0.001			0.002
				(0.002)			(0.003)
Hours Worked Last Week for Husband					0.002		0.004
					(0.004)		(0.004)
Hours Worked Last Week for Wife					−0.003		−0.005
					(0.003)		(0.004)
D(1=Non-Labor Force for Husband)					−0.079		−0.049
					(0.057)		(0.050)
D(1=Non-Labor Force for Wife)					−0.018		−0.021
					(0.024)		(0.025)
D(1=Not Healthy)						−0.009	−0.010
						(0.015)	(0.015)
Old-Age Security Motive Score						−0.006	−0.006
						(0.004)	(0.004)
D(1=Non-Necessity of Children)						−0.042***	−0.043***
						(0.008)	(0.008)
Number of Siblings						0.025***	0.024***
						(0.006)	(0.006)
Cohort Groups, Region, and Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	2085	2085	2085	2085	2085	2085	2085
Log Likelihood	−3095.212	−3095.197	−3094.189	−3095.040	−3094.998	−3092.170	−3090.791
AIC	6236.425	6238.395	6238.377	6240.080	6243.996	6238.340	6253.582

Note: Heteroskedasticity-consistent standard errors clustered by cohort year are in parentheses. Instrumental variables for the population density are the logarithm of population density in 1930 and its squared variable. Constant is not reported. * denotes statistical significance at the 10% level, ** at the 5% level, and *** at the 1% level.

Table OA.12: Poisson Regression Estimation Results for Dynamic Fertility Decision and City Size Using Ideal Number of Children

	Dependent Variable: Ideal Number of Children					
	Sample with Wife's Age < 50, Non-Migrants					
Explanatory Variables	(1)	(2)	(3)	(4)	(5)	(6)
Log(Population Density)	−0.019	−0.019	−0.017	−0.019	−0.026	−0.024
	(0.025)	(0.025)	(0.025)	(0.024)	(0.024)	(0.024)
Log(Population Density) × Wife's Age	−0.000	0.000	−0.000	−0.000	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Husband's Age	0.016	0.016	0.015	0.015	0.015	0.013
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Husband's Age Squared (×1/100)	−0.017	−0.017	−0.016	−0.016	−0.017	−0.014
	(0.013)	(0.013)	(0.013)	(0.013)	(0.012)	(0.012)
Wife's Age	−0.010	−0.009	−0.010	−0.010	−0.009	−0.008
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
Wife's Age Squared (×1/100)	0.012	0.010	0.013	0.012	0.008	0.008
	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)
D(1=University Graduate for Husband)		−0.041***				−0.041***
		(0.014)				(0.014)
D(1=University Graduate for Wife)		−0.005				−0.003
		(0.017)				(0.017)
Husband's Income			0.004*			0.006**
			(0.002)			(0.002)
Wife's Income			−0.002			0.003
			(0.003)			(0.004)
Hours Worked Last Week for Husband				0.002		0.003
				(0.005)		(0.005)
Hours Worked Last Week for Wife				−0.002		−0.003
				(0.004)		(0.005)
D(1=Non-Labor Force for Husband)				−0.093		−0.070
				(0.067)		(0.060)
D(1=Non-Labor Force for Wife)				0.010		0.008
				(0.027)		(0.028)
D(1=Not Healthy)					−0.011	−0.013
					(0.013)	(0.014)
Old-Age Security Motive Score					−0.006	−0.007
					(0.004)	(0.004)
D(1=Non-Necessity of Children)					−0.037***	−0.037***
					(0.009)	(0.009)
Number of Siblings					0.029***	0.028***
					(0.008)	(0.008)
Cohort Groups, Region, and Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	1585	1585	1585	1585	1585	1585
Log Likelihood	−2356.609	−2355.825	−2356.411	−2356.411	−2354.189	−2353.014
AIC	4761.219	4763.650	4764.822	4768.821	4764.377	4778.027

Note: Heteroskedasticity-consistent standard errors clustered by cohort year are in parentheses. Constant is not reported. * denotes statistical significance at the 10% level, ** at the 5% level, and *** at the 1% level.

Table OA.13: Income Effects and Opportunity Costs of Rearing Children

	Dependent Variable: Number of Children					
	Sample with Wife's Age < 50					
Explanatory Variables	(1)	(2)	(3)	(4)	(5)	(6)
Log(Population Density)	−0.077***	−0.076***	−0.080***	−0.068***	−0.064***	−0.067***
	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)
Husband's Age	0.087***	0.089***	0.085***	0.080***	0.085***	0.080***
	(0.029)	(0.028)	(0.028)	(0.027)	(0.027)	(0.027)
Husband's Age Squared (×1/100)	−0.095***	−0.097***	−0.093***	−0.088***	−0.092***	−0.088***
	(0.031)	(0.030)	(0.030)	(0.029)	(0.029)	(0.029)
Wife's Age	0.164***	0.164***	0.162***	0.164***	0.166***	0.163***
	(0.029)	(0.029)	(0.029)	(0.027)	(0.028)	(0.028)
Wife's Age Squared (×1/100)	−0.189***	−0.186***	−0.184***	−0.189***	−0.190***	−0.187***
	(0.034)	(0.035)	(0.035)	(0.033)	(0.033)	(0.033)
Husband's Income	0.009***		0.010***	0.014***		0.015***
	(0.003)		(0.003)	(0.003)		(0.003)
Wife's Income		−0.033***	−0.034***		−0.013**	−0.017***
		(0.007)	(0.007)		(0.006)	(0.006)
D(1=Migration)				−0.061**	−0.054*	−0.063**
				(0.028)	(0.029)	(0.028)
D(1=University Graduate for Husband)				−0.124***	−0.109***	−0.121***
				(0.023)	(0.022)	(0.023)
D(1=University Graduate for Wife)				−0.094***	−0.078***	−0.085***
				(0.020)	(0.021)	(0.021)
Hours Worked Last Week for Husband				0.009	0.009	0.006
				(0.010)	(0.010)	(0.010)
Hours Worked Last Week for Wife				−0.044***	−0.037***	−0.032***
				(0.010)	(0.011)	(0.011)
D(1=Non-Labor Force for Husband)				−0.089	−0.159	−0.092
				(0.172)	(0.169)	(0.170)
D(1=Non-Labor Force for Wife)				−0.103*	−0.100*	−0.098*
				(0.055)	(0.056)	(0.056)
D(1=Not Healthy)				−0.065**	−0.062**	−0.064**
				(0.028)	(0.028)	(0.028)
Old-Age Security Motive Score				0.008	0.010*	0.009
				(0.006)	(0.005)	(0.006)
D(1=Non-Necessity of Children)				−0.078***	−0.080***	−0.079***
				(0.019)	(0.018)	(0.018)
Number of Siblings				0.027**	0.023**	0.025**
				(0.011)	(0.011)	(0.011)
Cohort Groups, Region, and Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	2339	2339	2339	2339	2339	2339
Log Likelihood	−3330.405	−3324.395	−3322.692	−3301.773	−3303.963	−3300.614
AIC	6710.810	6698.789	6697.384	6675.546	6679.927	6675.229

Note: Heteroskedasticity-consistent standard errors clustered by cohort year are in parentheses. Constant is not reported. * denotes statistical significance at the 10% level, ** at the 5% level, and *** at the 1% level.

Table OA.14: Number of Children and Preference Heterogeneity for Quality of Children

	Dependent Variable: Number of Children			
	Sample with Wife's Age < 50 (Only 2006 JGSS)			
Explanatory Variables	(1)	(2)	(3)	(4)
Log(Population Density)	−0.097***	−0.093***	−0.086***	−0.087***
	(0.018)	(0.018)	(0.020)	(0.019)
D(1=Importance of Taking Lessons After-School)		−0.117*		−0.102*
		(0.061)		(0.058)
Husband's Age			−0.010	−0.012
			(0.069)	(0.071)
Husband's Age Squared (×1/100)			0.020	0.021
			(0.074)	(0.077)
Wife's Age			0.230***	0.243***
			(0.085)	(0.085)
Wife's Age Squared (×1/100)			−0.255**	−0.273***
			(0.101)	(0.102)
Cohort Groups and Region Dummies	No	No	Yes	Yes
Number of Observations	624	624	624	624
Log Likelihood	−921.908	−920.102	−891.758	−890.431
AIC	1847.816	1846.205	1819.516	1818.862

Note: Heteroskedasticity-consistent standard errors clustered by cohort year are in parentheses. Constant is not reported. * denotes statistical significance at the 10% level, ** at the 5% level, and *** at the 1% level. The 2006 JGSS asks the question "Generally speaking, how important do you think the following are for children?: Taking lessons after-school." The dummy variable D(1=Importance of Taking Lessons After-School) takes the value of 1 if individuals answer very important or important and 0 otherwise.

Table OA.15: Zero-Inflated Poisson Regression Estimation Results for Fertility Decision and City Size

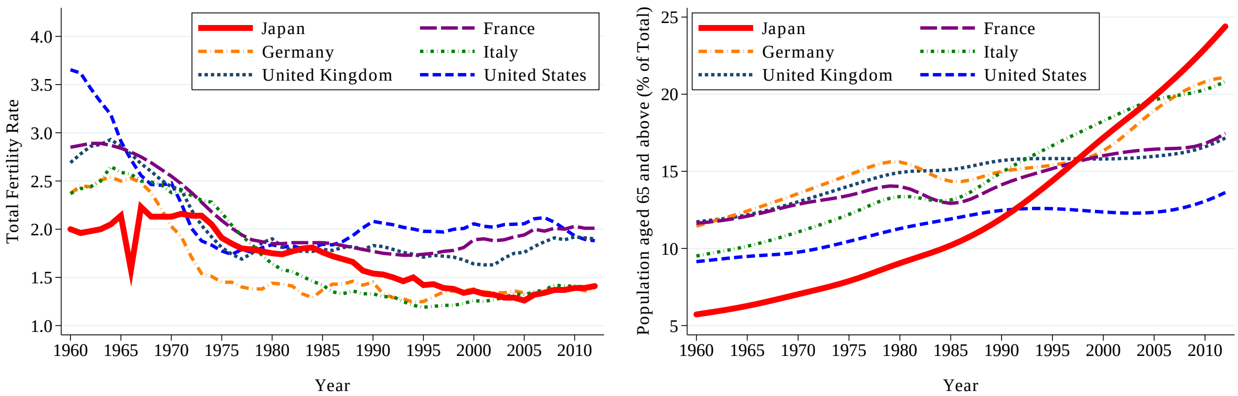
	Dependent Variable: Number of Children						
	Sample with Wife's Age < 50						
Explanatory Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Log(Population Density)	−0.072***	−0.067***	−0.062***	−0.079***	−0.081***	−0.070***	−0.067***
	(0.015)	(0.015)	(0.014)	(0.015)	(0.016)	(0.015)	(0.015)
Husband's Age	0.088***	0.087***	0.090***	0.083***	0.085***	0.087***	0.079***
	(0.028)	(0.028)	(0.028)	(0.028)	(0.028)	(0.028)	(0.027)
Husband's Age Squared (×1/100)	−0.097***	−0.095***	−0.099***	−0.092***	−0.093***	−0.095***	−0.087***
	(0.030)	(0.030)	(0.030)	(0.030)	(0.030)	(0.030)	(0.029)
Wife's Age	0.163***	0.165***	0.166***	0.159***	0.161***	0.164***	0.161***
	(0.028)	(0.028)	(0.028)	(0.028)	(0.028)	(0.028)	(0.027)
Wife's Age Squared (×1/100)	−0.188***	−0.190***	−0.190***	−0.181***	−0.185***	−0.189***	−0.185***
	(0.033)	(0.033)	(0.033)	(0.034)	(0.034)	(0.033)	(0.033)
D(1=Migration)		−0.069**					−0.063**
		(0.028)					(0.028)
D(1=University Graduate for Husband)			−0.122***				−0.120***
			(0.025)				(0.022)
D(1=University Graduate for Wife)			−0.075***				−0.073***
			(0.020)				(0.020)
Husband's Income				0.011***			0.015***
				(0.003)			(0.003)
Wife's Income				−0.033***			−0.017***
				(0.007)			(0.006)
Hours Worked Last Week for Husband					0.009		0.006
					(0.011)		(0.010)
Hours Worked Last Week for Wife					−0.044***		−0.031***
					(0.010)		(0.011)
D(1=Non-Labor Force for Husband)					−0.133		−0.089
					(0.175)		(0.169)
D(1=Non-Labor Force for Wife)					−0.100*		−0.096*
					(0.054)		(0.056)
D(1=Not Healthy)						−0.056**	−0.064**
						(0.028)	(0.028)
Old-Age Security Motive Score						0.009	0.009
						(0.006)	(0.006)
D(1=Non-Necessity of Children)						−0.064***	−0.074***
						(0.020)	(0.019)
Number of Siblings						0.036***	0.026**
						(0.011)	(0.011)
Cohort Groups, Region, and Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Inflation Equation							
Wife's Age	−0.177***	−0.177***	−0.188***	−0.183***	−0.181***	−0.183***	−0.204***
	(0.042)	(0.043)	(0.045)	(0.042)	(0.042)	(0.043)	(0.047)
D(1=University Graduate for Wife)	16.268***	16.266***	14.642***	15.218***	15.146***	15.222***	14.560***
	(0.668)	(0.668)	(0.911)	(0.672)	(0.684)	(0.673)	(1.178)
D(1=Non-Necessity of Children)	14.917***	14.914***	13.920***	13.870***	13.878***	13.235***	13.301***
	(0.842)	(0.831)	(0.673)	(0.763)	(0.731)	(1.139)	(0.965)
Number of Observations	2339	2339	2339	2339	2339	2339	2339
Number of Zero Observations	301	301	301	301	301	301	301
Log Likelihood	−3328.045	−3326.509	−3317.469	−3319.425	−3321.364	−3322.031	−3300.085
AIC	6712.090	6711.018	6694.938	6698.849	6706.728	6708.062	6682.170

Note: Heteroskedasticity-consistent standard errors clustered by cohort year are in parentheses. Constant is not reported. * denotes statistical significance at the 10% level, ** at the 5% level, and *** at the 1% level.

Table OA.16: Zero-Inflated Poisson Regression Estimation Results for Dynamic Fertility Decision and City Size

	Dependent Variable: Number of Children					
	Sample with Wife's Age < 50, Non-Migrants					
Explanatory Variables	(1)	(2)	(3)	(4)	(5)	(6)
Log(Population Density)	−0.242***	−0.243***	−0.230***	−0.244***	−0.245***	−0.237***
	(0.080)	(0.080)	(0.080)	(0.077)	(0.079)	(0.076)
Log(Population Density) × Wife's Age	0.004**	0.005**	0.004**	0.004**	0.004**	0.004**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Husband's Age	0.071**	0.071**	0.066**	0.067**	0.067**	0.059**
	(0.029)	(0.029)	(0.029)	(0.029)	(0.029)	(0.028)
Husband's Age Squared (×1/100)	−0.074**	−0.074**	−0.069**	−0.071**	−0.071**	−0.062**
	(0.032)	(0.031)	(0.032)	(0.031)	(0.032)	(0.031)
Wife's Age	0.124***	0.125***	0.123***	0.125***	0.125***	0.127***
	(0.034)	(0.034)	(0.035)	(0.034)	(0.034)	(0.034)
Wife's Age Squared (×1/100)	−0.186***	−0.189***	−0.179***	−0.186***	−0.190***	−0.188***
	(0.040)	(0.041)	(0.041)	(0.040)	(0.039)	(0.040)
D(1=University Graduate for Husband)		−0.111***				−0.116***
		(0.025)				(0.024)
D(1=University Graduate for Wife)		−0.104***				−0.096***
		(0.027)				(0.029)
Husband's Income			0.011***			0.015***
			(0.004)			(0.004)
Wife's Income			−0.031***			−0.014**
			(0.008)			(0.007)
Hours Worked Last Week for Husband				0.010		0.006
				(0.011)		(0.012)
Hours Worked Last Week for Wife				−0.037***		−0.025**
				(0.012)		(0.012)
D(1=Non-Labor Force for Husband)				0.019		0.048
				(0.143)		(0.144)
D(1=Non-Labor Force for Wife)				−0.052		−0.046
				(0.057)		(0.055)
D(1=Not Healthy)					−0.081***	−0.094***
					(0.025)	(0.025)
Old-Age Security Motive Score					0.005	0.007
					(0.007)	(0.006)
D(1=Non-Necessity of Children)					−0.069***	−0.077***
					(0.026)	(0.024)
Number of Siblings					0.044***	0.034***
					(0.011)	(0.012)
Cohort Groups, Region, and Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Inflation Equation						
Wife's Age	−0.149***	−0.159***	−0.156***	−0.152***	−0.155***	−0.246
	(0.051)	(0.055)	(0.050)	(0.049)	(0.051)	(0.181)
D(1=University Graduate for Wife)	16.512***	13.505***	14.835***	14.828***	15.631***	1.983
	(0.872)	(3.572)	(0.953)	(0.927)	(1.158)	(4.052)
D(1=Non-Necessity of Children)	15.113***	12.768***	13.492***	13.530***	13.783***	1.003
	(1.070)	(3.465)	(1.076)	(1.023)	(1.355)	(3.802)
Number of Observations	1779	1779	1779	1779	1779	1779
Number of Zero Observations	205	205	205	205	205	205
Log Likelihood	−2535.773	−2527.245	−2530.275	−2532.006	−2529.869	−2515.435
AIC	5129.547	5116.491	5122.551	5130.012	5125.738	5112.871

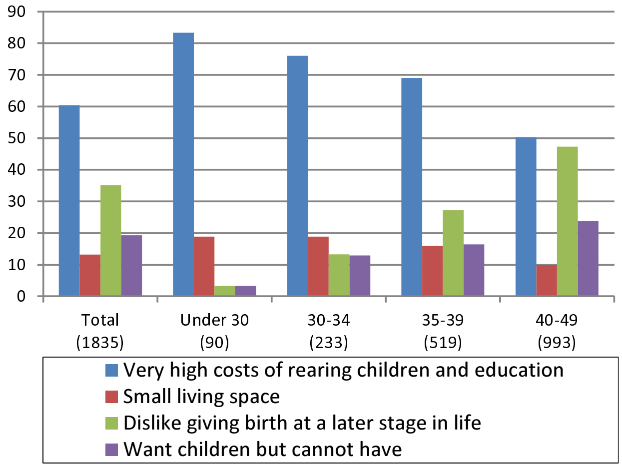
Note: Heteroskedasticity-consistent standard errors clustered by cohort year are in parentheses. Constant is not reported. * denotes statistical significance at the 10% level, ** at the 5% level, and *** at the 1% level.



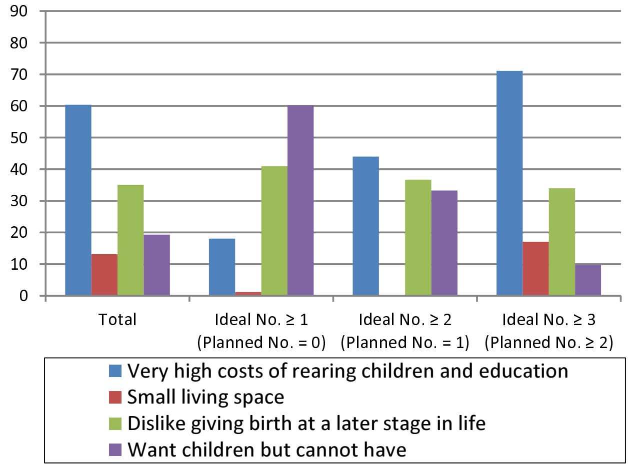
(a) Total Fertility Rate (b) Share of Population Aged 65 and Above

Figure OA.1: Total Fertility Rates and Population Aging Rate of Selective Developed Countries

Note: Created by author. Japan's fertility data are obtained from the Vital Statistics of the Ministry of Health, Labour and Welfare. Other data are obtained from the World DataBank of the World Bank.



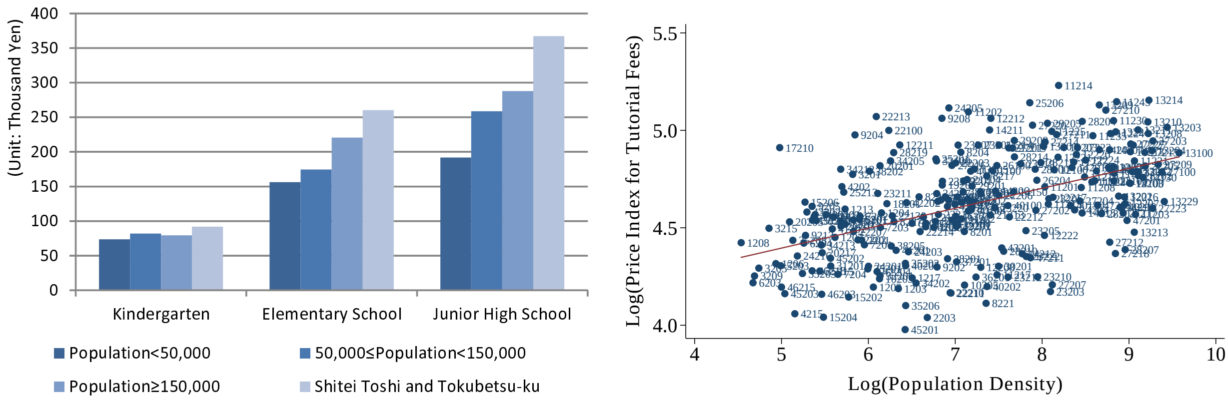
(a) By Age Group



(b) Compared with Planned Number of Children

Figure OA.2: Reasons Why Households Do Not Have Ideal Number of Children (Multiple answers allowed, %)

Note: Created by author based on 2010 Japanese National Fertility Survey Volume I, National Institute of Population and Social Security Research.

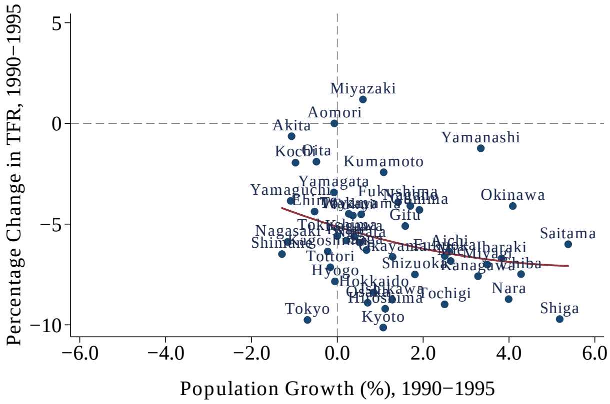


(a) Annual costs of extramural activities for public school students by city size, 2012 (Current Price)

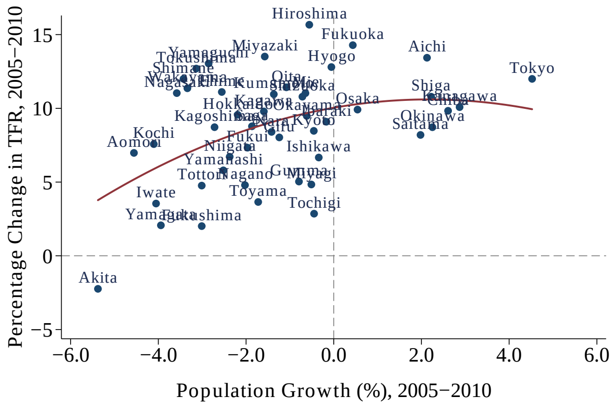
(b) Price Index for Tutorial Fees, 2007

Figure OA.3: Costs of Education and Agglomeration

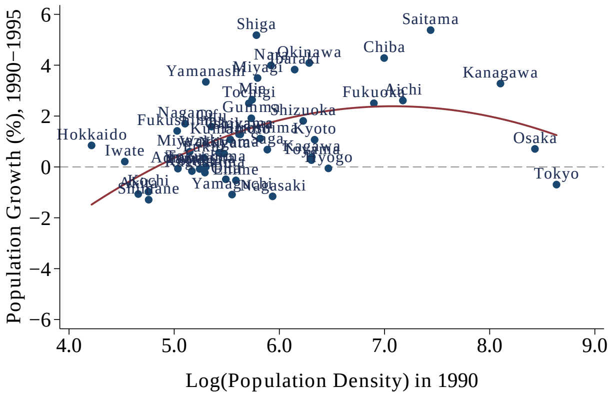
Note: Created by author. Panel (a) is based on 2012 Survey on Household Expenditures on Education per Student (Ministry of Education, Culture, Sports, Science and Technology). Panel (b) is based on tutorial fees from 2007 National Survey of Prices (Ministry of Internal Affairs and Communications). Numbers in Panel (b) represent the municipality code. Average population densities are calculated using 2005 and 2010 population censuses.



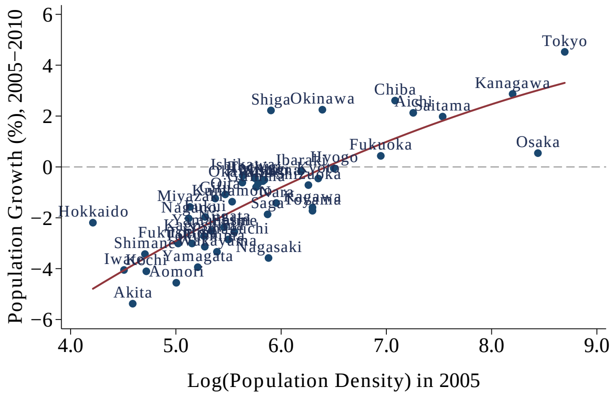
(a) Percentage Change in TFR, 1990-1995



(b) Percentage Change in TFR, 2005-2010



(c) Population Growth and Initial City Size, 1990–1995



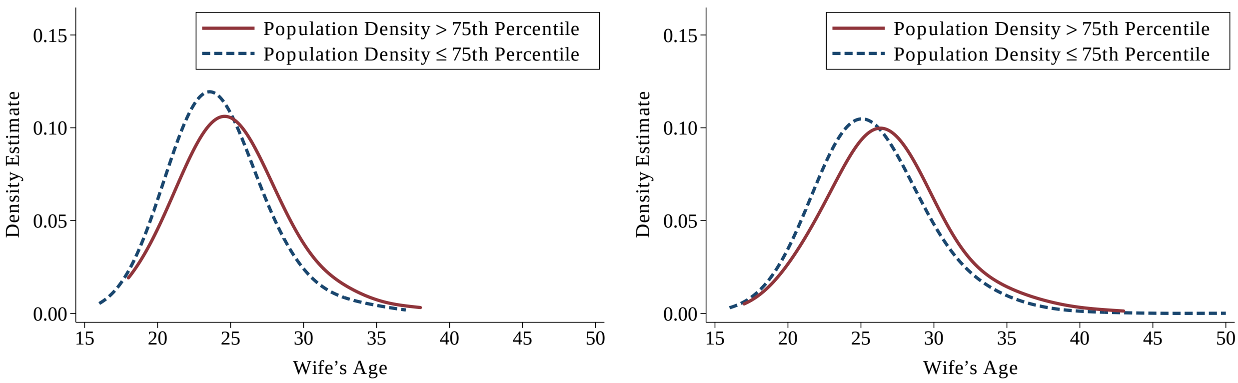
(d) Population Growth and Initial City Size, 2005–2010

Figure OA.4: Percentage Change in Total Fertility Rates and City Size

Note: Author's calculation. The total fertility rates by prefecture are taken from 2016 Vital Statistics (Ministry of Health, Labour and Welfare). The population by prefecture is taken from 1990, 1995, 2005, and 2010 Population Censuses (Statistics Bureau, Ministry of Internal Affairs and Communications). Percentage change in TFR of prefecture r is calculated as $(\mathrm{TFR}_{r,t} - \mathrm{TFR}_{r,t-5})/\mathrm{TFR}_{r,t-5}$. Population growth of prefecture r is calculated as the log-difference, $\log(\mathrm{Pop}_{r,t}) - \log(\mathrm{Pop}_{r,t-5})$.

Figure OA.5: Instrumental Variables for Population Density

Note: Author's calculation from the 1930, 1980, 1985, 1990, 1995, 2000, 2005, and 2010 population censuses. The vertical axis represents the population density in survey year for sample with wife's age < 50 and population density at age 50 for sample with wife's age ≥ 50. The geographical unit is based on 47 prefectures using a three-tiered category of municipalities (1: 23 wards of Tokyo and ordinance-designated city, 2: city, and 3: town/village)

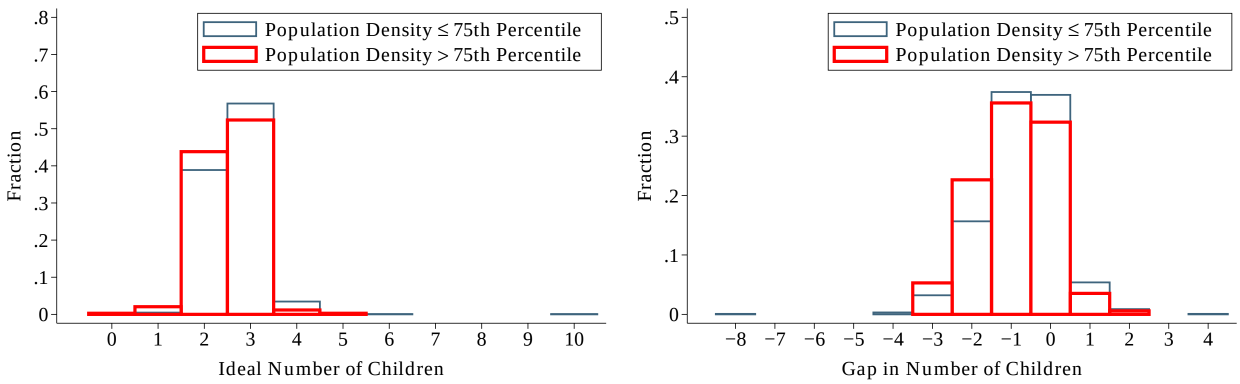


(a) Wife's Age at Marriage

(b) Wife's Age at Birth of the First Child

Figure OA.6: Distributions of Wife's Age between Large and Small Cities

Note: Author's calculation from Japanese General Social Surveys Cumulative Data 2000–2010. Sample does not include migrants. The 75th percentile is based on population densities in Table OA.1.

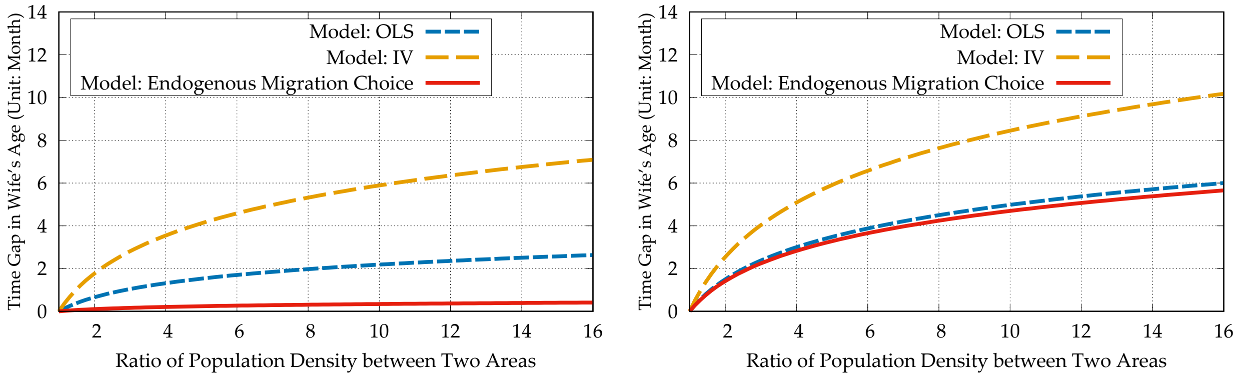


(a) Ideal Number of Children

(b) Gap in Number of Children

Figure OA.7: Histograms of Ideal Number of Children per Married Couple between Large and Small Cities

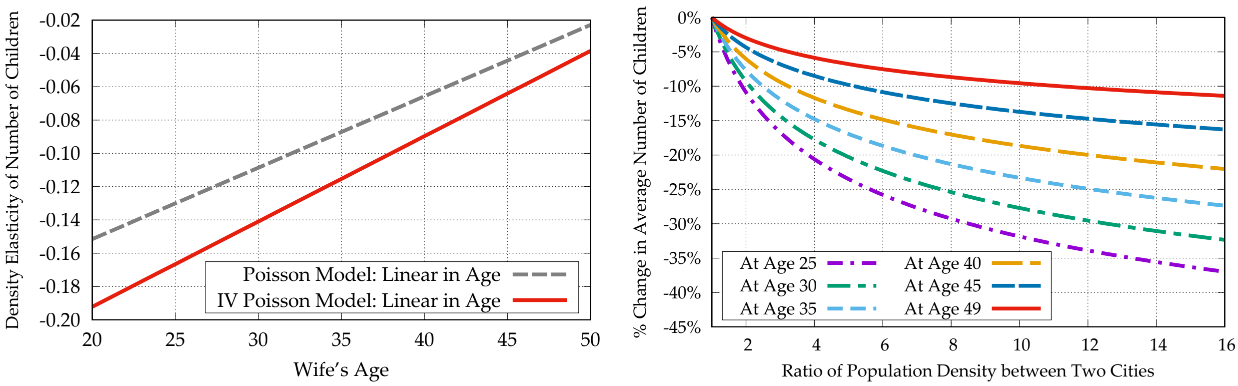
Note: Author's calculation from Japanese General Social Surveys Cumulative Data 2000–2010. The sample with wife's age < 50 is used and migrants are exclude from the sample. The gap in number of children measures the difference between the actual and ideal numbers of children.



(a) Gap in Wife's Age at Marriage (b) Gap in Wife's Age at Birth of the First Child

Figure OA.8: Gap in Wife's Age by City Size

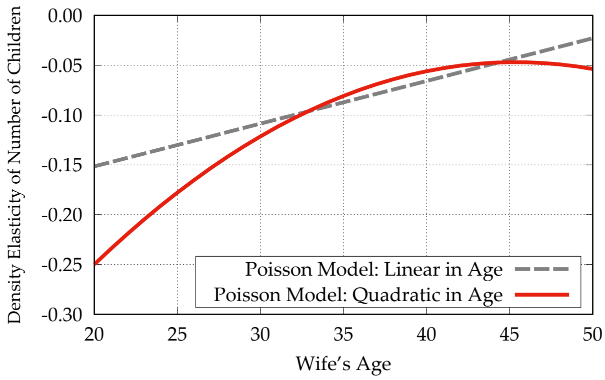
Note: The gap in wife's age is calculated as $\text{Age}^{\text{wife}}_{s,k} - \text{Age}^{\text{wife}}_{r,k} = \hat{\alpha}_k \times \log(\text{Ratio}_{sr})$, where $k \in$ {Marriage, Birth of the First Child}, Ratio_{sr} is the population density ratio between cities s and r, and households' characteristics are assumed to be identical. The time gap is measured in months. This numerical simulation in Panels (a) and (b) uses the estimates in Columns (5)–(8) of Tables 7 of the main text, Column (5) of Table OA.5, and Column (5) of Table OA.6.



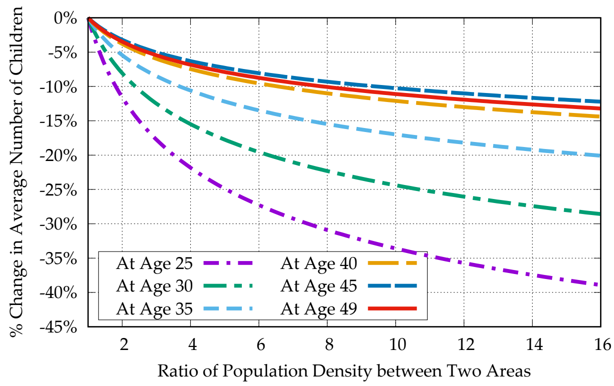
(a) Density Elasticity of Number of Children (b) Spatial Variation in Average Number of Children

Figure OA.9: Percentage Change in the Average Number of Children by City Size Simulated from IV Poisson Estimates

Note: The density elasticity of the number of children in Panel (a) is calculated as $\hat{\alpha} + \hat{\phi} \times \text{Age}$ using the estimates in Columns (6) of Table OA.4. The baseline model drawn in Panel (a) is the Poisson model with a linear process of dynamic fertility behavior (Figure 6 in the main text). The percentage change in the average number of children in Panel (b) is calculated as $[\lambda_s(\hat{\boldsymbol{\theta}}) - \lambda_r(\hat{\boldsymbol{\theta}})]/\lambda_r(\hat{\boldsymbol{\theta}}) = \text{Ratio}_{sr}^{\hat{\alpha}+\hat{\phi}\times\text{Age}} - 1$, where Ratio_{sr} is the population density ratio between cities s and r, and households' characteristics are assumed to be identical. This numerical simulation uses the estimates $\hat{\boldsymbol{\theta}}$ in Columns (6) of Table OA.4.



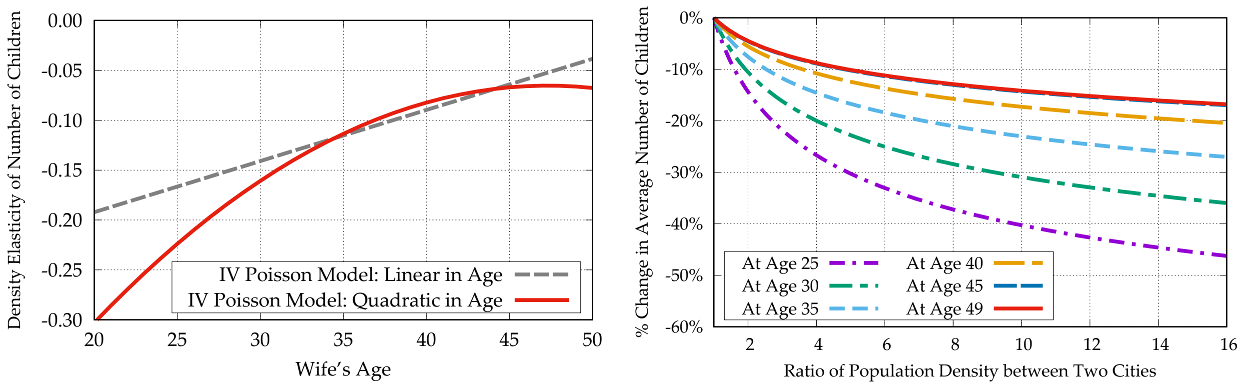
(a) Density Elasticity of Number of Children



(b) Spatial Variation in Average Number of Children

Figure OA.10: Percentage Change in the Average Number of Children by City Size Simulated from Poisson Estimates with Nonlinear Effects of Age

Note: The density elasticity of the number of children in Panel (a) is calculated as $\hat{\alpha}+\hat{\phi}_1\times\text{Age}+\hat{\phi}_2\times(\text{Age}^2/100)$ using the estimates in Columns (6) of Table OA.7. The baseline model drawn in Panel (a) is the Poisson model with linear process of dynamic fertility behavior (Figure 6 in the main text). The percentage change in the average number of children in Panel (b) is calculated as $[\lambda_s(\hat{\boldsymbol{\theta}}) - \lambda_r(\hat{\boldsymbol{\theta}})]/\lambda_r(\hat{\boldsymbol{\theta}}) = \text{Ratio}_{sr}^{\hat{\alpha}+\hat{\phi}_1\times\text{Age}+\hat{\phi}_2\times(\text{Age}^2/100)} - 1$, where Ratio_{sr} is the population density ratio between cities s and r, and households' characteristics are assumed to be identical. This numerical simulation uses the estimates $\hat{\boldsymbol{\theta}}$ in Columns (6) of Table OA.7.

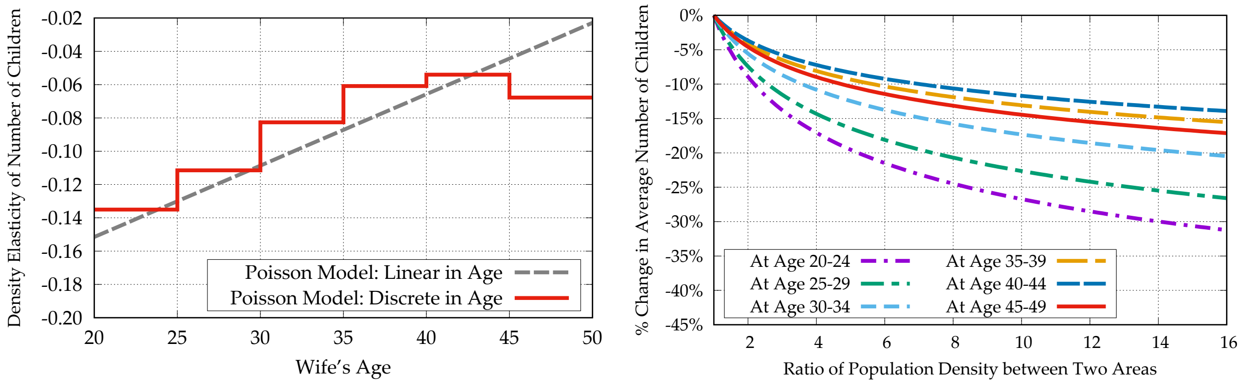


(a) Density Elasticity of Number of Children

(b) Spatial Variation in Average Number of Children

Figure OA.11: Percentage Change in the Average Number of Children by City Size Simulated from IV Poisson Estimates with Nonlinear Effects of Age

Note: The density elasticity of number of children in Panel (a) is calculated as $\hat{\alpha}+\hat{\phi}_1\times\text{Age}+\hat{\phi}_2\times(\text{Age}^2/100)$ using the estimates in Columns (6) of Table OA.8. The baseline model drawn in Panel (a) is the IV Poisson model with linear process of dynamic fertility behavior (Figure OA.9 in Online Appendix). The percentage change in average number of children in Panel (b) is calculated as $[\lambda_s(\hat{\boldsymbol{\theta}}) - \lambda_r(\hat{\boldsymbol{\theta}})]/\lambda_r(\hat{\boldsymbol{\theta}}) = \text{Ratio}_{sr}^{\hat{\alpha}+\hat{\phi}_1\times\text{Age}+\hat{\phi}_2\times(\text{Age}^2/100)} - 1$, where Ratio_{sr} is the population density ratio between cities s and r, and households' characteristics are assumed to be identical. This numerical simulation uses the estimates $\hat{\boldsymbol{\theta}}$ in Columns (6) of Table OA.8.



(a) Density Elasticity of Number of Children (b) Spatial Variation in Average Number of Children

Figure OA.12: Percentage Change in the Average Number of Children by City Size Simulated from Poisson Estimates with Discrete Effects for Each Age Group

Note: The density elasticity of the number of children in Panel (a) is calculated as $\hat{\alpha} + \sum_{g=1}^{5} \hat{\phi}_g \times D_g(\text{Age})$ using the estimates in Columns (6) of Table OA.9. The term $D_g(\text{Age})$ indicates the dummy variable of each age group as $g = 1$: 25–29, $g = 2$: 30–34, $g = 3$: 35–39, $g = 4$: 40–44, $g = 5$: 45–49. The baseline age group is 20–24. The baseline model drawn in Panel (a) is the Poisson model with linear process of dynamic fertility behavior (Figure 6 in the main text). The percentage change in the average number of children in Panel (b) is calculated as $[\lambda_s(\hat{\boldsymbol{\theta}}) - \lambda_r(\hat{\boldsymbol{\theta}})]/\lambda_r(\hat{\boldsymbol{\theta}}) = \text{Ratio}_{sr}^{\hat{\alpha}+\sum_{g=1}^{5}\hat{\phi}_g \times D_g(\text{Age})} - 1$, where Ratio_{sr} is the population density ratio between cities s and r, and households' characteristics are assumed to be identical. This numerical simulation uses the estimates $\hat{\boldsymbol{\theta}}$ in Columns (6) of Table OA.9.