

Living in a Ghost Town: The Geography of Depopulation and Aging

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Abstract

We study how depopulation and aging progress across regions within a country and how this process affects economic welfare across regions and generations. Using spatially disaggregated data from Japan for the last 40 years, we document that youths' out-migration accelerated rural depopulation and aging, leading to a decline in rural economic activity. Motivated by this evidence, we develop a dynamic life-cycle spatial equilibrium model of migration decisions. Using the calibrated model, we find that endogenous decline in rural amenities plays a crucial role in the past and future youths' out-migration, and hence accelerates the regional disparity in depopulation and aging. Shutting down cross-regional migration comes at a substantial welfare loss for the youths, while generating limited benefits even for the elderly in rural areas.

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1 Introduction

It is well known that aging and depopulation (population decline) are among the major challenges for the world this century. By 2050, 26 countries are estimated to reduce their population by more than 10 percent ([United Nations, 2019](#)). At the same time, 16 percent of the world population is estimated to be over age 65 by 2050, almost doubling from 9 percent in 2019. Academics and policy-makers have cautioned that the declining population size and labor force affect our lives, particularly by slowing economic growth and increasing the burden of economically sustaining the elderly.

What is less studied is that aging and depopulation mask critical spatial heterogeneity within a country. Anecdotal evidence highlights the strong incumbency of locations losing working-age populations rapidly (i.e., “ghost towns”) while some regions pullulate with youth. Since many aspects of our economic activity are influenced by the local economic activity (e.g., labor market, amenities, housing), the differential rates of depopulation and aging may affect regional disparity in economic activity and welfare. Notably, internal migration may affect the process of regional depopulation and aging while simultaneously affecting aggregate welfare and its heterogeneity across regions and generations. If this is the case, policies subsidizing migration to rural areas, as found in Japan and many European countries, may have important aggregate and distributional implications.

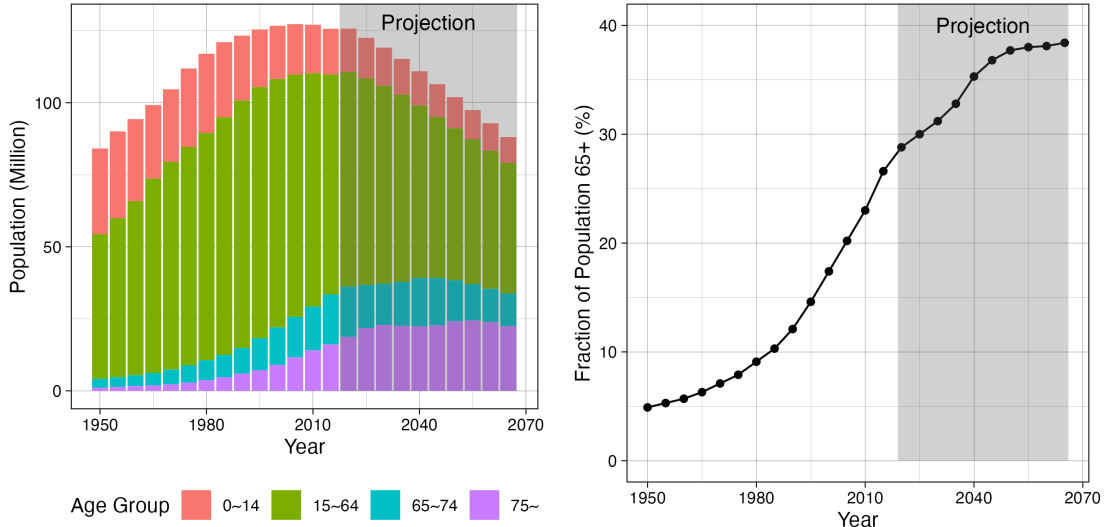
Against this background, this paper studies how depopulation and aging progress across regions within a country and how this process affects welfare across regions and generations. We argue that internal migration over the life cycle is critical to understanding these issues. Using spatially disaggregated data from Japan for the last 40 years, we document that youths’ out-migration accelerated rural depopulation and aging. This process led to a decline in rural economic activity. Motivated by this evidence, we develop a dynamic life-cycle spatial equilibrium model of migration decisions. Using the calibrated model, we find that endogenous decline in rural amenities plays a crucial role in the past and future youths’ out-migration, and hence rural depopulation and aging. Restricting this migration comes at a substantial welfare loss for the youths, while generating limited benefits even for the elderly in rural areas.

Japan is a natural setting to study these questions. As of 2015, Japan accommodates the world’s highest fraction of the aged population; 26 percent of the population was over 65 years old in 2015, and it is expected to rise to 37 percent by 2050 (Figure 1). The population has started declining since 2010 and is expected to shrink by nearly 20 percent relative to 2010 by 2050. Increasing life expectancy and falling fertility rates primarily drive this pattern (Figure

Figure 1: Aggregate Patterns of Depopulation and Aging in Japan

(a) Population Decomposition by Age

(b) Fraction of Population above 65 Years Old



Source: Official Statistics.

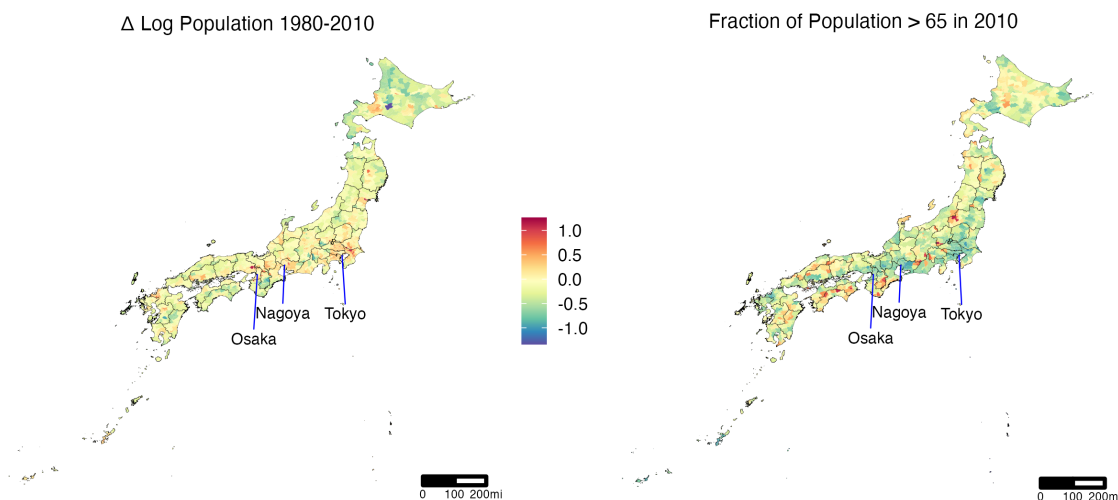
B.1).¹

At the same time, there is substantial heterogeneity in depopulation and aging across regions. The left panel of Figure 2 shows the population changes from 1980 to 2010 across municipalities in Japan (left figure). There is a huge variation in the changes in population size. Some municipalities are doubling their population over the 30 years, particularly those around major metropolitan areas in Japan, Tokyo, Osaka, and Nagoya. At the same time, some municipalities in rural areas have lost population by more than 100 percent. The right panel of Figure 2 shows the fraction of the population over 65 years old. Similarly, as the population size changes, there is a huge spatial variation. Around major metropolitan areas, the fraction of the elderly is 10-20 percent, significantly lower than the national average of 23 percent. At the same time, in some rural municipalities, over 50 percent of the population is elderly. The apparent heterogeneity of depopulation and aging across municipalities has alarmed policymakers. In a sensational book, “Extinctions of Rural Municipalities (*Chiho Shometsu*),” Hiroya Masuda, then the governor of Iwate prefecture, cautioned that nearly half of the municipalities in Japan may disappear by 2040 (*Chiho Shometsu*).

This paper is divided into three parts. In the first part, we document spatial patterns of

¹International migration plays a limited role in Japan because there has been limited international out- and in-migration in the past compared to major advanced economies.

Figure 2: Heterogeneity of Depopulation and Aging across Municipalities in Japan



Note: This figure reports the map of Japan at the municipality level. The left figure shows the patterns of the changes in population from 1980 to 2010. The right figure shows the fraction of the population over 65 years old. The solid black border indicates the prefecture boundaries. See Figure B.2 for the density distribution of these variables across municipalities.

depopulation and aging using spatially disaggregated data from Japan for the last 40 years. We show that depopulation has progressed more rapidly in rural areas than urban areas. We also show that this rural depopulation is accelerated by out-migration, in particular that of youths, on top of natural population changes (birth and death). Rural aging is accelerated by the fact that, while youths migrate out from rural areas, the elderly tend to stay in rural areas.

How do these regional depopulation and aging affect the local economy? To answer this question, we also document how regional depopulation and aging affect regional income, various dimensions of amenities, and land prices. To address the endogeneity of regional depopulation and aging, we adopt the strategy from migration literature to use the variation of regional depopulation and aging using pull and push migration shocks from other municipalities (e.g., [Boustan \(2010\)](#), [Derenoncourt \(2022\)](#) and [Bazzi et al. \(2023\)](#)). Using this design, we find that an increase in the working-age population increases average income per capita, while that of the elderly population decreases it. We also document that an increase in working-age and the elderly population have heterogeneous effects on different types of amenity proxies; the former increases amenities related to retail, health/medical, and child/education, while the latter increases the amenities related to the elderly service. Finally, we find that both the

working-age and elderly populations lead to an increase in land prices. Overall, we find that both the decline of working age and the elderly population affect various dimensions of local economic activity, while they have heterogeneous effects on different proxies.

Motivated by the empirical evidence, in the second part of the paper, we develop a quantitative dynamic spatial general equilibrium model to formalize the relationship between life-cycle migration decisions and regional economic activities. At every period, individuals of different ages make forward-looking decisions to migrate to other locations within a country depending on productivity, amenities, housing costs, and migration costs. The spatial population distribution, in turn, determines these regional economic variables. Together, the model allows us to connect endogenous lifecycle migration decisions with the aggregate dynamics of regional depopulation, aging, and local economic activities.

In the third part of the paper, we use our model to quantitatively assess the role of life-cycle migration decisions on the spatial patterns of depopulation and aging, as well as the economic welfare across regions and generations. We map our model to data by capturing the heterogeneity in location fundamentals, as productivity, amenity, and migration costs. We also estimate the agglomeration spillovers on regional productivity and amenity by combining the structure of the model with an empirical design similar to the one implemented in the reduced-form section of the paper. We find that productivity spillovers from the working-age population and the elderly population are both not significantly different from zero. In contrast, we find significant and positive amenity spillovers from a population size within age groups, while that of the cross-age groups (e.g., spillovers from the youth to the elderly) tend to be smaller and often not statistically significantly different from zero. These findings are consistent with the observation in the reduced-form section of the paper that the local population sizes of different age groups have different effects on different types of amenities (e.g., elderly service v.s. child/education).

Using the calibrated model, we first show that the interaction of local economic conditions and migration decisions is key to understanding the pattern of regional depopulation and aging. In particular, when we run a counterfactual simulation to shutting down the endogenous agglomeration spillovers in amenities, we find that the rates of rural depopulation and aging are significantly slower from 1990 to 2015. These effects of shutting down the endogenous amenity spillover are similar in magnitude to the counterfactual simulation to completely shut down the migration. These findings suggest that the endogenous decline of youth-specific amenities in rural areas is an important driver of the youths' out-migration from rural areas.

Second, we use our model to project future depopulation and aging from 2015 to 2050. Our baseline model projects that the population size will decrease by 14 percent in Tokyo Metropolitan Area and by 34 percent in the five oldest prefectures by 2050. When we shut down cross-regional migration, we find that both regions experience a similar rate of population decline (22 percent for Tokyo Metropolitan Area and 24 percent for the five oldest prefectures). Therefore, the unequal rates of depopulation are primarily driven by the migration of the population from rural to urban areas. Furthermore, when we allow for migration but shut down agglomeration amenity spillovers, we find that Tokyo's population decreases by 17 percent (as opposed to 14 percent in our baseline specification) and that of the five oldest prefectures falls by 28 percent (as opposed to 34 percent in baseline specification). These findings suggest that the endogenous amenity decline in rural areas continues to accelerate rural-urban migration and depopulation of rural areas. We find a similar pattern of results for the regional disparity of aging.

Finally, we use our model to assess the welfare implications of the regional depopulation and aging induced by the migration from rural to urban areas. To answer this question, we compute the changes in consumption-equivalent flow utility (inclusive of amenity values) for each age group, region, and time, and assess how they differ in our future projection depending on whether we allow for or shut down migration. In both scenarios, we find that the flow utility of both youths and the elderly will decline from 2015 to 2050 by about 10-15 percent due to the increased fiscal cost of pension financing and the decline in local amenities due to the nationwide population decline. By comparing our simulation results with and without migration, we find that youths' flow utility declines substantially more when migration is not possible, largely because they are stuck in rural areas that give lower flow utility. At the same time, restricting migration has minimal effects on the elderly's flow utility. In particular, the rural elderly does not benefit from restricting out-migration of youths, because of the limited local amenity spillovers from the youth to the elderly and increased pressure on housing rents.

These results indicate that, while restricting migration flows may slow down the regional disparity in rural depopulation and aging, its implications for local economic activity and aggregate welfare are ambiguous. In ongoing work, we plan to assess the implications of the ongoing migration subsidy to rural areas.

Related Literature Our paper contributes to several related pieces of literature. First, we contribute to the literature on the aggregate and intergenerational effects of depopulation and aging. Following the seminal work by [Auerbach and Kotlikoff \(1987\)](#), this literature has

analyzed these effects using the overlapping-generations framework (e.g., [De Nardi et al., 1999](#); [Auclert et al., 2021](#)). In particular, this framework has been applied to Japanese contexts to study labor market outcomes and fiscal issues under depopulation and aging ([Braun and Joines, 2015](#); [Kitao, 2015](#); [Kitao and Mikoshiba, 2020](#)). In contrast to this literature, this paper highlights the regional incidence of depopulation and aging and its implication for aggregate and distributional welfare.²

Second, we contribute to the literature on the life cycle dynamics of an individual’s location decisions. This literature has traditionally modeled forward-looking migration decision as a dynamic discrete choice problem and studied its implication for local economic activity ([Artuç et al., 2010](#); [Kennan and Walker, 2011](#); [Dix-Carneiro, 2014](#); [Caliendo et al., 2019](#); [Kleinman et al., 2021](#)). More recently, a new set of papers in the quantitative spatial literature has incorporated agents’ heterogeneous decisions of migration over their life-cycle ([Giannone et al., 2020](#), [Suzuki, 2021](#), [Komissarova, 2022](#)). We contribute to this literature by connecting the life-cycle migration decisions to the aggregate dynamics of depopulation and aging.

More broadly, a growing number of papers have highlighted that people of different age groups make different residential location decisions. [Couture and Handbury \(2020\)](#) and [Moreno-Maldonado and Santamaria \(2022\)](#) document that people at different timing of their life cycles make different location decisions. We contribute to this studies suggesting that depopulation and aging create long-lasting effects on aggregate welfare as well. [Gagné and Thisse \(2009\)](#) and [Takahashi \(2022\)](#) theoretically analyze how these heterogeneous decisions affect the implication for the nationwide aging under as stylized geography. Our contribution is to analyze these patterns using a quantitative general equilibrium framework capturing realistic geography and migration costs using the Japanese context as a case study.

Lastly, our paper contributes to the literature on demography on local population projection ([Smith et al., 2006, 2013](#)). While this literature also highlights the role of internal migration in local population projection, they tend to abstract how migration decisions endogenously change the local economic activity and how it changes the migration decisions in turn. We contribute to this literature by showing that these endogenous migration decisions are crucial for future projection and for the regional and inter-generational welfare implications.

The rest of this paper proceeds in the following way. In [Section 2](#), we describe our main data sources. In [Section 3](#), we document spatial patterns of depopulation and aging in Japan

²Other papers studying the macro-economic implications of aging and depopulation focus on innovation and economic growth ([Acemoglu and Restrepo, 2022](#) and [Jones, 2020](#)) and business dynamism ([Karahan et al., 2019](#), [Hopenhayn et al., 2021](#), [Engbom, 2019](#)).

and how it affects the local economy. In section 4, we develop a dynamic life-cycle spatial equilibrium model. In Section 5, we calibrate our model to the population and migration data from Japan. In Section 6, we use our calibrated model to project future spatial patterns of depopulation and aging and discuss its welfare implications.

2 Data Sources

In this section, we describe our main data sources, the main variables of interest, and the geographic units of Japan. The details and the source of each piece of information are found in Appendix Table A.1.

Geographic Units. Japan is divided into 47 prefectures. Each prefecture is further divided into municipalities. There are 1741 municipalities in Japan as of 2015. The average geographic size of the municipality is approximately 220 square kilometers. The average population size is 72,000, despite the large heterogeneity across municipalities as we document below. The number of municipalities has significantly decreased over the last 20 years due to municipality mergers. To keep the spatial units of our analysis consistent across years, we use the crosswalk of municipalities across time developed by [Kondo \(2019\)](#) and take the spatial unit at the level of municipalities in 2010.

Population Census. Population censuses in Japan are conducted every 5 years by the Statistics Bureau of the Ministry of Internal Affairs and Communications. The population censuses collect individual demographic characteristics (e.g., age, gender) and the current residential location. Furthermore, every 10 years (and every 5 years after 2010), the population censuses also report where each individual resided 5 years before, allowing us to compute migration flows. Lastly, we use employment status data by age, gender, and municipality to calibrate labor compensation per capita.

Vital Statistics. Vital statistics are collected annually by the Ministry of Health, Labor, and Welfare. This data reports the number of birth for each prefecture disaggregated by the mothers' age that we use to construct fertility rates by mothers' age for each prefecture. This data also reports the number of death for each prefecture disaggregated by age and gender.³ We construct mortality rates by age and gender for each prefecture using this information.

³Since 2010 this data is also available at the municipality level.

Projected Fertility and Mortality Rates Data. We use the projected fertility and mortality rates at the national level from 2015 to 2065 produced by the National Institute of Population and Social Security Research (IPSS) in Japan in the calibrated of our model.

Tax Base Data. We measure the average taxable income of the residents in each municipality collected by the Ministry of Internal Affairs.

Economic Census: We use data from the Economic Census on total employment and the number of establishments by municipality and sector.

Basic Survey on Wage Structure. We extract labor compensation by gender and age group from the Basic Survey on Wage Structure. It is an annual survey conducted on a random sample of establishments across Japan by the Ministry of Health, Labour, and Welfare. This data is available at the prefecture level. We extract average wages for each prefecture, age group, gender, and occupation.

Land Price Data. We measure the changes in land prices using the official posting of land prices of designated plots across Japan posted by the Ministry of Land, Infrastructure, Transport and Tourism. For each plot, the data reports the evaluated land prices based on the characteristics of the plot and the surrounding environment. This data is typically used as a reference for property tax collection and land transactions.

Amenity Index. We collect various proxies for residential amenities. For our purpose, we classify the amenities into five categories: (1) retail (number of retail stores, large retail stores, clothing stores, food and beverage retail stores, restaurants, barber shops and beauty salons); (2) health/medical (number of general hospitals, clinics, medical doctors, nurses); (3) elderly services (number of nursing homes, community centers, senior citizen clubs); (4) child/education (number of daycares, schools, teachers); (5) environment/transportation (road length, paved road length, number of parks, number of police stations). Following [Diamond \(2016\)](#), for each category, we create an index using principal component analysis (PCA). Appendix Table [A.2](#) reports the loading coefficients of each variable within each category.

3 Reduced-Form Facts

In this section, we document Japan’s spatial pattern of depopulation and aging and how it has affected the local economy.

3.1 How has depopulation and aging progressed across regions?

We first document how the spatial pattern of depopulation and aging in Japan has evolved since 1980. Figure 3 shows the growth rates of population size from 1980 to 2010 for the top and bottom 10 percentile municipalities in terms of population density in 1980. This section calls the former “urban” and the latter “rural,” respectively. Solid lines labeled “data” indicate the population size of these two sets of municipalities normalized by the values in 1980. “Urban” municipalities have become even denser, while “rural” municipalities have been rapidly losing population.⁴

How much of this change is driven by natural population change (birth and death), and how much is driven by migration across regions? To answer this question, we compute a hypothetical population change assuming there was no migration across municipalities. More specifically, let $L_t^n(a)$ denote the observed population of age a in municipality n in year t . The hypothetical population without migration, $L_t^{n*}(a)$, is sequentially constructed from $t = 1980$ as

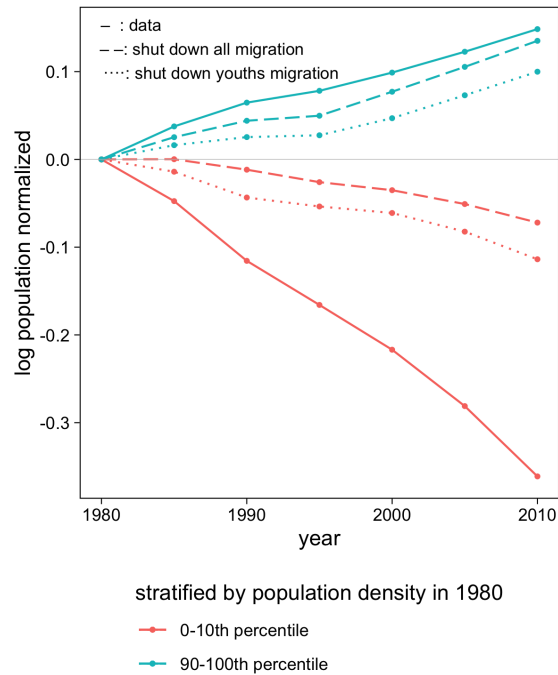
$$\frac{L_t^{n*}(a)}{L_{t-5}^{n*}(a)} = \frac{L_t^n(a)}{L_{t-5}^n(a)} \times (1 + \text{Net-Migration-Rate}_t^n(a)), \quad (1)$$

where we start from $L_{1980}^{n*}(a) = L_{1980}^n(a)$, and $\text{Net-Migration-Rate}_t^n(a)$ is defined as the net out-migrated population from n between $t - 5$ and t whose age is a in year t divided by $L_t^n(a)$. Intuitively, the expression recovers the population of age a that would have been in municipality n if there had been no internal migration in the past 5 years.

The dashed line labeled “shut down all migration” of Figure 3 plots the population size changes in this hypothetical scenario. The Figure shows that the population decline in “rural” municipalities and population increase in “urban” municipalities would have been slower in the absence of migration. Out-migration from “rural” municipalities and in-migration to “urban” municipalities have accelerated rural depopulation and urban concentration. However,

⁴In Appendix Figure B.3, we show that the change in population size is roughly monotonic across different levels of population density in 1980, except that the relationship is slightly decreasing at the highest-density levels, likely driven by the saturation of population in urban core areas.

Figure 3: Changes in Population Size across Municipalities and Role of Migration



Note: This figure shows the population size (in log scale) from 1980 to 2010 for the top and bottom 10 percentile municipalities in population density in 1980, normalized by the value in 1980. The solid line labeled “data” reports the values as observed in the population census. The dashed line labeled “shut down all migration” reproduces the hypothetical simulation of shutting down all migration. The dotted line labeled “shut down youths migration” plots the hypothetical population size change under the simulation of shutting down youths (age 15-24) migration. See the main text for how we undertake this hypothetical simulation.

even in the absence of migration, population size had declined in “rural” municipalities and increased in “urban” municipalities. This is primarily because there was more population under reproductive age in urban areas than in rural areas in 1980. Nonetheless, the contribution of internal migration is more important in explaining this pattern than the natural population change due to birth and death.⁵

We now show that youths’ migration is particularly relevant for the spatial patterns of depopulation. The dotted line labeled “shut down youths migration” of Figure 3 plots the population size changes when we hypothetically shut down migration for a subset of the population that falls in the 15-24 years old. More specifically, we compute the hypothetical population changes using equation (1) for these age groups while taking the population size of

⁵There has been limited *international* migration from and to Japan, and it has limited contribution to these processes.

other age groups as observed. We find that, for “rural” areas, shutting down youths’ migration would lead to a slightly faster but similar rate of depopulation than when we shut down all migration. This pattern indicates that youths’ outmigration explains a large fraction of the depopulation due to migration. For “urban” areas, shutting down youth migration would lead to slower population growth than when we shut down all migration. This pattern indicates that populations of other age groups on net migrate from the “urban” areas.⁶

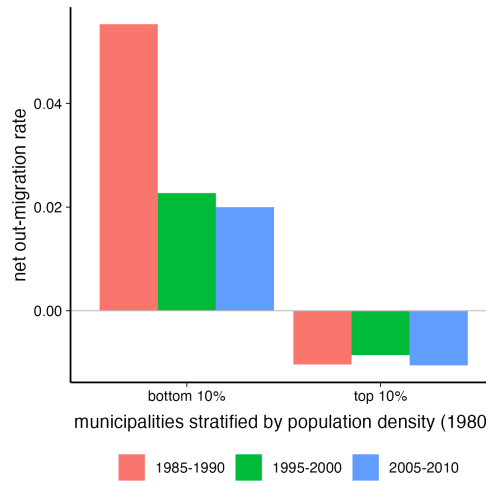
Figure 4 shows the observed net migration rates in “urban” municipalities and “rural” municipalities (top and bottom 10 percentile municipalities by population density in 1980, respectively) are consistent with the patterns explained so far. Panel (a) shows the net out-migration rate for “urban” and “rural” municipalities for three census years (1990, 2000, 2010). Throughout the years, the loss of population in less dense municipalities is associated with positive net out-migration, while negative net out-migration of denser municipalities contributed to their growth. Panels (b) and (c) of Figure 4 present the same information disaggregated by end-of-the-period age groups. In the “rural” municipalities in Panel (b), a considerable spike in net out-migration is observed in the 15-24 age group. There is a slight drop in the 25-29 age group, likely due to return migration after education. However, this drop is not significant enough to offset the surge in the 15-24 age group, and net out-migration rates are relatively flat after these age groups. In “urban” municipalities in Panel (c), net in-migration is primarily driven by the 15-24 age group. All other age groups exhibit a small but positive net out-migration rate. These findings reinforce the results in Figure 3 that youths on net migrate out from “rural” municipalities and into “urban” municipalities. The older cohort does not offset these flows.

Internal migration affects not only the pattern of depopulation but also regional aging. Figure 5 shows the fraction of the elderly (over 65 years old) from 1980 to 2010 for “urban” and “rural” municipalities. We also overlay the patterns under the hypothetical scenario of shutting down migration and youths’ migration following the same procedure in Figure 3. We find that the fraction of the elderly is consistently higher in “rural” municipalities than “urban” municipalities throughout the period. We also find that the increase of the fraction of the elderly is substantially less when we shut down migration (“shut down all migration”). This is because net out-migration from “rural” municipalities is concentrated among youths (Figure

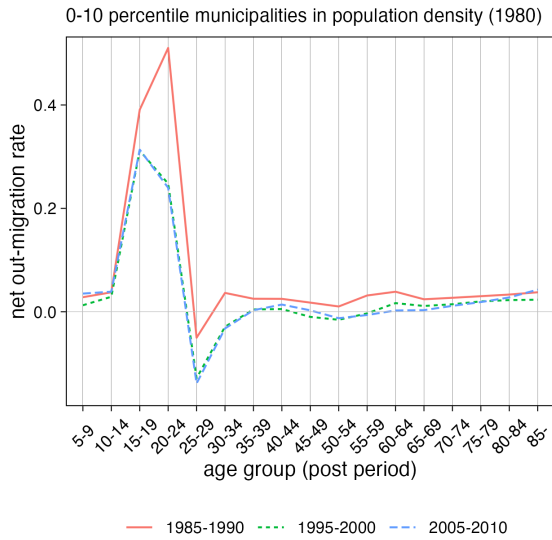
⁶In Appendix Figure B.3, we show that for median municipalities (40-60 percentiles of population density in 1980), shutting down youths’ migration would lead to faster population growth than when we shut down all migration, suggesting that population outside age 15-24 tend to migrate out from top municipalities to median municipalities.

Figure 4: Net Out-Migration by Location and Age

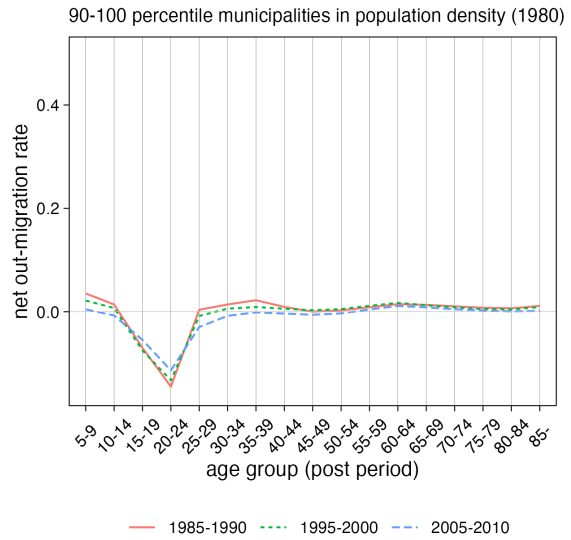
(a) Net Out-Migration Rate



(b) Net Outmigration by Age:
Bottom 10% in Population Density (1980)



(c) Net Outmigration by Age:
Top 10% in Population Density (1980)

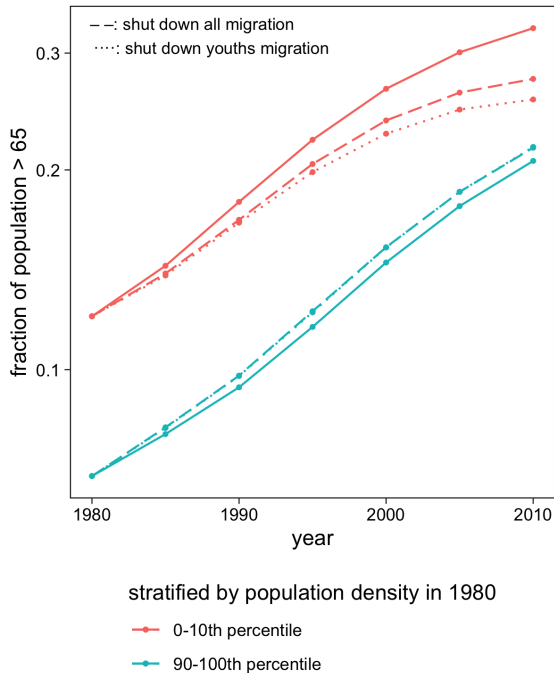


Note: Panel (a) reports the five-year net out-migration rate for the top and bottom 10 percentile municipalities in population density in 1980 for three census years (1990, 2000, 2010). The net out-migration in a municipality is defined by the number of people who have moved out minus those who have moved into the municipality, divided by the population size in the municipality five years before. Panels (b) and (c) report the same patterns by further disaggregating by age groups.

4), hence shutting down migration would decrease the fraction of the elderly in the region. Similarly, shutting down the migration of youths only (“shut down youths migration”) would lead to a further decline in the fraction of the elderly because this scenario does not shut down the net out-migration of the population outside youths. These findings are consistent

with the interpretation that youths’ out-migration from “rural” areas is not perfectly offset by the out-migration of older cohorts, leaving elderlies behind in depopulated and aging rural areas.

Figure 5: Decomposition of Aging by Net Out-Migration



Note: This figure shows the fraction of the population over 65 years old from 1980 to 2010 for the top and bottom 10 percentile municipalities in population density in 1980. The solid line shows the transition from the data, the dashed line labeled “shut down all migration” shows the hypothetical simulation of shutting down all migration, and the dotted line labeled “shut down youths migration” shows the hypothetical simulation of shutting down youths (age 15-24) migration. See the main text for how we undertake these hypothetical simulations.

3.2 How do depopulation and aging affect local economy?

In the previous subsection, we documented substantial spatial heterogeneity in the rate of depopulation and aging. In this subsection, we study how they affect the local economy, such as production, amenity, and land prices. In particular, we study how local economic conditions respond to depopulation and aging using the following regression specification:

$$\Delta \log Y^n = \beta_1 \Delta \ln Pop(age \in [15, 64])^n + \beta_2 \Delta \ln Pop(age \geq 65)^n + \mathbf{X}_{1980}^n \boldsymbol{\beta} + PrefFE^n + \varepsilon^n, \quad (2)$$

where n indicates the municipality; Δ indicates the long difference between 1980-2010 (or the closest years depending on the availability of outcome variables); $\Delta \log Y^n$ are a set of outcome variables proxying for the changes in local economic activity (e.g., average income, amenity, land prices); and $PrefFE_n$ denotes prefecture fixed effects. $\Delta \ln Pop(age \geq 15)^n$ is the growth rate of working-age population size and $\Delta \ln Pop(age \geq 65)^n$ is the growth rate of the elderly population. \mathbf{X}_{1980}^n denotes a vector of control variables that includes the employment shares of the secondary and tertiary industries, municipality area (in logs) and population density (in logs) as of 1980.

A key endogeneity concern of this specification is that unobserved factors related to the changes in local economic conditions, captured by ε^n , may be associated with the changes in local population. For example, regions experiencing an economic boom may experience an increase in working-age population. Similarly, regions with improved amenities for the elderly, such as an increase in nursing homes or senior citizens clubs, may attract an inflow of the elderly.

To address these concerns, we adopt the same strategy from the literature on the consequences of internal migration on the local labor market (e.g., [Boustan \(2010\)](#), [Derenoncourt \(2022\)](#) and [Bazzi et al. \(2023\)](#)). In particular, we build instrumental variables (IV) for the changes in the local population of a municipality based on age-specific push and pull migration shocks in other municipalities within Japan. The basic idea for push migration IV is to predict the in-migration to municipality n solely from the predetermined migration patterns in the baseline period (1980) and the fact that municipalities that tend to send population to municipality n experience an overall out-migration (not specifically to destination n) during 1980-2010. For example, if a municipality n tends to receive a large inflow of migrants from a municipality i of a specific age group, and if municipality i happens to experience an outflow of this population (for example due to the economic decline in municipality i), municipality n is likely to experience an increase in in-migration of this specific age group. The idea for the pull migration shock is similar: We predict the out-migration from municipality n solely from the predetermined migration patterns in the baseline period (1980) and the fact that municipalities that tend to receive population from municipality n experience an overall

in-migration (not specifically from origin n) during 1980-2010.⁷

Following this idea, we construct our push IV based on the cumulative hypothetical inflows for age group a in municipality n in 2010 from the push migration shocks, starting from 1980, as follows:

$$\tilde{\mathcal{I}}^d(a) = \sum_{o \neq d} \sum_{s=1990,2000,2010} \tilde{\mu}_{1980}^{od}(a - (2010 - s)) \mathcal{O}_s^o(a - (2010 - s)), \quad (3)$$

where $\mathcal{O}_t^n(a)$ indicate the observed inflow and outflow data of age group a in municipality n in t ; and $\tilde{\mu}_{1980}^{od}(a)$ indicates the estimated share of out-migrants from municipality o going to municipality d from 1980 to 1985. Notice that, the push shock in year s for age group $a - (2010 - s)$ contributes to the population size of the age group a in year 2010. Similarly, we construct our pull IV based on the cumulative hypothetical outflows for age group a in municipality n in 2010 from the pull migration shocks, starting from 1980, as follows:

$$\tilde{\mathcal{O}}^o(a) = \sum_{d \neq o} \sum_{s=1980,1990,2000} \check{\mu}_{1980}^{od}(a - (2010 - s)) \mathcal{I}_s^o(a - (2010 - s)), \quad (4)$$

where $\mathcal{I}_t^n(a)$ indicates the observed inflow and of age group a in municipality n in t ; and $\check{\mu}_{1980}^{od}(a)$ indicates the estimated share of out-migrants from municipality o going to municipality d from 1980 to 1985. After we construct $\tilde{\mathcal{I}}^d(a)$ and $\tilde{\mathcal{O}}^o(a)$, we add these variables to the observed population distribution in 1980, $\{\tilde{L}_{1980}^n(a)\}$, to construct the predicted changes in the working-age population size and the elderly population size attributed to the push and pull shocks, respectively. We then transform these changes into percentiles and use them as IVs of the first two regressors in equation (2).⁸

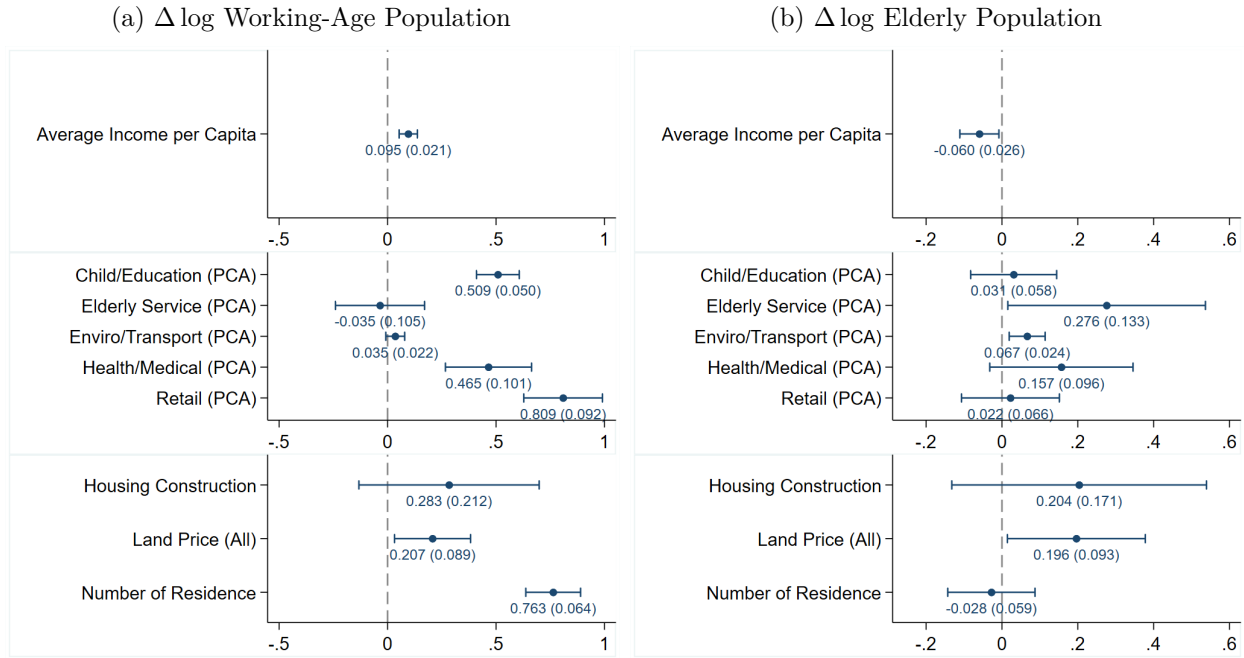
Figure 6 shows the regression coefficients of the IV specification (2). Panel (a) shows the coefficients and the 95-percentile confidence intervals on the log change in the working-age

⁷Econometrically, our strategy falls into a version of the “shift-share design” (Adao et al., 2019; Goldsmith-Pinkham et al., 2020; Borusyak et al., 2022), where we use the predetermined migration patterns as a “share”, and we use the origin- or destination-specific changes in out- and in-migration as a “shift” to construct the IVs. In this literature, identification is established through the exogeneity of the share (Goldsmith-Pinkham et al., 2020) or of the shift (Adao et al., 2019; Borusyak et al., 2022). In our context, it is more plausible to take the view that the shift is exogenous, i.e., whether the municipalities connected within migration networks happen to experience push or pull shocks is exogenous to the corresponding municipality.

⁸One challenge in implementing this idea is that we do not have data on age-specific bilateral migration flows in 1980. Therefore, instead, we construct these migration shares using the parametrized migration costs as a function of distance estimated from bilateral migration data in 2015, combined with the gross in- and out-migration for each municipality in 1980. See Appendix C.4 for details of the migration cost estimation. Once we estimate the bilateral migration costs, we search for the unique set of origin- and destination-shifters to perfectly fit each municipality’s out- and in-migration flows in 1980.

population size for each outcome variable indicated in the horizontal axis, and Panel (b) shows those on the log change in the elderly population size. All variables except for amenity proxies are defined as log changes. For amenity proxies in the middle panel, we standardize the growth rates of these proxies to a standard deviation of one.

Figure 6: Impacts of Depopulation and Aging on Local Economy



Note: This figure reports the coefficient estimates of equation 2 where each dependent variable is in changes of local economy determinants. The left panel reports the coefficients on $\Delta \log$ working-age population, and the right panel reports the coefficients on $\Delta \log$ elderly population. All variables except for amenity proxies in the middle panel are defined as log changes. For each amenity proxy in the middle panel, we standardize the growth rates of these proxies to a standard deviation of one.

The top panel reports the impacts on the average taxable income per capita. We find that a one percentage point increase in the working-age population increases the income per capita by 0.095 log points, while a one percentage point increase in the elderly population decreases it by 0.60 log points. Notice that the average taxable income is the average across all age groups. Therefore, the effect of an increase in the working-age population (conditional on the elderly population) could be driven both by the composition effect (higher average income as the fraction of the working-age population increases) or the increase of income conditional on age groups. In Section 5, we revisit this finding by imputing age-specific labor compensation by combining age-specific labor compensation available at the prefecture level.

The middle panel reports the impacts on the PCA indices of the five categories of amenities: (1) Child/Education, (2) Elderly Services, (3) Environment/Transportation,

(4) Health/Medical, (5) Retail.⁹ We standardize the growth rates of these proxies to a standard deviation of one. Our findings are summarized as follows. First, we find substantial heterogeneity in the impacts of the size of working-age and elderly populations across amenity categories. Second, we find that working-age population size has positive and statistically significant effects on all categories of amenities except for “Elderly Service,” which is negative but not significantly different from zero. The heterogeneous relationship between various types of local amenities and age composition is in line with the findings of [Komissarova \(2022\)](#), who shows this relationship using cross-sectional data from the United States. Third, we find that the elderly population size has significant positive effects on “Elderly Service” and “Environment and Transport.” The effects on the other amenity proxies are not significantly different from zero.

The last panel reports the impacts on land prices. We find that working-age population size has a significantly positive effect on land prices and the number of residences. We also find that the elderly population size has positive effects on land prices, but it does not have significant effects on the number of residences.

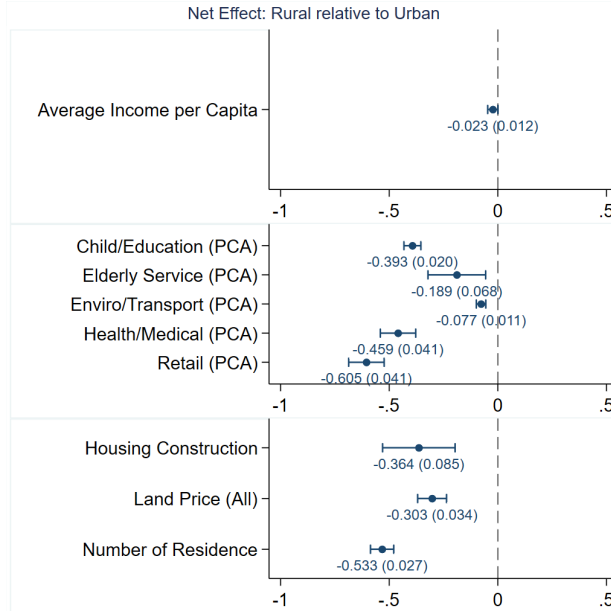
To facilitate the interpretation of the magnitudes of these estimates, we now illustrate how these regression coefficients lead to the differences in the growth rates in income, amenity, and land prices in “rural” municipalities (the bottom 10 percentile of population density in 1980) relative to “urban” municipalities (the top 10 percentile of population density in 1980). The working-age population size has declined by 0.59 log points in “rural” municipalities between 1980 and 2010 while that in “urban” municipalities increased by 0.13 log points, leading to 0.72 log points differences in $\Delta \ln Pop(age \in [15, 64])_n$. Similarly, the elderly population has increased by 0.59 log points in “rural” municipalities between 1980 and 2010 while that in “urban” municipalities increased by 1.36 log points, leading to 0.77 log differences in $\Delta \ln Pop(age \geq 65)_n$. Therefore, $-(\hat{\beta}_1 \times 0.72 + \hat{\beta}_2 \times 0.77)$ is the net effects of “rural” areas relative to “urban” areas from the depopulation and aging.

Figure 7 presents the results. On net, we find that average income falls in “rural” municipalities, all categories of amenities fall with varying degrees, and land price falls.

Together, the evidence of this section shows that depopulation and aging have a significant impact on the local economy. Together with the findings in Section 3.1 that out-migration from “rural” areas accelerates depopulation and aging of rural areas, the findings of this subsection suggest important regional and intergenerational welfare implications. In the

⁹See Section 2 for how we classify the original variables into these categories and construct the PCA index, and Appendix B.3.1 for the impacts on the original variables within each classification.

Figure 7: Predicted Net Impacts of Depopulation and Aging on Rural Economies



Note: This figure reports the predicted differential growth rates in each variable in “rural” municipalities (the bottom 10 percentile of population density in 1980) relative to “urban” municipalities (the top 10 percentile of population density in 1980) based on the estimates of the regression (2). See the text for how we compute these values.

next section, we build a spatial dynamic general equilibrium model with life-cycle migration decisions to assess the welfare implications of this phenomenon.

4 Model

In this section, we develop a model of migration decisions over the life cycle. We discuss how the process of birth, death, and migration decisions shape the aggregate spatial dynamics of depopulation and aging. The economy is partitioned by a finite number of locations, denoted by $i \in N$. Time is discrete and denoted by $t = 0, 1, 2, \dots$. Age is indexed by $a \in 0, 1, \dots, \bar{a}$ and agents die stochastically. In each period t , newborns across locations depend on the specific location age structure and fertility rates. $L_t^i(a)$ denotes the the population residing in location i of age a at time t . Below we describe how forward-looking migration decisions and natural population change (births and deaths) shape the evolution of $\{L_t^i(a)\}$.

4.1 Households

In each period, agents in location n and \underline{a} years old or older supply one unit of labor inelastically and receive a location-specific competitive market wage. They value final goods consumption c , housing services, h and residential amenity χ that is location-age specific. Agents before turning \underline{a} years old only value residential amenity. The instantaneous utility function u of an agent a years old at time t in location n is given by :

$$u_t^n(c_t^n(a), h_t^n(a), \chi_t^n(a)) = \begin{cases} (1 - \theta) \ln c_t^n(a) + \theta \ln h_t^n(a) + \ln \chi_t^n(a) & \text{if } a \geq \underline{a} \\ \ln \chi_t^n(a) & \text{if } a < \underline{a}. \end{cases} \quad (5)$$

where $c_t^n(a)$ is the consumption good that is freely traded across regions and we normalize the price of final goods to one as a numeraire. $h_t^n(a)$ is housing consumption that can be rented at R_t^n per unit. $\chi_t^n(a)$ proxies amenity value of location n for age group a at period t . The amenity value has two components; an exogenous component that is location-age specific that proxies for location characteristics (e.g., access to the ocean, river, forests) and an endogenous component that depends on the age structure of local population. Details are described below.

Individuals with age above the legal working age \underline{a} earn labor income, profits from land ownership and pay taxes. Agents become retirees at age a^* and receive pension payments. Pensions are financed with labor income taxes as defined explicitly below. Therefore, the budget constraint is given by:¹⁰

$$c_t^n(a) + R_t^n h_t^n(a) = (1 - \kappa_t) w_t^n(a) + \pi_t^n(a) + T_t \times 1[a \geq a^*] \quad (6)$$

The left-hand side of the equation is the expenditure for final goods and housing consumption. On the right-hand side, $w_t^n(a)$ is the labor compensation specific to location n , age a , and time t ; κ_t is the income tax rate for labor income; $\pi_t^n(a)$ is the profit from land ownership and $T_t^n(a)$ is the pension for individuals above the legal retirement age a^* . We assume that agents do not have saving technology, and hence they spend all their income on the composite of the final good consumption and housing in every period.

However, the agents's problem is dynamic. Agents are forward looking and discount the future at rate β . Agents every period receive additive idiosyncratic location preference shocks $\epsilon_t^n(a)$ and decide where to locate. Migration decisions are subject to bilateral migration costs

¹⁰As mentioned before, agents \underline{a} years old or less do not consume or receive income.

$\tau_t^{n\ell}(a)$. We assume that migration costs can flexibly depend on the origin, destination, time and age groups.

Timing and Location Choices over the Life Cycle

The timing for the household's problem and decisions is as follows. At the end of each period t , and before the realization of the death shock, the preference location choice is realized. Agents, that are forward looking and have perfect foresight, forecast the income and rents in all markets and make forward-looking migration decisions on whether to migrate to a different location or stay in the current location. After the migration decision taking place, the death shock realizes and agents optimally choose their final good consumption bundle and housing. The life-time utility of a survived agent of age a at beginning of time t (after migration decision) in location n is given by:

$$V_t^n(a) = \max_{c_t^n(a), h_t^n(a)} u_t^n(c_t^n(a), h_t^n(a), \chi_t^n(a)) + \mathbb{E}_t \left\{ \max_{\{\ell\}_{\ell=1}^N} s_t^\ell(a) \beta V_{t+1}^\ell(a+1) - \tau_t^{n\ell}(a) + \nu \varepsilon_t^\ell(a) \right\}$$

$$\text{s.t. } c_t^n(a) + R_t^n h_t^n(a) = (1 - \kappa_t) w_t^n(a) + \pi_t^n(a) + T_t \times 1[a \geq a^*] \quad \text{if } a \geq \underline{a}$$
(7)

where ν determines the variance of the idiosyncratic taste shock ε and $s_t^\ell(a)$ is the survival rate that depends on the migration destination. Expectations, \mathbb{E}_t , are taken over future realizations of the idiosyncratic shock and population distribution across space.

The agent's maximization can be broken in two parts that are solvable independently; a static consumption decision and a dynamic forward-looking migration decision. Assuming that this idiosyncratic location preference shock is drawn from the Type-I extreme value distribution with mean zero, we can derive the migration share of agents with age group a moving from n to market i as

$$\mu_t^{ni}(a) = \frac{\exp \left[s_t^i(a) \beta V_{t+1}^i(a+1) - \tau_t^{ni}(a) \right]^{1/\nu}}{\sum_{\ell}^N \exp \left[s_t^\ell(a) \beta V_{t+1}^\ell(a+1) - \tau_t^{n\ell}(a) \right]^{1/\nu}}.$$
(8)

Therefore, the expected lifetime utility for agents with age group a in location n at time t can be defined as

$$V_t^n(a) = u_t^n(a) + \nu \log \sum_{\ell}^N \exp \left[s_t^\ell(a) \beta V_{t+1}^\ell(a+1) - \tau_t^{n\ell}(a) \right]^{1/\nu},$$
(9)

where $u_t^n(a)$ is the indirect flow utility that solves the static consumption problem.

4.2 Population by Age and Location

The population distribution across age and location depends on the relationship between births, deaths and migration decisions. We assume that both the fertility $\varkappa_t^n(a)$ and death rates $s_t^n(a)$ differ across age groups, location and time. Given the endogenous migration flows $\mu_t^{ni}(a)$ defined in equation (8), the law of motion for the population size $\{L_t^n(a)\}$ with migration is given as follows:

$$L_{t+1}^n(a) = \begin{cases} \sum_{a'} \varkappa_{t+1}^n(a') L_{t+1}^n(a') & \text{if } a = 0 \\ \sum_{\ell} s_t^{\ell}(a-1) \mu_t^{\ell n}(a-1) L_t^{\ell}(a-1) & \text{if } 0 < a < \bar{a} \\ \sum_{\ell} s_t^{\ell}(\bar{a}-1) \mu_t^{\ell n}(\bar{a}-1) L_t^{\ell}(\bar{a}-1) + \sum_{\ell} s_t^{\ell}(\bar{a}) \mu_t^{\ell n}(\bar{a}) L_t^{\ell}(\bar{a}) & \text{if } a = \bar{a} \end{cases} \quad (10)$$

For computational reasons, we bound the aging space $[0, \bar{a}]$. We assume that agents once reach age \bar{a} they remain in that age group until dying. This accounting relationship is called the “demographic balancing equation” in the demography literature, and it is a building block to the local population projection (Smith et al., 2013). The key distinction between our model and the traditional “demographic balancing equation” is that we also consider migration flows $\mu_t^{\ell n}(a)$ across regions that are endogenously determined in the equilibrium depending local conditions and migration costs. Given that fertility rates, death rates and migration flows differ across age groups, location and time, the evolution of population on aggregate and across space depends on the population distribution across location and the age composition within location. As we show below, considering migration makes a substantial difference in the future population projection.

4.3 Production and Income

Production of Final Goods

In each location, there is a continuum of perfectly competitive producers that use labor as inputs and produce local final goods. We assume that labor is perfectly substitutable across different age groups, but the efficiency of one unit of labor supplied depends on the age-location combination. $\varphi_t^n(a)$ denotes the efficiency per unit of labor supplied by a worker of age a in location n at time t . We allow the total working population has an agglomeration

spillover effect on labor efficiency.

$$\varphi_t^n(a) = \tilde{\varphi}_t^n(a) \times f^\varphi(\{L_t^n(\cdot)\}), \quad (11)$$

where $\tilde{\varphi}_t^n(a)$ is an exogenous age-location-time specific productivity component and the function $f^\varphi(\{L_t^n(\cdot)\})$ capture the agglomeration spillovers in productivity, which potentially depends on the local population size of each age group. Therefore, the aggregate local productivity depends simultaneously on the size of each location and on the age composition within location. We assume a production function that exhibits constant returns to scale and perfect substitutability across age groups, defined as:

$$Y_t^n = \sum_{a \geq \underline{a}} \varphi_t^n(a) L_t^n(a)$$

Wages and Pensions

The assumptions defined above together with perfect competition in the local labor market implies that the labor compensation per agent of age a in location n at period t is given by

$$w_t^n(a) = \varphi_t^n(a), \quad a \geq \underline{a}. \quad (12)$$

Labor income is taxed at rates κ_t and the revenues are exclusively used to finance pensions of retired agents that are assumed to be common across locations. Given government budget neutrality, pension per retiree are given by:

$$T_t = \frac{\sum_{\ell=1}^N \sum_{a \geq \underline{a}}^{a^*-1} \kappa_t w_t^n(a) L_t^n(a)}{\sum_{\ell=1}^N \sum_{a \geq a^*} L_t^n(a)} \quad (13)$$

Housing Sector

Following the conventional approach in the urban economics literature (e.g., [Epple et al., 2010](#)), we assume that housing is supplied by a local competitive construction sector using a Cobb-Douglas technology with land Z^n and effective labor $L_t^{n,H} = \sum_{a \geq \underline{a}} \varphi_t^n(a) L_t^n(a)$ as inputs:

$$H_t^n = \xi^n \left(L_t^{n,H} \right)^\mu \left(Z_t^n \right)^{1-\mu} \quad (14)$$

where ξ^n denotes the housing sector productivity that differs across locations. Land is supplied inelastically and set exogenously $\{\bar{Z}^n\}$. Each unit of land costs P_t^n that it's determined in

equilibrium. The returns of land are rebated to local population as described below.

The housing supply that solves the profit maximization of the housing sector is given by:

$$R_t^n = \tilde{\xi}^n (H_t^n)^{\frac{1-\mu}{\mu}}, \quad (15)$$

where $\tilde{\xi}^n = \xi^{-\frac{1}{\mu}} \mu^{-1} (\bar{Z}^n)^{-\frac{1-\mu}{\mu}}$. The housing supply depends on the level of land available and implies a housing supply elasticity of $\frac{1-\mu}{\mu}$.¹¹

The equilibrium rent, R_t^n is determined by the market clear condition in each market. The aggregate demand for housing that solves agent's problem (7) is given by:

$$\tilde{H}_t^n = \theta \frac{\sum_{a>\underline{a}} L_t^n(a) \left((1 - \kappa_t) w_t^n(a) + \pi_t^n(a) + T_t \times 1[a \geq a^*] \right)}{R_t^n} \quad (16)$$

The price of land is determined by the market clearing condition in the land market that equates the demand and supply of housing. Due to perfect competition in the housing sector, the price of land is such that drives the profits of the housing sector to zero. We assume that the factor payment to land, $(1 - \mu) R_t^n H_t^n$, is rebated to all local population above working age population proportionally to their disposable income so that the rebate rate $\tilde{\pi}_t^n$ is given by

$$\tilde{\pi}_t^n = \frac{(1 - \mu) R_t^n H_t^n}{\sum_{a>\underline{a}} L_t^n(a) \left((1 - \kappa_t) w_t^n(a) + T_t \times 1[a \geq a^*] \right)} \times 1[a > \underline{a}]^{12,13} \quad (17)$$

4.4 Amenities

We allow for amenities to vary across locations and age groups. We assume that amenities are composed by two components. An exogenous component that is location-age specific that may vary across time denoted by $\tilde{\chi}_t^n(a)$. We also consider an endogenous agglomeration amenity spillover (or congestion) effect specified by $f^x(a, \{L_t^n(\cdot)\})$ that depends on the demographic structure of the location. It is important to note this endogenous component is also age-specific, allowing us to capture the idea that there are different types of amenities specific to age groups. This specification accommodates the possibility that population sizes

¹¹This equation already takes into account free labor mobility across sectors within locations implies equal wages in both sectors and our choice of wage per effective unit of labor as numeraire, $w_t^n = 1$.

¹²Note that the total rebate $\pi_t^n(a)$ received by an agent of age a in location n at time t is given by $\pi_t^n(a) = \tilde{\pi}_t^n ((1 - \kappa_t) w_t^n(a) + T_t \times 1[a \geq a^*])$. Therefore, the budget constrained defined in equation (6) can be re-written as $p_{c,t}^n c_t^n(a) + R_t^n h_t^n(a) = (1 + \tilde{\pi}_t^n) ((1 - \kappa_t) w_t^n(a) + T_t \times 1[a \geq a^*])$.

¹³In equilibrium, π_t^n is a constant and doesn't vary across locations and over time. To see this, replace the demand for housing defined in equation (16) in equation (17). Solving for $\tilde{\pi}_t^n$ we get $\tilde{\pi}_t^n = \frac{(1-\mu)\theta}{1-(1-\mu)\theta}, \forall n, t$.

of different age groups may generate a different degree of amenity spillovers (e.g., elderly service for the elderly population, child/education for the young population). Amenity index for age group a in location n at time t is then defined by:

$$\chi_t^n(a) = \tilde{\chi}_t^n(a) \times f^x(a, \{L_t^n(\cdot)\}) \quad (18)$$

4.5 Equilibrium

For notation simplicity, we denote the distribution across age groups and locations of an allocation x at time t by $x_t = \{x_t^n(a)\}_{a=0, n=1}^{\bar{a}, N}$. For prices, $q_t = \{q_t^n\}_{n=1}^N$. Given an initial allocation of agents of different ages across locations L_0^n and the sequence of $\{\tilde{\varphi}_t, \tilde{\chi}_t, \tilde{Z}_t, \tau_t, \varkappa_t, s_t\}_{t=0}^\infty$, respectively, the exogenous components of productivities, amenities, land, migration costs, fertility rates and survival rates, a sequential competitive equilibrium is a sequence $\{L_t, \mu_t, H_t, w_t, R_t, P_t \kappa_t, T_t\}_{t=0}^\infty$ that solves agents problem (7-8), satisfies law of motion of population (10), firms optimization conditions(12), housing market clear conditions (15-16) and profits redistribution (17) and government budget constrained (13).¹⁴

5 Calibration

In this section, we calibrate our model to the Japanese economy. To do so, we need to set various structural parameters $\{\nu, \beta, \theta, \mu\}$, productivity and amenity spillover functions $\{f^\varphi(\{L_t^n(\cdot)\}), f^x(a, \{L_t^n(\cdot)\})\}$, as well as the location-time-age specific fundamentals including fertility rates $\{\varkappa_t^n(a)\}$, survival rates $\{s_t^n(a)\}$, exogenous components of productivities $\{\tilde{\varphi}_t^n(a)\}$, bilateral migration costs $\{\tau_t^{ni}(a)\}$, and amenities $\{\tilde{\chi}_t^n(a)\}$, and the rules for the income tax rates κ_t and pension payment T_t .

We proceed with our calibration in two steps. First, we establish procedures in which we recover the sequence of exogenous productivity $\{\tilde{\varphi}_t^n(a)\}$, bilateral migration costs $\{\tau_t^{ni}(a)\}$, and amenities $\{\tilde{\chi}_t^n(a)\}$, to exactly fit the patterns of labor income and observed transition of population distribution over time and across space given all other structural parameters. Second, we discuss how we set these structural parameters.

We use 1990 as the initial year ($t = 0$) of the economy, and the frequency of the model is five years. Accordingly, we use 5-year age groups and have 70 or older as the oldest age group ($\bar{a} = 14$). The legal working age is 15 in Japan, corresponding to $\underline{a} = 3$. The locations are the

¹⁴ $\tau_t = \{\tau_t^{n\ell}(a)\}_{a=0; n, \ell=1}^{\bar{a}; N}$ and $\mu_t = \{\mu_t^{n\ell}(a)\}_{a=0; n, \ell=1}^{\bar{a}; N}$

47 prefectures of the country.

5.1 Inversion of Productivity, Amenity, and Migration Costs

First, we establish the procedures implemented to recover the sequence of exogenous productivity $\{\tilde{\varphi}_t^n(a)\}$, bilateral migration costs $\{\tau_t^{ni}(a)\}$, and amenities $\{\tilde{\chi}_t^n(a)\}$, to exactly fit the patterns of labor income and observed transition of population distribution over time and across prefectures given all other structural parameters. Our approach to recover the fundamentals that exactly fit the observed data patterns is isomorphic to the “dynamic-hat algebra” approach in [Caliendo et al. \(2019\)](#) but accommodates the life-cycle dimensions of agents’ decisions and age-specific fundamentals in our framework.

Productivity $\{\tilde{\varphi}_t^n(a)\}$. From equation (11), labor productivity $\{\tilde{\varphi}_t^n(a)\}$, or the efficiency unit of labor supply for each age group, prefecture, and time, corresponds to their labor compensation per capita, $w_t^n(a)$. Therefore, we recover this value as follows:

$$\varphi_t^n(a) = \text{employment rate}_t^n(a) \times \text{annual labor compensation}_t^n(a). \quad (19)$$

Using the calibrated labor productivity and equation (11), and the productivity spillover function $f^\varphi(\{L_t^n(\cdot)\})$, we invert the exogenous component of the productivity such that $\tilde{\varphi}_t^n(a) = \varphi_t^n(a) [f^\varphi(\{L_t^n(\cdot)\})]^{-1}$.

Amenity $\{\tilde{\chi}_t^n(a)\}$ **and Migration Costs** $\{\tau_t^{ni}(a)\}$. We start by introducing two sets of normalization of these variables. First, we normalize the exogenous amenity $\tilde{\chi}_t^n(a)$ to one for all n, t, a , since exogenous amenity is isomorphic to migration costs in the previous period ($\tau_{t-1}^{in}(a-1)$ for all i) under our additive utility specification. Second, we normalize migration costs within a region such that $\tau_t^{nm}(a) = 0$ for all t , since the in-migration cost is isomorphic to out-migration costs in the subsequent period ($\tau_{t+1}^{ni}(a+1)$ for all i). Note that these normalizations do not affect our equilibrium allocation and welfare implications, hence this is without loss of generality.

We back out off-diagonal elements of migration frictions, $\{\tau_t^{ni}(a)\}$, to precisely replicate the evolution of population distribution over time and space. Specifically, we proceed in two steps. We first back out those in the last data period, $t = T$, using the migration flow in period T , $\{\mu_T^{ni}(a)\}$, and the future evolution of fundamentals and transfers. Here, we also assume that bilateral migration frictions do not change after 2015. Once we obtain $\{\mu_T^{ni}(a)\}$,

we sequentially back out $\{\tau_t^{ni}(a)\}$ for $t < T$ backward starting from $t = T - 1$ using migration flows $\{\mu_{ijt}(a)\}$ in each period. Appendix C.2 describes more details of this procedure.

5.2 Parameter Calibration and Estimation

We now explain our calibration of the other structural parameters. We summarize our calibrated parameters in Table 1.

Table 1: Calibrated Parameters and Exogenous Variables

Parameters	Description	Values / Sources
ν	shape parameter for migration preference shocks	0.4
β	discount factor	0.97 ⁵
θ	consumption expenditure share of housing	0.33
μ	labor share in housing construction	0.9
$\{s_t^n(a)\}$	survival rates by age and year	official statistics (past and projection)
$\{z_t^n(a)\}$	fertility rates by age, year, locations	official statistics (past and projection)
T_t	pension payment per elderly population	aggregate pension payment = 110% of elderly labor income
κ_t	income tax rate	set to finance pension payment
$f^\varphi(\{L_t^n(\cdot)\})$	productivity spillover function	Section 5.2.2
$f^X(a, \{L_t^n(\cdot)\})$	amenity spillover function	Section 5.2.3

5.2.1 Calibrated structural parameters and exogenous variables

We start by calibrating a subset of structural parameters directly from the data and using the central estimates from the literature. Fertility rates $\{z_t^n(a)\}$ and survival rates $\{s_t^n(a)\}$ before 2015 are calibrated using the births and deaths from the Vital Statistics and the population from the Census data. After 2015, we use the projected fertility and mortality rates by the National Institute of Population and Social Security Research.¹⁵

We set the inverse of migration elasticity to $\nu = 0.4$. This value is in line with the estimates from Suzuki (2021) who estimates the migration elasticity for cross-migration within the context of Japan. We set the discount factor $\beta = 0.97^5$ following a standard discount factor value for 5 year periods. We set the housing expenditure share to $\theta = 0.333$ using the average share of housing-related expenditure in Japan. We set the labor share in housing construction to $\mu = 0.9$. This value is on a higher end compared to the literature and implies the inverse housing supply elasticity of $(1 - \mu)/\mu = 1/9$ (equation 15), which is consistent with the relatively elastic housing supply over time in Japan (Appendix C.3).

¹⁵When we run a simulation, in order to have a steady state in the long-run, we assume that each location has a replacement level fertility rate starting in period $t = 200$, 1000 years after the initial period.

To determine the pension and income tax $\{T_t, \kappa_t\}$, we use the fact that aggregate pension payment is about 50 trillion in Japan in 2020, which accounts for about 10% of Japanese GDP.¹⁶ To reflect this in our model, we assume that in 2015, aggregate pension payment is 10% of aggregate labor income. This in turn implies a 110% pension rate relative to the labor income of the elderly (aggregate pension payment/total elderly labor income). We assume that this rate stays constant over time. Formally, pension payment per elderly population is given by

$$T_t = \frac{110\% \times \sum_n^N \sum_{a \geq a^*} w_t^n(a) L_t^n(a)}{\sum_n^N \sum_{a \geq a^*} L_t^n(a)},$$

and the income tax to finance this pension payment is given by:

$$\kappa_t = \frac{110\% \times \sum_n^N \sum_{a \geq a^*} w_t^n(a) L_t^n(a)}{\sum_n^N \sum_{a \geq a} w_t^n(a) L_t^n(a)}.$$

Notice as population aging proceeds, the fraction of the elderly population increases. This implies an increasing income tax rate over time. However, pension per person does not remain constant over time as population aging also impacts aggregate productivity.

5.2.2 Productivity Spillover Function $f^\varphi(\{L_t^n(\cdot)\})$

To facilitate the estimation of this productivity spillover function, we start by parametrizing the productivity spillover function such that:

$$f^\varphi(\{L_t^n(\cdot)\}) = \left(\sum_{a^* > a \geq \underline{a}} L_t^n(a) \right)^{\gamma^Y} \left(\sum_{a \geq a^*} L_t^n(a) \right)^{\gamma^O}, \quad (20)$$

where γ^Y and γ^O correspond to the elasticity of agglomeration productivity spillovers with respect to the local size of working-age population ($\sum_{a^* > a \geq \underline{a}} L_t^n(a)$) and retirement-age population ($\sum_{a \geq a^*} L_t^n(a)$). This specification accommodates the possibility that agents of different age groups may generate different levels of agglomeration productivity spillovers. From the expression for productivity (11), we can express changes in productivity for each age group and location as:

$$\Delta \log \varphi_t^n(a) = \gamma^Y \Delta \log \sum_{a^* > a \geq \underline{a}} L_t^n(a) + \gamma^O \Delta \log \sum_{a \geq a^*} L_t^n(a) + \Delta \log \tilde{\varphi}_t^n(a). \quad (21)$$

¹⁶Please see <https://www.mhlw.go.jp/content/000706195.pdf>.

Given the proxy for the labor productivity $\varphi_t^n(a)$ recovered from wage and employment data in section 5.1 and the observed changes in population size, we can estimate the productivity spillovers γ^Y and γ^O .

Estimating such elasticities poses two challenges. First, estimating this equation by OLS is likely to suffer from the endogeneity issue because of the correlation between changes in population size and the unobserved changes in productivity ($\Delta \log \tilde{\varphi}_t^n(a)$). To deal with this issue, we implement the Push and Pull IVs as we implement in Section 3.2.

Second, observing only 47 prefectures, we lack statistical power to estimate these spillover parameters. Therefore, we estimate this equation at the municipality level as in section 3.2. Doing so requires data on labor compensation by municipality, age, and year. Lacking such data, we impute these values using the municipality-year-level taxable income data (aggregated across age groups; as used in Section 3.2) and the prefecture-year-age-level labor compensation and employment rate data. The basic idea is to allocate the municipality-year-level taxable income into different age groups to replicate the age profile of labor compensation within the prefecture. See Appendix C.1 for the details.

Table 2 presents the results using the long difference from 1985 to 2010. Column (1) reports the results of the OLS specification. Column (2) reports the results of the IV specification following the same Pull and Push IV as in Section 3.2. The coefficients are not statistically different from zero, with relatively small standard errors. In particular, we cannot reject the hypothesis that there is no productivity spillover from population size from the working-age population and the retired population size in this context. Based on these results, we set the spillovers $\gamma^Y = \gamma^O = 0$ for our baseline quantitative analysis.¹⁷

5.2.3 Amenity Spillover Function $f^X(a, \{L_t^n(\cdot)\})$

To facilitate the estimation, we parameterize the amenity spillover function such that

$$f^X(a, \{L_t^n(\cdot)\}) = \begin{cases} (L_t^{n,W})^{\zeta^{W,Y}} (L_t^{n,O})^{\zeta^{O,Y}} & \text{if } a^M > a > \underline{a} \\ (L_t^{n,W})^{\zeta^{W,M}} (L_t^{n,O})^{\zeta^{O,M}} & \text{if } a^* > a \geq a^M . \\ (L_t^{n,W})^{\zeta^{W,O}} (L_t^{n,O})^{\zeta^{O,O}} & \text{if } a \geq a^* \end{cases} \quad (22)$$

¹⁷In Figure 6, we document that the impacts of the working-age population on average taxable income (averaged across age groups) are significant and positive, and that of the elderly population is significant and negative. The finding of Table 2 suggests that the patterns in Figure 6 is primarily driven by the composition effects (working-age population tends to earn higher income), rather than the productivity spillovers (population size affects income conditional on age groups).

Table 2: Estimation Results of Productivity Spillovers

VARIABLES	(1)	(2)
	$d \log \bar{\varphi}_t^n$ Municipality OLS	$d \log \bar{\varphi}_t^n$ Municipality IV
$\Delta \log(\text{Working-Age Pop})$	0.008 (0.017)	-0.033 (0.029)
$\Delta \log(\text{Elderly Pop})$	-0.039 (0.030)	0.005 (0.037)
Observations	1,733	1,733
FE and Cluster	Pref	Pref
Controls	Yes	Yes
Kleibergen-Paap F		76.81

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Note: We control for the share of secondary industry, the share of tertiary industry, the log of population density, and the log of the area in the starting year and include prefecture fixed effects. We estimate the clustered standard errors, using the prefecture as a cluster.

where $L_t^{n,W} = \sum_{a^* > a \geq a} L_t^n(a)$ is the working-age population size (age 15-64) and $L_t^{n,O} = \sum_{a \geq a^*} L_t^n(a)$ is the elderly population size (age over 65); $\{\zeta^{W,Y}, \zeta^{O,Y}\}$ is the agglomeration amenity spillovers from the working-age and the elderly to the young-age population (aged 15-39); $\{\zeta^{W,M}, \zeta^{O,M}\}$ is the agglomeration amenity spillovers from the working-age and the elderly to the middle-age population (aged 40-64), and $\{\zeta^{W,O}, \zeta^{O,O}\}$ is the agglomeration amenity spillovers from the working-age and the elderly to the elderly population (age over 65). We allow for the flexible combination of the spillover elasticity to capture the high-dimensionality of amenity proxies and how they relate to the population size across different age groups, as documented in Section 3.2.

We estimate these spillover parameters $\{\zeta^{W,Y}, \zeta^{O,Y}, \zeta^{W,M}, \zeta^{O,M}, \zeta^{W,O}, \zeta^{O,O}\}$ in the following step-wise procedure. First, we use migration flows (implied by the population changes) to back out the sequence of continuation values $\{V_t^n(a)\}$. By combining the demographic balancing equation (10) and the migration share equation (8), we have:

$$L_{t+1}^i(a) = \sum_i \left(\frac{\exp [s_t^i(a)\beta V_{t+1}^i(a+1) - \tau_t^{ni}(a)]^{1/\nu}}{\sum_\ell^N \exp [s_t^\ell(a)\beta V_{t+1}^\ell(a+1) - \tau_t^{n\ell}(a)]^{1/\nu}} s_t^n(a-1)L_t^n(a-1) \right). \quad (23)$$

Given the observed data for the population distribution $\{L_t^n(a)\}$, survival rates $\{s_t^n(a)\}$, and parameters $\{\beta, \nu\}$, and the migration costs $\{\tau_t^{ni}\}$, we can uniquely calibrate the continuation

values $\{V_t^n(a)\}$ (up to scale).¹⁸ For the migration costs, we parametrize them as a function of log bilateral distance and estimate them using the bilateral gravity equations from 2015 Census (see Appendix C.4).

Second, we combine the calibrated continuation values $\{V_t^n(a)\}$ and the Bellman equation (9) to estimate the proxies for the amenity (“hat” indicates that the estimated amenity are identified up to scale):

$$\log \hat{\chi}_t^n(a) = V_t^n(a) - \nu \log \sum_{\ell}^N \exp \left[s_t^\ell(a) \beta V_{t+1}^\ell(a+1) - \tau_t^{n\ell}(a) \right]^{1/\nu} - \log \frac{y_t^n(a)}{(R_t^n)^\theta}, \quad (24)$$

where $y_t^n(a) = (1 - \kappa_t)w_t^n(a) + \pi_t^n(a) + T_t \times 1[a \geq a^*]$ is the nominal income and $(R_t^n)^\theta$ corresponds to the local price index.¹⁹

Finally, we take the time difference of the estimated amenity to obtain our estimating equations for the amenity spillovers:

$$\Delta \log \hat{\chi}_t^n(a) = \beta^W \Delta \log L_t^{n,W} + \beta^O \Delta \log L_t^{n,O} + \Delta \log \hat{\chi}_t^n(a). \quad (25)$$

We estimate these regressions separately for the young population (age 15-39; $a^M > a > \underline{a}$), middle-age population (age 40-64; $a^* > a > a^M$), and old population (age over 65; $a > a^*$), where each of these regression coefficients $\{\beta^W, \beta^O\}$ reveal the spillover elasticities $\{\zeta^{W,Y}, \zeta^{O,Y}\}$, $\{\zeta^{W,M}, \zeta^{O,M}\}$, $\{\zeta^{W,O}, \zeta^{O,O}\}$, respectively.

Similarly to estimating productivity spillovers in Section 5.2.2, we execute these estimation procedures at the municipality level, instead of prefectures, to obtain statistical precision. We estimate this equation by OLS by controlling for the same set of variables as in the reduced-form analysis.²⁰

Table 3 presents the results of the OLS regression using the time difference between 1985

¹⁸As shown in Allen and Arkolakis (2014) and Redding and Rossi-Hansberg (2017) in the static contexts, this inversion uniquely identifies $\{V_t^n(a)\}$ up to scale. Note that one equation is redundant, and hence we can only identify the continuation values up to scale.

¹⁹For computing time changes in housing rents R_t^n , we use the model-implied rents as $1 - \mu$ times log changes in aggregate income as implied by equations (15) and (?? the total housing expenditure divided by model-implied housing stock (equations ?? and 16), instead of using actual data, since the data of housing stock and rents are only available for a subset of municipalities (mostly in urban areas). In Appendix D, we show that our results are robust to using the housing rents observed in the data for this subset of municipalities (Table D.1).

²⁰Estimating this equation by OLS is likely to suffer from the endogeneity issue because of the correlation between changes in population size and the unobserved changes in amenity ($\Delta \log \hat{\chi}_t^n(a)$). We are currently working on obtaining the IV estimates using Push and Pull IVs as we implement in Section 3.2.

Table 3: OLS Estimation Results of Amenity Spillovers

VARIABLES	(1)	(2)	(3)
	$\Delta \log$ Amenity (w. Model Rent) Young	Middle	Elderly
$\Delta \log(\text{Working-Age Pop})$	0.234*** (0.015)	0.120*** (0.016)	-0.002 (0.043)
$\Delta \log(\text{Elderly Pop})$	0.028 (0.029)	0.084*** (0.025)	0.131** (0.059)
Observations	8,665	8,665	3,466
FE and Cluster	Pref-Age	Pref-Age	Pref-Age
Controls	Yes	Yes	Yes

Robust standard errors in parentheses

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Note: We control for the share of secondary industry, the share of tertiary industry, the log of population density, and the log of the area in the starting year and include prefecture-age group fixed effects. We estimate the clustered standard errors, using the prefecture-age group as a cluster. The model rents are imputed by applying equations (C.6) and (16) with the observed taxable income data of the municipality. See Appendix C.3 for the details of the imputation.

and 2010.²¹ We find that the elasticity of spillover effects from the working-age population size is significantly positive and greater for the Young group, while the elasticity of spillover effects from the elderly population size is significantly positive and greater for the Elderly group. The elasticities for the Middle group lie between those for the Young and Elderly groups. These results are in line with the findings from our reduced-form analysis, which indicate that amenity variables relevant to the Young group (e.g., child/education and retail PCAs) increase more with the working-age population size, while the amenity variable for the Elderly group (i.e., elderly service PCA) increases significantly only with the elderly population size. We use these point estimates of $\{\zeta^{W,Y}, \zeta^{O,Y}, \zeta^{W,M}, \zeta^{O,M}, \zeta^{W,O}, \zeta^{O,O}\}$ for our baseline specification in the following section.

6 Quantitative Analysis

In this section, we use our calibrated model to undertake a sequence of simulations that illustrate the role of life-cycle migration decisions in regional depopulation and aging patterns. We show that endogenous life-cycle migration decisions are crucial in shaping its process and the welfare implications across generations and regions.

²¹Note that population data for consecutive periods are necessary to calibrate value functions. Moreover, the population data from the 2020 Census is not used due to concerns about potential bias resulting from the pandemic. Thus, the longest time difference available for estimation is between 1985 and 2010.

6.1 Migration, Regional Depopulation, and Aging in 1990-2015

We begin our quantitative analysis showing how endogenous life-cycle migration decisions have affected the patterns of regional depopulation and aging in the past using the calibrated model to the 47 prefectures in Japan from 1990 to 2015 as described in the previous section. Recall that our procedure exactly fits our model to the population distribution at every period and in every prefecture to the data. Using the calibrated model, we undertake a counterfactual simulation to shut down migration completely, as well as to shut down the endogenous responses of local economic activity (amenity spillovers and rents).

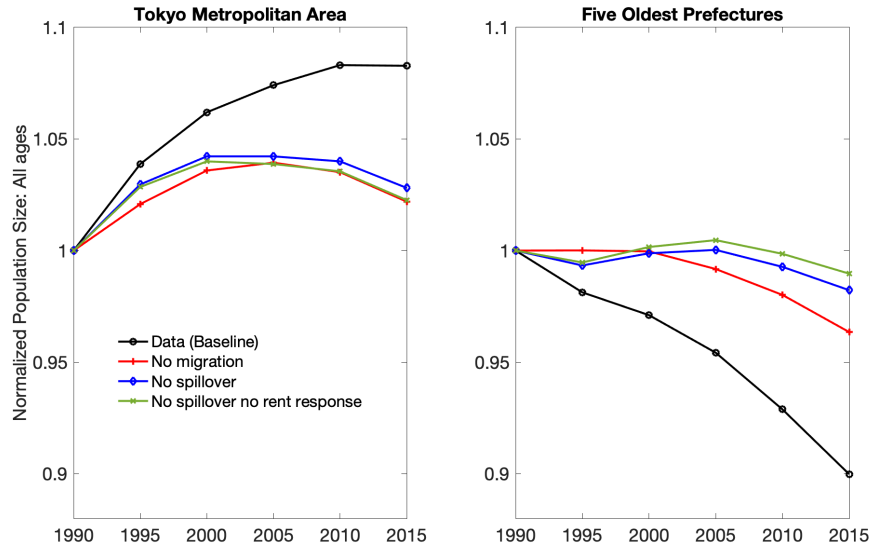
Figure 8 presents our results. Panel (A) presents the pattern of population size for Tokyo Metropolitan Area (Tokyo, Kanagawa, Saitama, and Chiba prefectures) in the left panel and that of the five oldest prefectures in 1990 (Akita, Shimane, Yamaguchi, Tokushima, and Kochi). In both panels, we normalize the population size to one in 1990 to focus on their growth rates. We find that the population size increased in Tokyo Metropolitan Area by nearly 10 percent over this period, while that of the five oldest prefectures decreased by nearly 10 percent, consistent with the observations in Section 3.1.

To understand the role of migration in this process, we undertake a counterfactual simulation that completely shuts down migration ($\tau_t^{ni} \rightarrow \infty$ for $i \neq n$). Note that this counterfactual simulation is analogous to the ones executed in Section 3.1. Under this counterfactual simulation, we find that the population growth in Tokyo Metropolitan Area would have been slower and have turned negative in 2000, while the population decline of the five oldest prefectures would have been slower, consistent with the findings in Section 3.1.

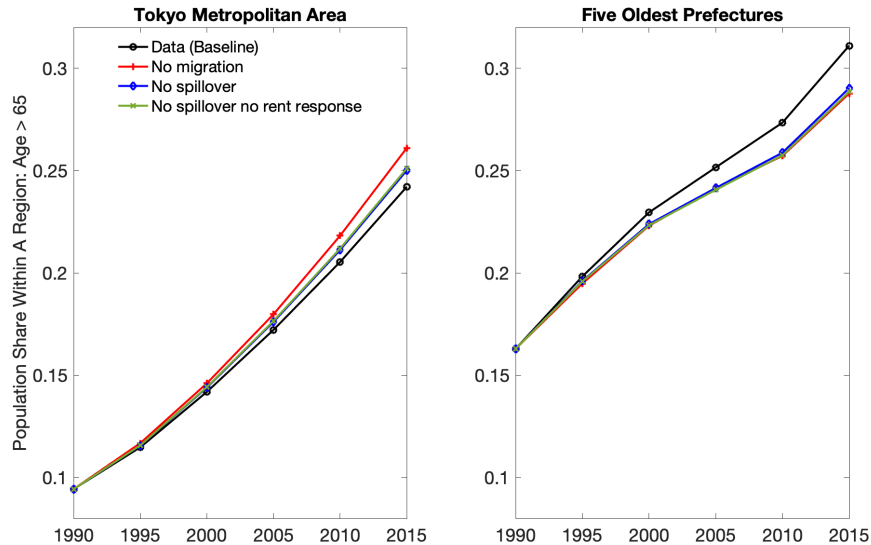
Given that migration plays a crucial role, a natural question is: how are these migration decisions affected by the endogenous local economic activity, and how does it in turn affect the patterns of regional depopulation and aging? To answer this question, we undertake an additional counterfactual simulation to shut down the agglomeration spillovers. Specifically, we take our calibrated model with our estimated agglomeration spillovers in amenity ($\{\zeta^{W,Y}, \zeta^{O,Y}, \zeta^{W,M}, \zeta^{O,M}, \zeta^{W,O}, \zeta^{O,O}\}$) to zero (recall that in our baseline specification, productivity spillover ($\{\gamma^Y, \gamma^O\}$) is already zero). To ensure that this counterfactual simulation does not affect the level of productivity and amenity differences in the baseline period, we recalibrate the exogenous component of amenity in 1990 $\{\tilde{\chi}_{1990}^n(a)\}$ so that the productivity and amenity net of spillovers $\{\chi_{1990}^n(a)\}$ coincide with those in our baseline specification. We find that this counterfactual simulation decreases the population growth in Tokyo Metropolitan Area and attenuates the population loss in the five oldest prefectures. The magnitudes of the differences

Figure 8: Regional Depopulation and Aging: 1990-2015

(A) Population Size



(B) Fraction of the Elderly



from our baseline specification are large and comparable to the ones where we completely shut down migration. These findings suggest that endogenous amenity plays a crucial role in facilitating the process of population movement from rural to urban areas.

Finally, in addition to shutting down the agglomeration externalities, we further assume that the housing supply is perfectly elastic to demand ($\mu = 1$) so that the housing rents

do not respond to local economic activity. Under this counterfactual simulation, income, amenity, and housing rents are exogenous and do not respond to the equilibrium population distribution. This counterfactual simulation yields a similar pattern of results to the ones where we only shut down amenity spillovers.²² Therefore, the additional contribution of rent responses to the patterns of depopulation seems modest compared to those of the amenity spillovers.

In Panel (B) of Figure 8, we present the observed and counterfactual patterns of the fraction of the elderly population in each region. Consistent with the patterns documented in Section 3.1, the fraction of the elderly is lower in Tokyo Metropolitan Area than in the five oldest prefectures in 1990, and this gap persists over the time periods of our data. If we shut down migration, the gap in the fraction of the elderly would almost converge in 2015. We also find that shutting down agglomeration amenity spillovers would increase the growth rates of the fraction of the elderly in Tokyo Metropolitan Area and decrease it in the five oldest prefectures. In Appendix Figure E.2, we present the patterns on the population size of each region by age groups, and we show that these patterns of the fraction of the elderly are primarily driven by the changes in youths' outmigration patterns. These findings indicate that endogenous amenities particularly affect youths' migration patterns and play a crucial role in regional aging patterns.

6.2 Future Projection of Depopulation and Aging

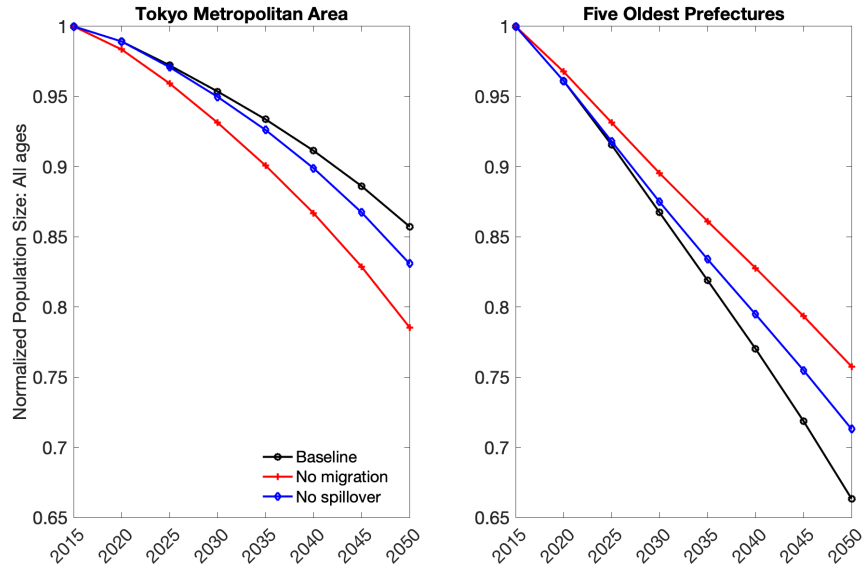
We now use our calibrated model to project the future patterns of the regional population and aging. We assume that exogenous productivity, amenity, and migration costs will remain constant from 2015 onward, and solve the model forward. We use the projected regional fertility and survival rates from the National Institute of Population and Social Security Research as discussed in Section 5. To highlight the role of migration decisions and endogenous amenity spillovers, we undertake this simulation under three scenarios: using our baseline model, shutting down migration across regions, and shutting down agglomeration amenity spillovers.

²²Relative to only shutting amenity spillovers, this counterfactual simulation results in a slightly slower population growth in Tokyo and a slightly slower population decline in the five oldest prefectures. These patterns are driven by the fact that, once we shut down amenity spillovers, aggregate income (and hence housing demand) grows slower in Tokyo than in the five oldest prefectures. Even though the population growth is faster in Tokyo Metropolitan Areas, it is driven primarily by the increase of retired people, whose effective income is smaller than those of the retired population. See Appendix E.2 for the changes in population size by age groups and by region.

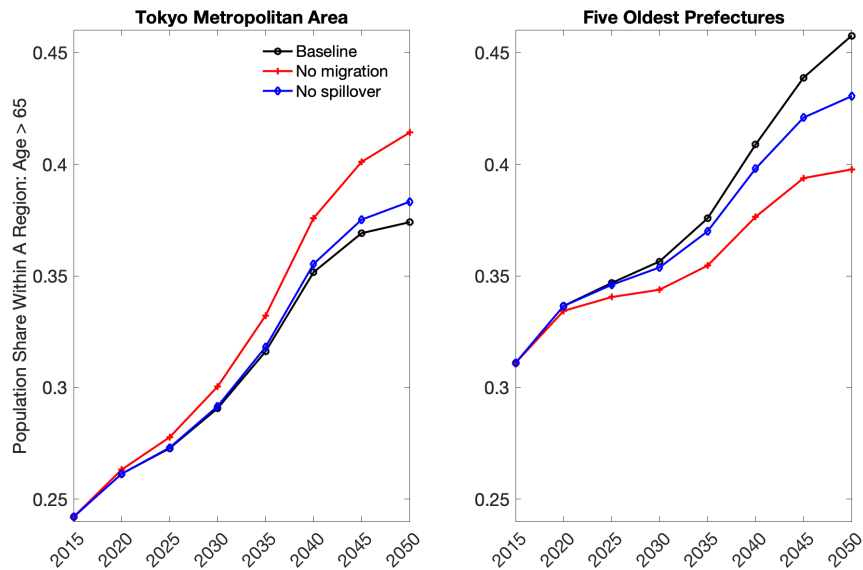
Figure 9 presents the simulation results. Panel (A) presents the projected patterns of the population size in Tokyo Metropolitan Area and the five oldest prefectures as defined in the previous section. We normalize the population size to one in 2015 to highlight its growth rate. Panel (B) presents the patterns for the fraction of the elderly over 65.

Figure 9: Regional Depopulation and Aging: Future Projection

(A) Population Size



(B) Fraction of the Elderly



Our baseline model projects that the population size will decrease by 14 percent in Tokyo

Metropolitan Area and by 34 percent in the five oldest prefectures by 2050. Therefore, our baseline model predicts that the regional disparity in the population decline will persist in the future. When we shut down cross-regional migration, both regions experience a similar rate of population decline (22 percent for Tokyo Metropolitan Area and 24 percent for the five oldest prefectures). Therefore, the unequal rates of depopulation are primarily driven by the migration of the population from rural to urban areas. Furthermore, when we allow for migration but shut down agglomeration amenity spillovers, we find that Tokyo's population decreases by 17 percent (as opposed to 14 percent in our baseline specification) and that of the five oldest prefectures falls by 28 percent (as opposed to 34 percent in baseline specification). These findings suggest that the endogenous amenity decline in rural areas accelerates rural-urban migration and depopulation of rural areas.

In Panel (B) of Figure 9, we present the projected patterns of the fraction of the elderly. Our baseline model projects that the fraction of elderly will increase from 24 to 36 percent from 2015 to 2050 in Tokyo Metropolitan Area and from 31 to 46 percent in the five oldest prefectures. Therefore, the regional gap in aging is also expected to persist. When we shut down migration, we find that the fraction of the elderly increases more rapidly in Tokyo Metropolitan Area than in the five oldest prefectures. The fraction of the elderly would reach 41 percent in Tokyo Metropolitan Area in 2050, larger than 39 percent in the five oldest prefectures. This pattern arises because the fertility rate in Tokyo Metropolitan Area is lower, and hence the fraction of the elderly would be higher, absent the inflow of youths' population in the long run. Consistent with this observation, in Appendix Figure E.4, we show that the differences in the baseline scenario and in the scenario shutting down migration primarily arise because of the changes in youths' migration patterns. We also find that allowing for migration but shutting down endogenous agglomeration spillovers accelerates the aging of Tokyo Metropolitan Area and slows it down for the five oldest prefectures. This pattern reinforces the idea that endogenous agglomeration spillovers crucially affect the projected patterns of regional aging.

6.3 Welfare Implications

Given the large contribution of migration decisions and agglomeration spillovers in shaping the patterns of regional depopulation and aging, a natural question is their implications for aggregate and distributional welfare across regions and generations. To answer this question, we use our model to compute the changes in consumption-equivalent flow utility (inclusive of

amenity values) for each age group, region, and time.²³ To highlight the role of migration, we compute this measure for each period from 2015 to 2050, under two scenarios: using our baseline specification and shutting down migration.

Figure 10 presents the results. Panel (A) presents the changes in consumption-equivalent flow utility of the youths (age 25-30, solid line) and of the elderly (age over 65, dashed line), aggregated across all regions, using our baseline specification (blue) and by shutting down migration (red). Panel (B) presents the same results, decomposed by the Tokyo Metropolitan Area (left) and the five oldest prefectures (right).

Several patterns are notable. First, in our baseline scenario, the consumption-equivalent flow utility will fall both for the youth and the elderly from 2015 to 2050. This decline is driven primarily by two forces. First, the expected nationwide aging (increase in the fraction of the elderly in the total population) leads to an increase in tax burden to finance pension (Figure 11). Second, the shrinking population in every location implies that amenity declines everywhere in the country. Since the amenity spillover depends on the population size of the different age groups, these amenity declines have different implications for the youths and the elderly. In particular, the flow utility of the elderly exhibits a non-monotonic pattern: while it is in an overall declining trend, it increases from 2025 to 2040. This pattern is driven by the fact that the elderly population increases during these periods even though the overall population size declines (Appendix Figure E.3). Since the elderly population enjoys amenity spillovers predominantly from the size of the elderly population, not from the working-age population (Table 3), this nationwide transition of population pyramids generates nonmonotonic patterns of the flow utility for the elderly population.

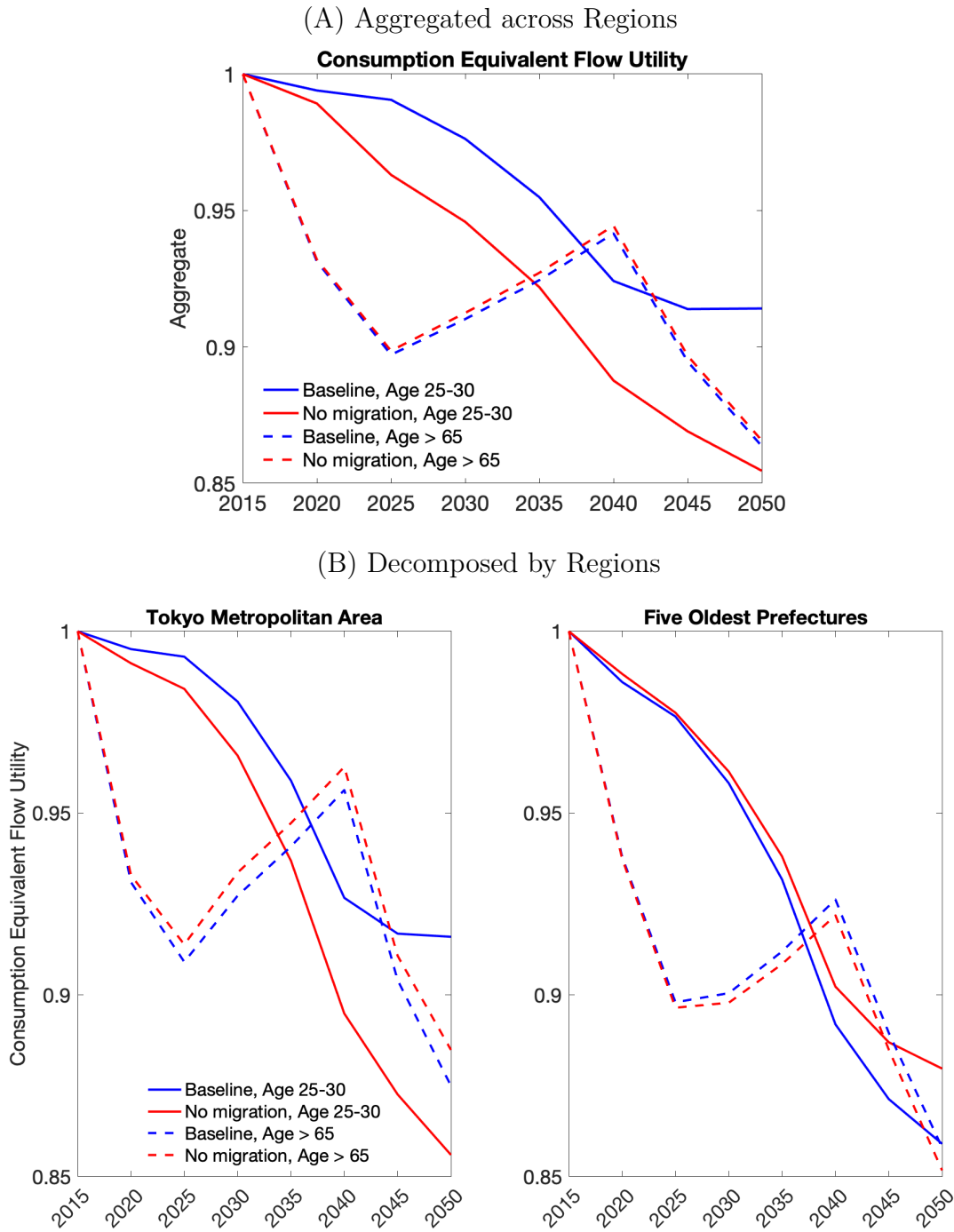
Second, by comparing the baseline scenario and the counterfactual where we shut down migration, we find that the youths' flow utility falls significantly by shutting down migration. This effect arises primarily because of two reasons. First, by shutting down migration, the youths lose the opportunity to move from rural to urban areas. Since the population generally

²³Specifically, for each future year t , given region N_w and age group a_w , our measure of the changes in consumption-equivalent flow-utility (relative to 2015) is given by δ_t at satisfies:

$$\begin{aligned} & \sum_{n \in N_w} \sum_{a \in a_w} \frac{L_{2015}^n(a)}{\sum_{n \in N_w} \sum_{a \in a_w} L_{2015}^n(a)} \exp \left(\ln \left(\delta_t \frac{I_{2015}^n(a)}{(R_{2015}^n)^\theta} \right) + \ln \chi_{2015}^n(a) \right) \\ &= \sum_{n \in N_w} \sum_{a \in a_w} \frac{L_t^n(a)}{\sum_{n \in N_w} \sum_{a \in a_w} L_t^n(a)} \exp \left(\ln \left(\frac{I_t^n(a)}{(R_t^n)^\theta} \right) + \ln \chi_t^n(a) \right), \end{aligned}$$

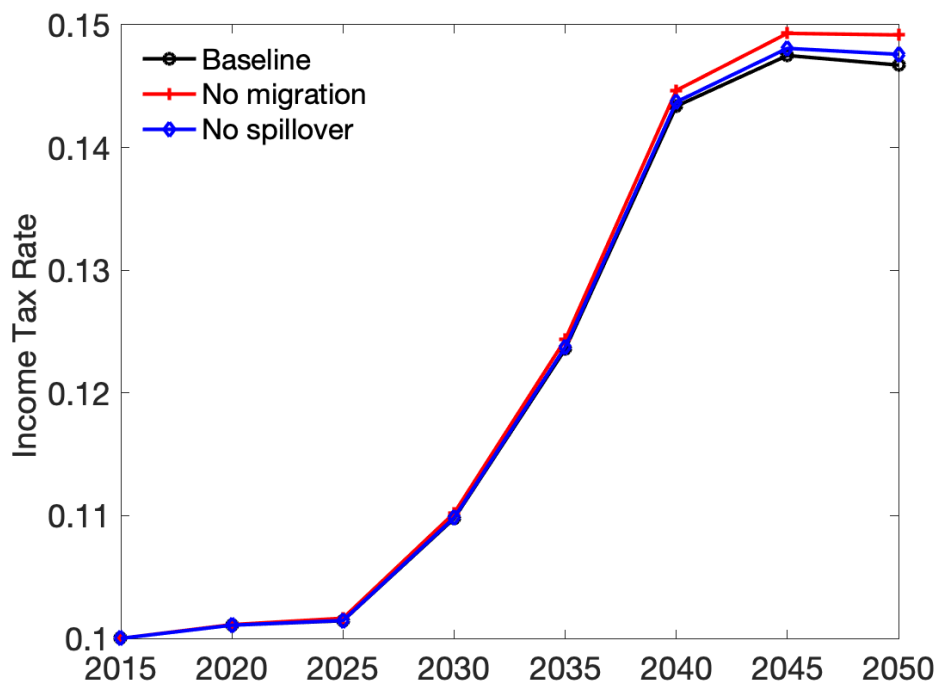
where $I_t^n(a)$ is the final income (after income tax, pension, and land profit rebate) for age group a in location n and period t .

Figure 10: Changes in Consumption-Equivalent Flow Utility



moves from regions that give low flow utility to high flow utility (conditional on migration costs and continuation values), shutting down this population movement leads to a decline in flow utility. Second, by shutting down migration, there is a decline in flow utility in Tokyo

Figure 11: Changes in Income Tax Rate for Pension Financing



Metropolitan Area and an increase in flow utility in the five oldest prefectures (Panel B) for this age group.²⁴ Since the population is concentrated more in Tokyo Metropolitan Area, this shift generates an overall decline in flow utility for youths.

Third, by comparing the baseline scenario and shutting down migration, we find that the elderly’s flow utility increases slightly by shutting down migration. However, the difference is significantly smaller than that of the youths. These modest contributions of migration in the flow utility of the elderly, as opposed to the youths, primarily occur for two reasons. First, the migration rates of the elderly are significantly lower than the youths (as documented in Section 3.1). Therefore, the effect of shutting down the population relocation from regions with low flow utility to high flow utility is small for the elderly than for the youths. Second, shutting down migration does not affect the flow utility of the elderly conditional on each location as much as it does for youths (Panel B). This pattern arises because the endogenous amenity spillover from youths to the elderly is limited in our baseline estimates (Table 3). In fact, shutting down migration decreases the flow utility of the elderly in the five oldest

²⁴Consistent with this interpretation, when we evaluate the flow utility without taking into account the effect of amenity, we find a smaller decline in flow utility for youths (Appendix Figure E.6).

prefectures because of increased housing rents (Appendix Figure E.5). Given that shutting down migration primarily affects the population distribution of youths, but not the elderly population, the endogenous changes in amenities have modest effects on the elderly, both in rural and urban areas.

These findings suggest that, even though the youths' out-migration is a key driver of rural depopulation and aging, its welfare implication is not necessarily negative, even for the elderly in rural areas.

7 Conclusion

We study how depopulation and aging progress across regions within a country and how this process affects economic welfare across regions and generations. Using spatially disaggregated data from Japan for the last 40 years, we document that youths' out-migration accelerated rural depopulation and aging, leading to a decline in rural economic activity. Using the quantitative dynamic spatial general equilibrium model of life-cycle migration decisions, we find that endogenous decline in rural amenities plays a crucial role in the past and future youths' outmigration, and hence accelerates the regional disparity in depopulation and aging. Shutting down cross-regional migration comes at a substantial welfare loss for the youths, while generating limited benefits even for the elderly in rural areas.

Our results indicate that, while restricting migration flows may slow down the regional disparity in rural depopulation and aging, its implications for local economic activity and aggregate welfare are ambiguous. In ongoing work, we plan to assess the implications of the ongoing migration subsidy to rural areas.

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Online Appendix for “Living in a Ghost Town: The Geography of Depopulation and Aging”

July 2023

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A Data Sources

Table A.1: Data Sources

Category	Variables	Spatial Unit	Statistics Name	Source
(A) Population	Population by Age, Gender, and Residence 5 Years Ago	Municipality	Population Census	Ministry of Internal Affairs
	Fertility Rates by Mothers' Age	Prefecture	Vital Statistics	Ministry of Health, Labour and Welfare
	Death Rates by Age and Gender	Prefecture	Vital Statistics	Ministry of Health, Labour and Welfare
	Projected Fertility and Mortality Rates	National		Institute of Population and Social Security Research
(B) Income / Employment	Taxable Income	Municipality	Tax Statistics	Ministry of Internal Affairs
	Number Of Workers by Sector	Municipality	Economic Census	Ministry of Internal Affairs
	Number Of Establishments by Sector	Municipality	Economic Census	Ministry of Internal Affairs
	Wage by Age, Gender, Sector, Occupation	Prefecture	Basic Survey on Wage Structure	Ministry of Health, Labour and Welfare
(C) Housing / Land	Total Number Of Residences	Municipality	Housing and Land Survey	Ministry of Internal Affairs
	Posted Land Price	Municipality	Posted Land Price Statistics	Ministry of Land, Infrastructure, Transport and Tourism
(D) Amenity Retail	Number Of Retail Stores	Municipality	Economic Census	Ministry of Internal Affairs
	Number Of Large Retail Stores	Municipality	Economic Census	Ministry of Internal Affairs
	Number of Clothing Stores	Municipality	Economic Census	Ministry of Internal Affairs
	Number of Food and Beverage Retail Stores	Municipality	Economic Census	Ministry of Internal Affairs
	Number Of Restaurants	Municipality	Economic Census	Ministry of Internal Affairs
	Number Of Barber Shops And Beauty Parlors	Municipality	Report on Public Health Administration and Services	Ministry of Health, Labour and Welfare
Public Service	Number Of Libraries	Municipality	Prefecture Statistics	Prefecture Office
	Number Of Post Office	Municipality	Post Office Statistics	Post Office
	Road Length	Municipality	Road Infrastructure Statistics	Ministry of Land, Infrastructure, Transport and Tourism
	Paved Road Length	Municipality	Road Infrastructure Statistics	Ministry of Land, Infrastructure, Transport and Tourism
	Number Of Parks	Municipality	Park Statistics	Ministry of Land, Infrastructure, Transport and Tourism
	Area Of Parks	Municipality	Park Statistics	Ministry of Land, Infrastructure, Transport and Tourism
Eldery Service	Number Of Police Stations	Municipality	Prefecture Statistics	Prefecture Office
	Number Of Nursing Homes	Municipality	Report on Public Health Administration and Services	Ministry of Health, Labour and Welfare
	Number Of Community Centers	Municipality	Social and Education Statistics	Ministry of Education, Culture, Sports, Science and Technology
Child/Education	Number Of Senior Citizen Clubs	Municipality	Prefecture Statistics	Prefecture Office
	Number Of Daycares	Municipality	Social and Welfare Statistics	Ministry of Health, Labour and Welfare
	Number Of Schools (Elementary, Middle, and High)	Municipality	Prefecture Statistics	Prefecture Office
Health/Medical	Number Of Teachers (Elementary, Middle, and High)	Municipality	School Statistics	Ministry of Education, Culture, Sports, Science and Technology
	Number Of General Hospitals	Municipality	Survey of Medical Institutions	Ministry of Health, Labour and Welfare
	Number Of General Clinics	Municipality	Survey of Medical Institutions	Ministry of Health, Labour and Welfare
	Number Of Medical Doctors	Municipality	Statistics of Physicians, Dentists and Pharmacists	Ministry of Health, Labour and Welfare
	Number Of Nurses	Municipality	Prefecture Statistics	Prefecture Office

Table A.2: PCA Loading for Amenity Categories

	Loading
<i>Panel A. Retail</i>	
Number Of Retail Stores	.418
Number of Clothing Stores	.411
Number of Food and Beverage Retail Stores	.411
Number Of Restaurants	.411
Number Of Large Retail Stores	.384
Number Of Barber Shops And Beauty Parlors	.413
<i>Panel B. Health Medical</i>	
Number Of General Hospitals	.477
Number Of General Clinics	.505
Number Of Medical Doctors	.517
Number Of Nurses	.499
<i>Panel C. Elderly Service</i>	
Number Of Community Centers	.547
Number Of Senior Citizen Clubs	.632
Number Of Nursing Homes	.550
<i>Panel D. Child Education</i>	
Number Of Daycares	.567
Number Of Schools (Elementary, Middle, and High)	.576
Number Of Teachers (Elementary, Middle, and High)	.589
<i>Panel E. Environment / Transportation</i>	
Road Length	.526
Paved Road Length	.564
Number Of Parks	.394
Number of Police Stations	.500

B Appendix for Reduced-Form Facts

B.1 Aggregate Statistics

Figure B.1: Life Expectancy and Fertility Rates

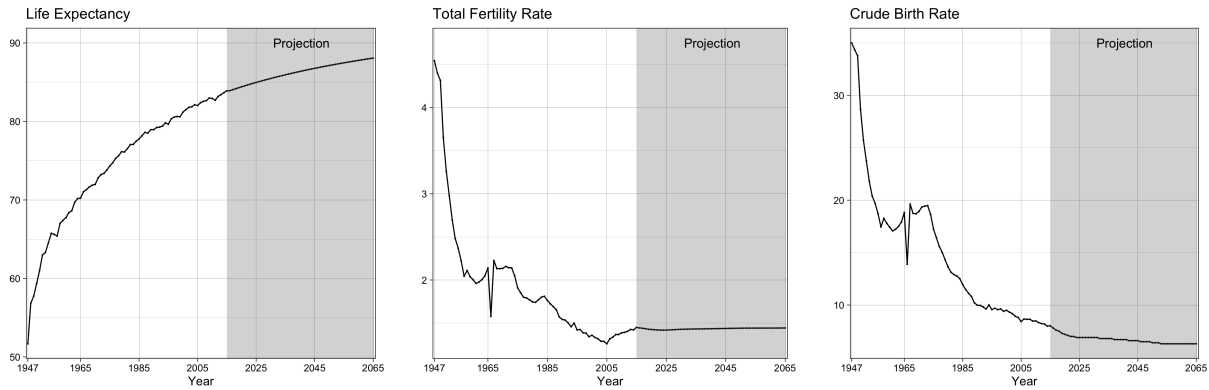
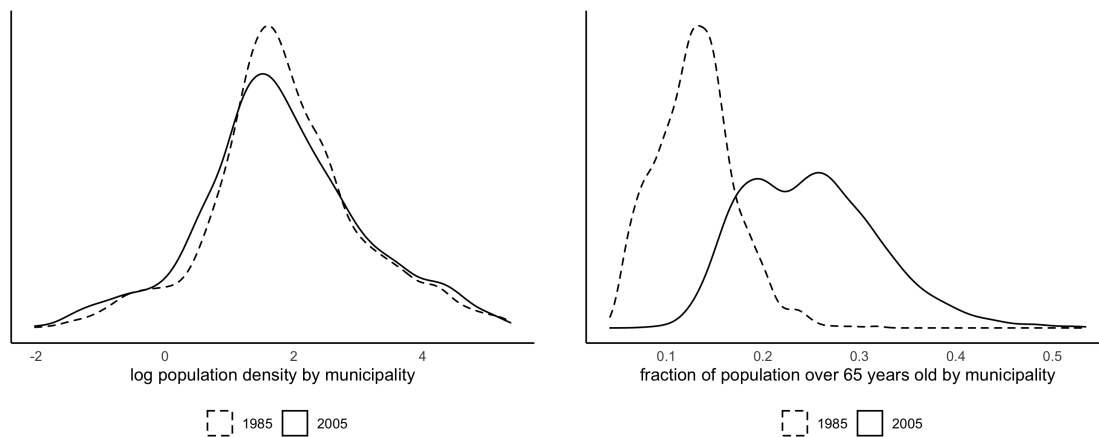


Figure B.2: Heterogeneity of Depopulation and Aging across Municipalities in Japan

(a) Population Density

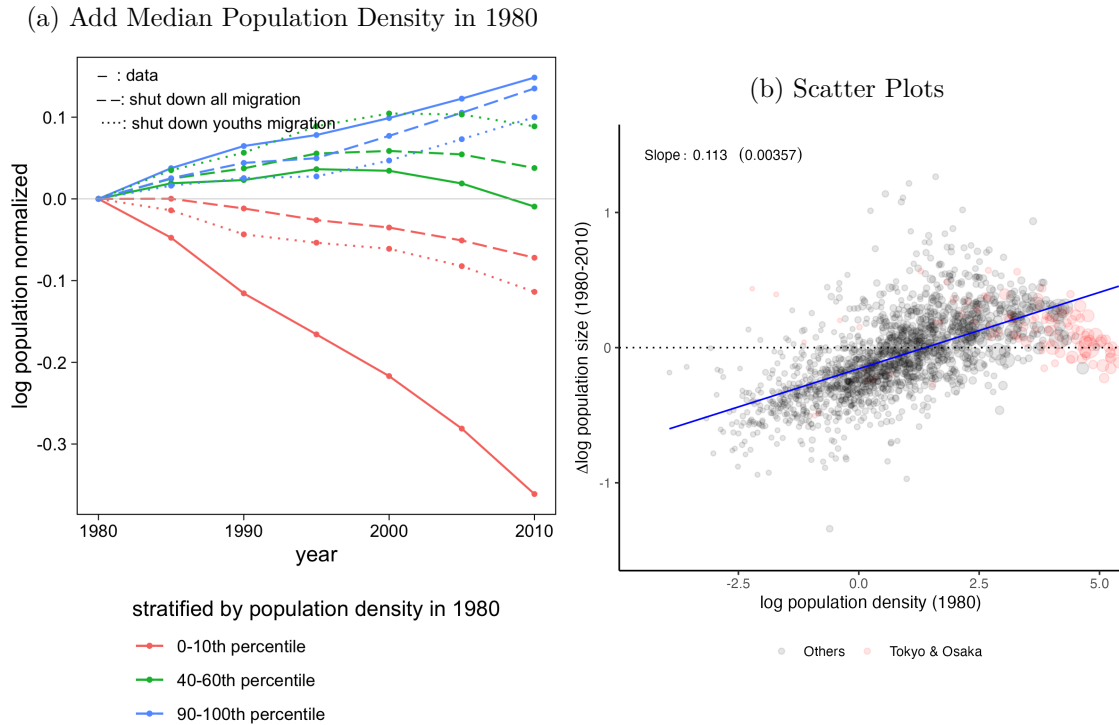
(b) Fraction of Population above 65 Years Old



Note: This figure reports the distribution of population densities across Japanese municipalities in 1985 and 2005 in panel a. Panel b reports the distribution of fraction of population above 65 years old across Japanese municipalities.

B.2 Geographic Pattern of Depopulation and Aging

Figure B.3: Changes in Population Size across Municipalities and Role of Migration: Additional Heterogeneity across Population Density in 1980



Note: Panel (a) reports a version of Figure 3 to include the patterns of municipalities with median (40-60) percentile in terms of population density in 1980. Panel (b) reports the relationship between the log change in population size from 1980 to 2010 against the log population density in 1980. Population density is defined by the population size divided by geographic area. The size of the dot corresponds to the population size of the municipality in 1980. Municipality boundaries are defined at the point of 2010.

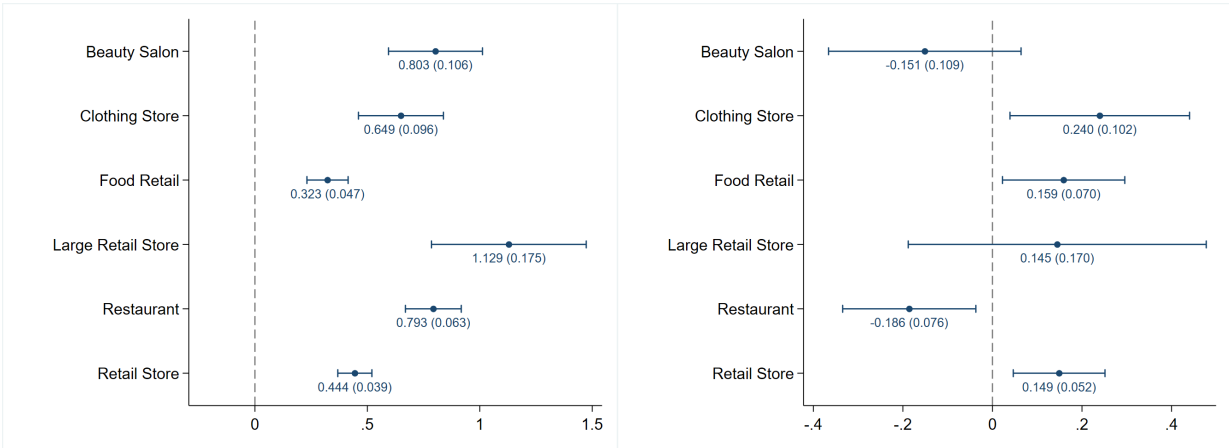
B.3 Impacts of Depopulation and Aging

B.3.1 Additional Figures for Second Stage

Figure B.4: Impacts of Depopulation and Aging on Local Economy: Retail

(a) $\Delta \log$ Working-Age Population

(b) $\Delta \log$ Elderly Population

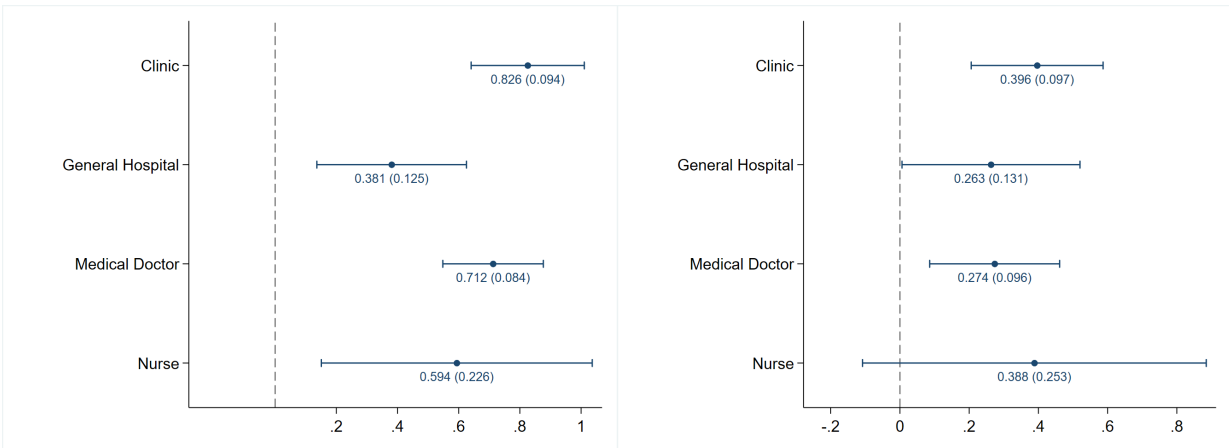


Note: This figure reports the coefficient estimates of equation 2 where each dependent variable is in changes of local economy such as retail. The left panel reports the coefficients on $\Delta \log$ working-age population and the right panel reports the coefficients on $\Delta \log$ elderly population.

Figure B.5: Impacts of Depopulation and Aging on Local Economy: Health/Medical

(a) $\Delta \log$ Working-Age Population

(b) $\Delta \log$ Elderly Population

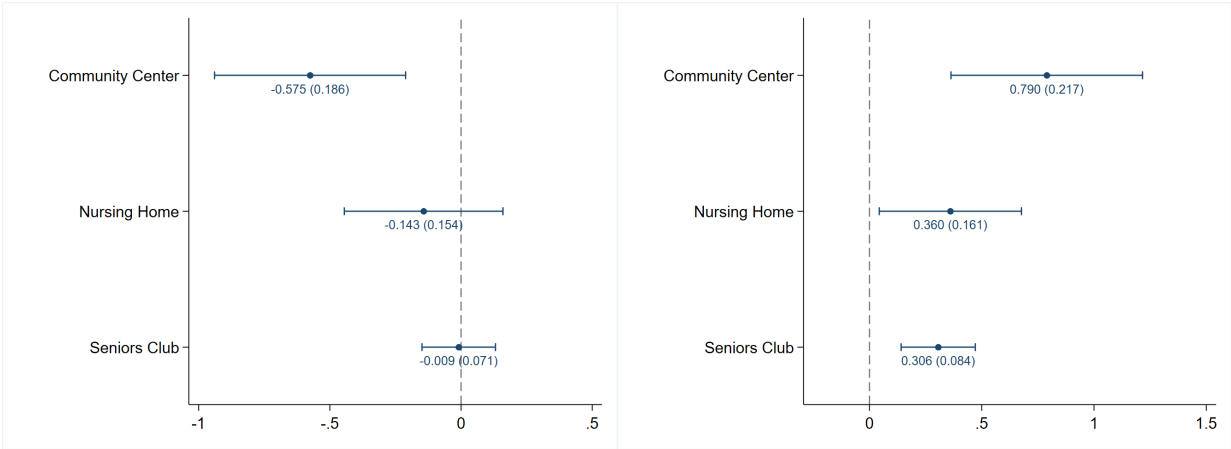


Note: This figure reports the coefficient estimates of equation 2 where each dependent variable is in changes of local economy such as health and medical services. The left panel reports the coefficients on $\Delta \log$ working-age population and the right panel reports the coefficients on $\Delta \log$ elderly population.

Figure B.6: Impacts of Depopulation and Aging on Local Economy: Elderly Service

(a) $\Delta \log$ Working-Age Population

(b) $\Delta \log$ Elderly Population

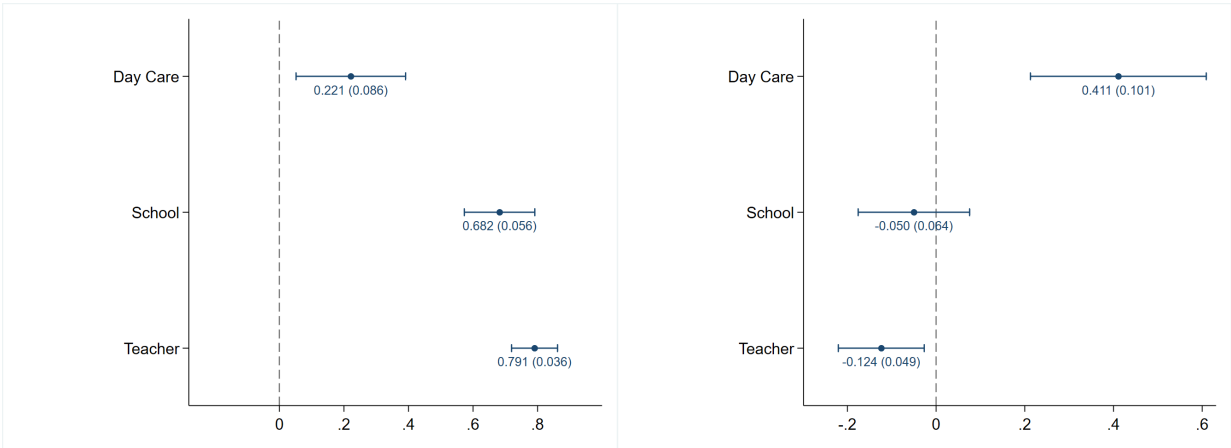


Note: This figure reports the coefficient estimates of equation 2 where each dependent variable is in changes of local economy such as elderly services. The left panel reports the coefficients on $\Delta \log$ working-age population and the right panel reports the coefficients on $\Delta \log$ elderly population.

Figure B.7: Impacts of Depopulation and Aging on Local Economy: Child/Education

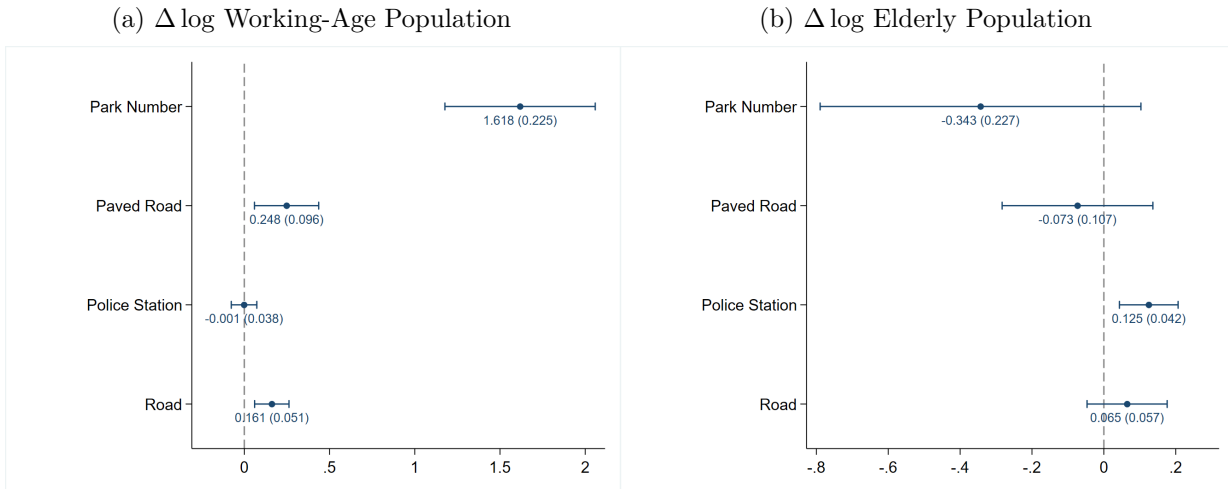
(a) $\Delta \log$ Working-Age Population

(b) $\Delta \log$ Elderly Population



Note: This figure reports the coefficient estimates of equation 2 where each dependent variable is in changes of local economy such as child/education. The left panel reports the coefficients on $\Delta \log$ working-age population and the right panel reports the coefficients on $\Delta \log$ elderly population.

Figure B.8: Impacts of Depopulation and Aging on Local Economy: Environment/Transportation



Note: This figure reports the coefficient estimates of equation 2 where each dependent variable is in changes of local economy such as public services. The left panel reports the coefficients on $\Delta \log$ working-age population and the right panel reports the coefficients on $\Delta \log$ elderly population.

C Calibration Details

C.1 Imputation of Labor Compensation by Municipality-Age-Year

Due to the unavailability of labor income data by age group at the municipality level, we impute the municipality-level effective wage for age group a :

$$\varphi_t^n(a) = \bar{\varphi}_t^n \times w_t^{pref}(a) \times \text{Employment Rate}_t^{pref}(a), \quad (\text{C.1})$$

where $\bar{\varphi}_t^n$ represents the TFP of municipality n , $w_t^{pref}(a)$ represents the wage for age group a within the prefecture of the municipality, and $\text{Employment Rate}_t^{pref}(a)$ is the employment rate for the age group within the prefecture. Our underlying assumption is that wage rates and employment rates change consistently in the same way over the life cycle across municipalities within the same prefecture. We calibrate $\bar{\varphi}_t^n$ to align the total effective wage bill of the municipality with the observed taxable income data ($\text{Taxable Income}_t^n = \sum_a \varphi_t^n(a)$). Applying this equation, we can calibrate the municipality-level TFP by year as follows:

$$\bar{\varphi}_t^n = (\text{Taxable Income}_t^n) / \left(\sum_a w_t^{pref}(a) \times \text{Employment Rate}_t^{pref}(a) \right) \quad (\text{C.2})$$

By construction, there is no variation in productivity within the same prefecture and age group apart from the TFP. Therefore, we focus our estimates on productivity spillovers on TFP.

C.2 Calibration of Amenity and Migration Costs

We start by introducing two sets of normalization of these variables. First, we normalize the exogenous amenity $\tilde{\chi}_t^n(a)$ to one for all n, t, a , since exogenous amenity is isomorphic to in-migration costs in the previous period ($\tau_{t-1}^{in}(a-1)$ for all i) under our additive utility specification. Second, we normalize migration costs within a region such that $\tau_t^{nn}(a) = 0$ for all t , since the in-migration cost is isomorphic to out-migration costs in the subsequent period ($\tau_{t+1}^{ni}(a+1)$ for all i). Note that these normalizations do not affect our equilibrium allocation and welfare implications; hence this is without loss of generality.

We back out off-diagonal elements of migration frictions, $\{\tau_t^{ni}(a)\}$, to precisely replicate the evolution of population distribution over time. Specifically, we proceed in two steps. We first back out those in the last data period, $t = T$, using the migration flow in period T , $\{\mu_T^{ni}(a)\}$, and the future evolution of fundamentals and transfers. Here, we also assume that bilateral migration frictions do not change after 2015. Once we obtain $\{\mu_T^{ni}(a)\}$, we sequentially back out $\{\tau_t^{ni}(a)\}$ for $t < T$ backward starting from $t = T - 1$ using migration flows $\{\mu_{ijt}(a)\}$ in each period.

Assuming that the functional form of and spillover elasticities on productivity and amenity as well as the other structural parameters and fundamentals are known, we can calibrate the set $\{\tau_t^{ni}(a)\}$ to precisely match the observed bilateral migration flows $\{\mu_t^{ni}(a)\}$ through the following procedure:

1. Guess the set of value functions $\{V_{T+1}^n(a+1)\}_n$.
2. Using the observed migration flow data at T , we first calibrate $\{\tau_T^{in*}(a)\}$ using the following equation derived from equation (8):

$$\frac{\mu_T^{in}(a)}{\mu_T^{ii}(a)} = \exp \left[s_T^n(a) \beta V_{T+1}^n(a+1) - s_T^i(a) \beta V_{T+1}^i(a+1) - \tau_T^{in}(a) \right]^{1/\nu}, \quad (\text{C.3})$$

3. Given the parameters, functional forms, and the assumption that $\tau_t^{in}(a) = \tau_T^{in}(a)$ for all $t > T$, we can simulate the model forward starting at $t = T$ all the way toward $t = \infty$ and update the guess of the set of value functions $\{V_{T+1}^{n,implied}(a+1)\}_n$.
4. Iterate the steps from 1 to 3 until we find a fixed point in $\{V_{T+1}^{n,implied}(a+1)\}_j \rightarrow \{V_{jT+1}^n(a+1)\}_j$.
5. Starting from $t = T$, we go backward period by period to obtain $\{\tau_t^{ni}(a)\}$. Using $\{V_{t+1}^n(a+1)\}_n$ and the flow utility $\{u_t^n(a)\}$, we first calibrate $\{V_t^n(a)\}_n$:

$$V_t^n(a) = u_t^n(a) + \nu \log \sum_{\ell}^N \exp \left[s_t^\ell(a) \beta V_{t+1}^\ell(a+1) - \tau_t^{n\ell*}(a) \right]^{1/\nu}, \quad (\text{C.4})$$

and then calibrate the bilateral costs $\{\tau_{t-1}^{in}(a-1)\}$ by using the following equation:

$$\frac{\mu_{t-1}^{in}(a-1)}{\mu_{t-1}^{ii}(a-1)} = \exp \left[s_{t-1}^n(a-1) \beta V_t^n(a) - s_{t-1}^i(a) \beta V_t^i(a) - \tau_{t-1}^{in}(a-1) \right]^{1/\nu}. \quad (\text{C.5})$$

C.3 Housing Supply Elasticity

In order to estimate the housing supply elasticity, or equivalently the share of labor in the housing production function, we estimate the housing supply equation (15), combined with the housing demand equation (16). We can derive that

$$\Delta \log H_t^n = \mu \Delta \log(\text{Total Income})_t^n, \quad (\text{C.6})$$

We estimate this equation with the same set of control variables as used in the reduced-form analysis and we also control the log of housing density (the number of housing per area) in the initial year. For housing supply, we utilize observed data. For total income of the municipality, we use the taxable income as a proxy. Estimating the equation by OLS is likely to suffer from the endogeneity issue arising from the unobserved changes in productivity in housing construction. Therefore, we implement the Push and Pull IVs as we implement in Section 3.2.

Table C.1 presents the results of the housing supply elasticity estimation. The IV estimate using the housing supply data shows that the labor share in housing production is 0.9, indicating that labor input plays a significant role in the production of housing.

Table C.1: Estimation of Housing Supply Elasticity

VARIABLES	(1) OLS $\Delta \log \text{Housing}$	(2) IV $\Delta \log \text{Housing}$
$\Delta \log \text{Taxable Income}$	0.659*** (0.044)	0.852*** (0.053)
Observations	653	653
FE and Cluster	Pref	Pref
Controls	Yes	Yes
Kleibergen-Paap F		23.94

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Note: We control for the share of secondary industry, the share of tertiary industry, the log of population density, log of housing density, and the log of the area in the starting year and include prefecture fixed effects. We estimate the clustered standard errors, using the prefecture as a cluster.

C.4 Migration Costs

We estimate migration costs for each age group separately by implementing Pseudo-Poisson Maximum Likelihood (PPML) estimator and using five-year bilateral migration flow data from the 2015 Census by age group.

More precisely, we estimate the following equation which is consistent with the migration share equation (8):

$$\text{Migration}_{2015}^{ni}(a) = \exp(\mathbf{X}^n \boldsymbol{\beta}(\mathbf{a}) + \text{Origin}_n(a) + \text{Destination}_i(a)) + \varepsilon_{ni}(a), \quad (\text{C.7})$$

where $\text{Origin}_n(a)$ and $\text{Destination}_i(a)$ are fixed effects for origin and destination locations. \mathbf{X}_{1980}^n is a vector of bilateral variables including the log of bilateral distance and various dummy variables. These dummy variables include indicators for home, within-prefecture migration, within-area migration, within-island migration, east-west border migration, and adjacency of prefectures (see [Wrona \(2018\)](#) for the definition of the area, island, and border dummy variables). We also include interaction terms that involve the within-prefecture dummy variable with log of distance and with log of the area of the prefecture, respectively. We use the estimated results of this equation to estimate the migration costs ($-\hat{\tau}^{ni}(a)/\nu = \mathbf{X}^n \hat{\beta}(\mathbf{a})$).

D Amenity Spillovers Estimated Using Data Rents

Table D.1: OLS Estimation Results of Amenity Spillovers

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
	$\Delta \log$ Amenity (w. Data Rent)			$\Delta \log$ Amenity (w. Model Rent)		
	Young	Middle	Elderly	Young	Middle	Elderly
$\Delta \log(\text{Working-Age Pop})$	0.201*** (0.027)	0.110*** (0.024)	-0.030 (0.065)	0.234*** (0.015)	0.120*** (0.016)	-0.002 (0.043)
$\Delta \log(\text{Elderly Pop})$	0.039 (0.055)	0.090*** (0.027)	0.104** (0.049)	0.028 (0.029)	0.084*** (0.025)	0.131** (0.059)
Observations	3,265	3,265	1,306	8,665	8,665	3,466
FE and Cluster	Pref-Age	Pref-Age	Pref-Age	Pref-Age	Pref-Age	Pref-Age
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Note: We control for the share of secondary industry, the share of tertiary industry, the log of population density, and the log of the area in the starting year and include prefecture-age group fixed effects. We estimate the clustered standard errors, using the prefecture-age group as a cluster. The model rents used to calibrate amenity in columns (4) to (6) are imputed by applying equations (C.6) and (15) with the observed taxable income data of the municipality. The number of observations varies between the amenity imputed using the data rents and using the model rents. This discrepancy arises because the data rents are available only for cities, which represent 648 out of the total 1741 municipalities, along with a few other municipalities.

E Appendix for Quantitative Analysis

Figure E.1: Population Size By Age Groups all over Japan, 1990-2015

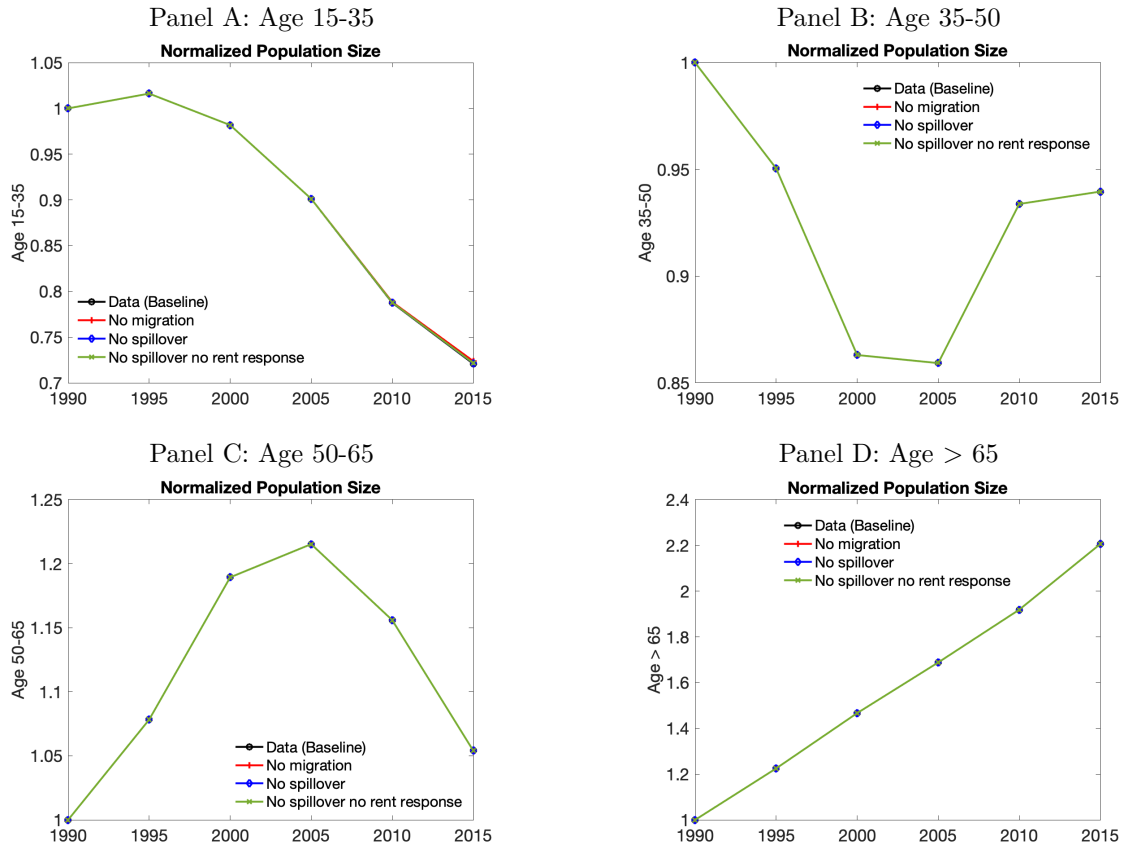


Figure E.2: Population Size By Age Groups and Region, 1990-2015

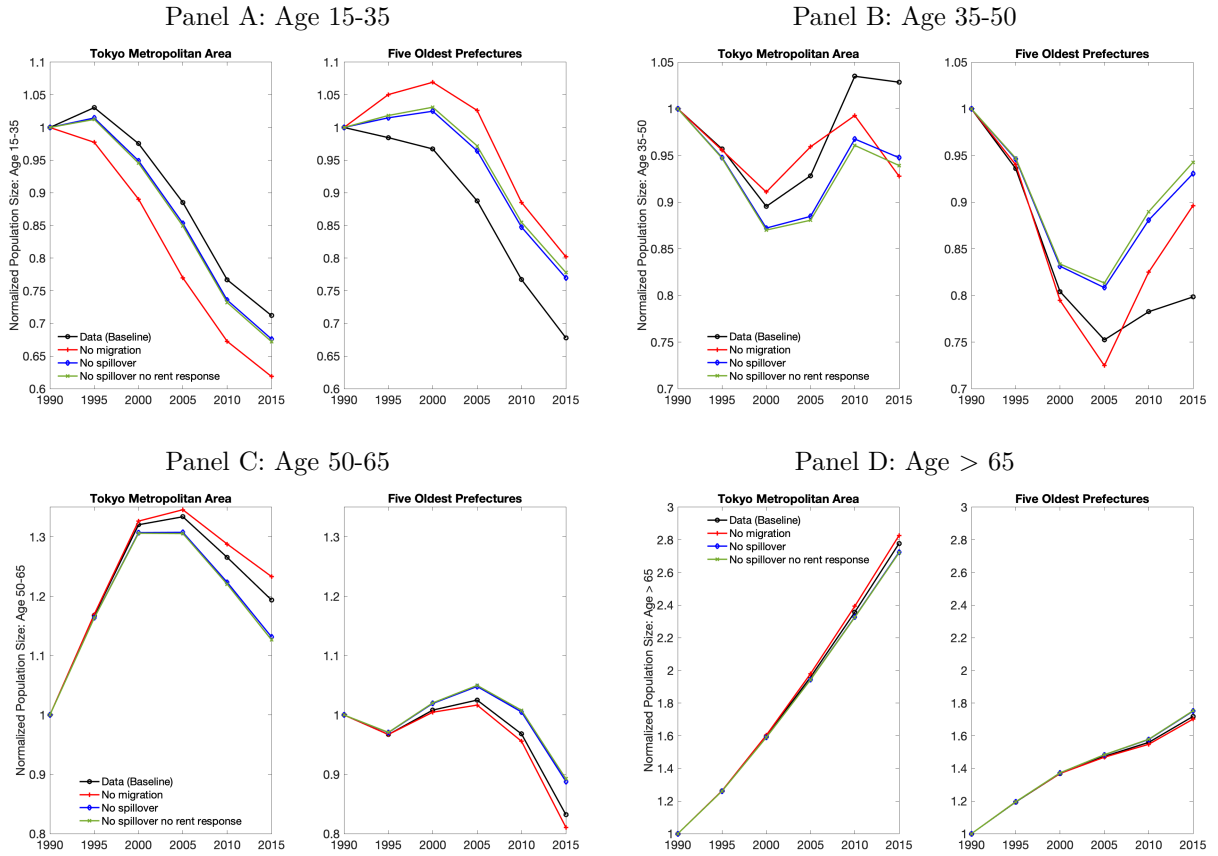


Figure E.3: Population Size By Age Groups all over Japan, Future Projection

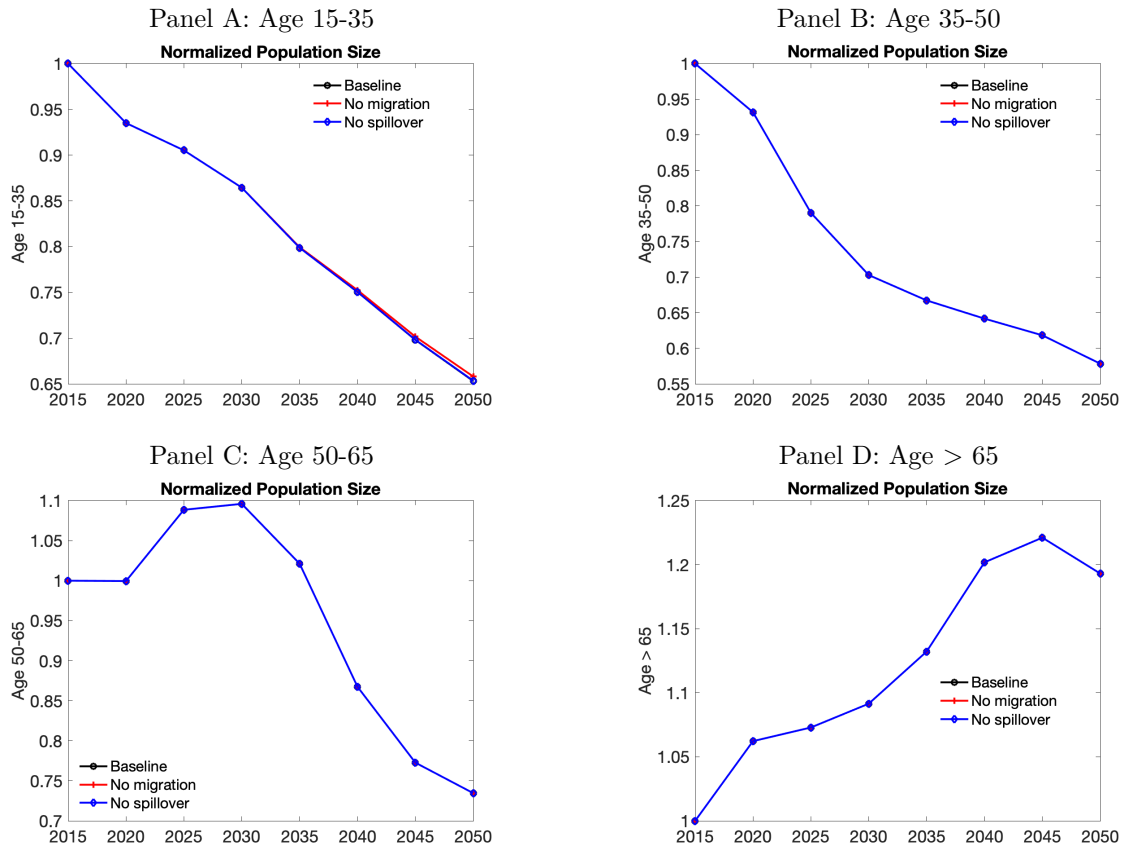


Figure E.4: Population Size By Age Groups and Region, Future Projection

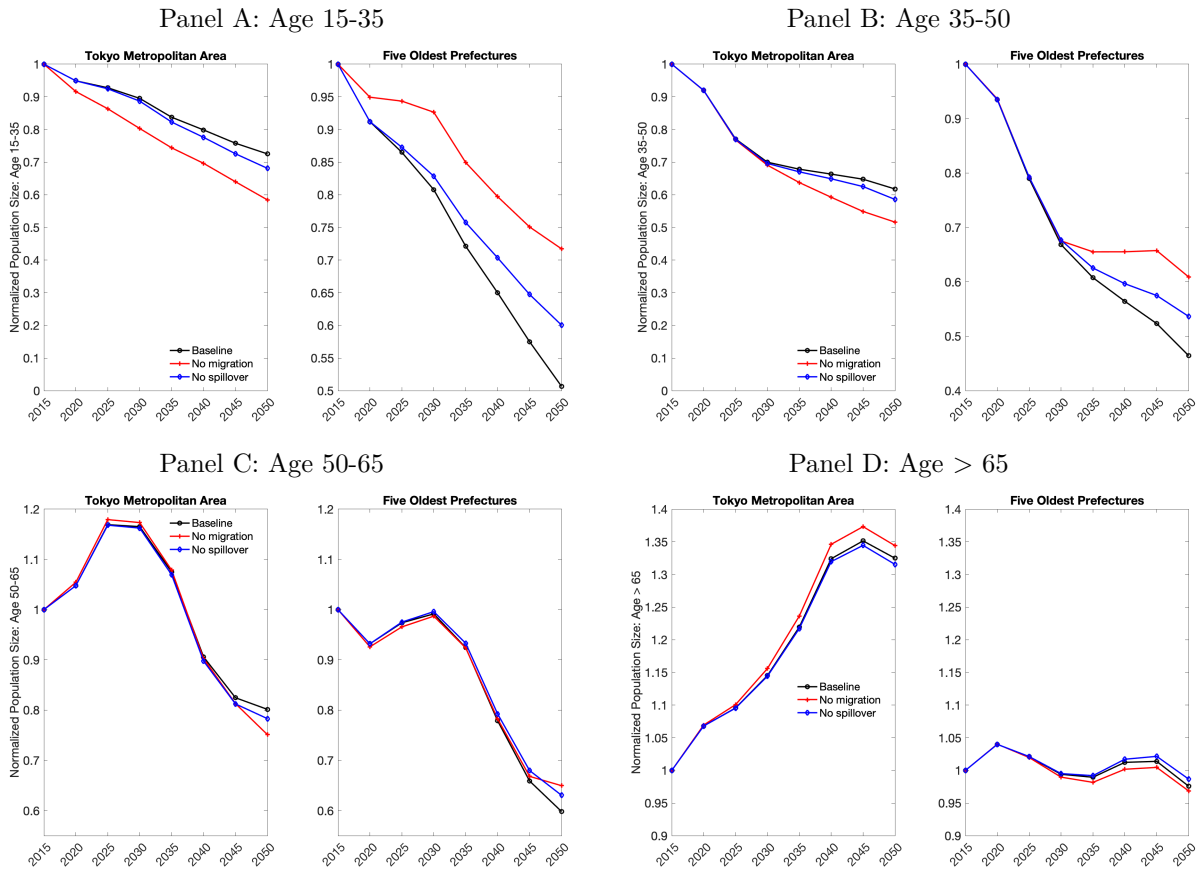


Figure E.5: Housing Rent By Region, Future Projection

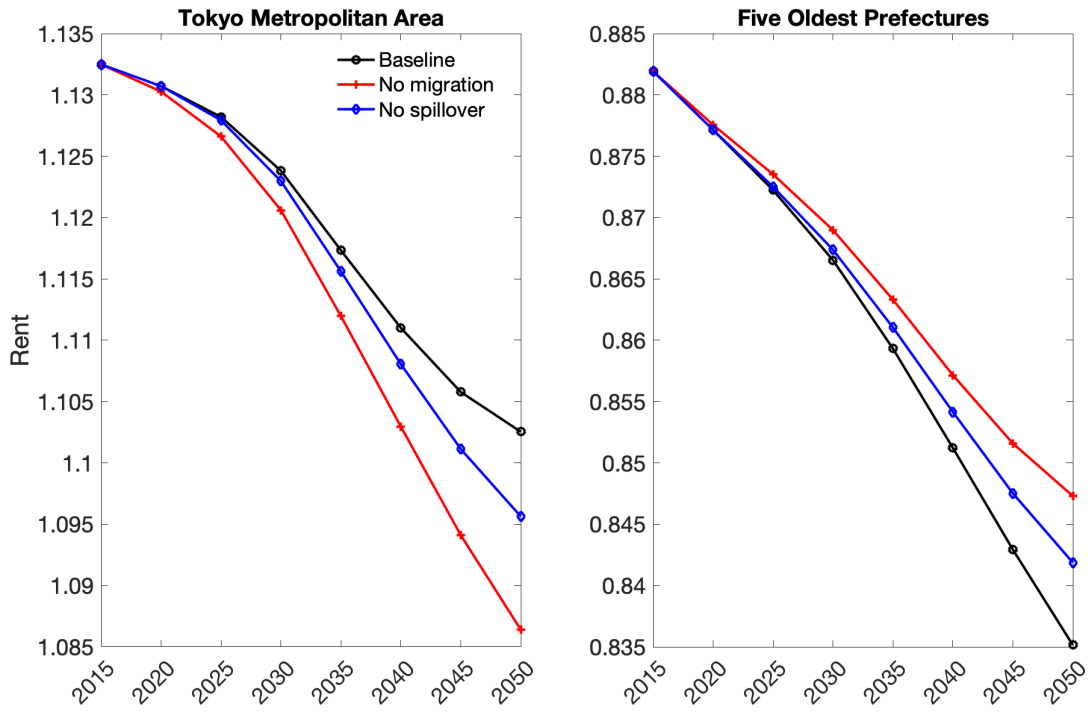
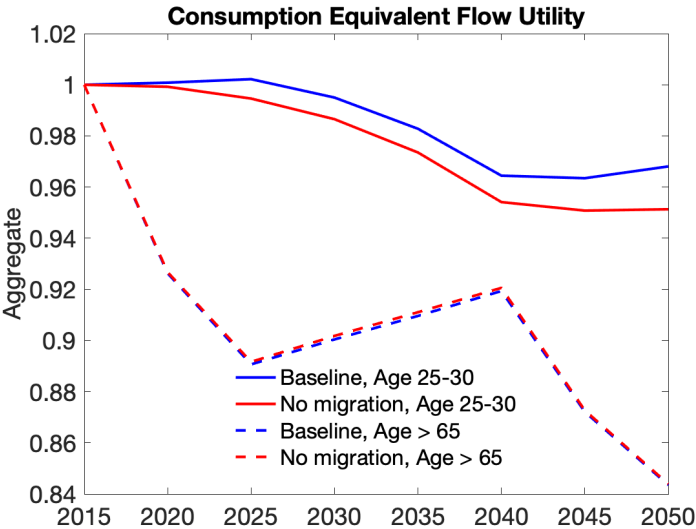


Figure E.6: Changes in Consumption-Equivalent Flow Utility, No Amenity-adjusted

(A) Aggregated across Regions



(B) Decomposed by Regions

