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1 Introduction

It is well-documented that individuals with better socioeconomic conditions can expect to live longer, and that there is a causal effect from economic conditions on health. Rudolf Virchow's famous statement "Medicine is a social science, and politics nothing but medicine at a larger scale," still resonates today. The importance of understanding how socioeconomic conditions shape the inequality in mortality and life expectancy is self-evident. However, the quantitative contribution of various socioeconomic factors, such as wealth and medical insurance coverage, is still not clear.

This paper studies inequality in life expectancy at sixty in China across city tiers and sectors of pre-retirement employment (public VS private), two dimensions with salient socioeconomic heterogeneities.[1] Based on the China Health and Retirement Longitudinal Study (CHARLS), we show that life expectancy increases with city size, with a gap of about 4.4 years between residents in tier-one and tier-three cities. The fact that larger cities in China have higher life expectancy stands in contrast to findings in other middle-income countries (Bilal et al., 2021). The life expectancy of city residents is about 8.3 years higher than that of rural residents on average, and the gap between rural residents and tier-one city public sector retirees reaches a staggering number of 11.6 years. The gap in life expectancy at age sixty exceeds 4.7 years between retirees from the public sector and the private sector. As we will show, the more generous health care coverage enjoyed by public sector retirees contributes significantly to their higher life expectancy, and the policy that equalizes medical insurance coverage can significantly reduce the inequality in life expectancy.

To quantitatively understand the contributing factors of the observed inequality and their policy implications, we construct a dynamic optimization model with endogenous health investment, housing choices, and bequest motives. Life expectancy in our model is jointly determined by exogenous health shocks and endogenous health investment, and the latter depends on an individual's income, wealth, and medical insurance coverage, which in turn depend on the individual's region of residence and sector of pre-retirement employment. The dynamic optimization model is estimated via the simulated method of moments, and the estimated model well captures the inequality in life expectancy that we document. Through the lens of the estimated structural model, we find that the inequality is largely attributable to the heterogeneity

[1] The lists of tier-one, tier-two, and tier-three cities are reported in Table B.1. The public sector includes governments, the military, schools, universities, and state-owned enterprises. We emphasize the public-private heterogeneity because of the large gap between the two sectors in medical insurance coverage and retirement income that dates back to the pre-reform era. One persistent goal of reforms in the past decades is to decrease and ultimately eliminate the gap, as we discuss in appendix A. While research based on the U.S. data find a strong link between life expectancy and ethnicity, ethnicity is less important in China because it is highly homogeneous in China.

in income, in the coverage of publicly funded health insurance, and in the housing investment market. Specifically, the heterogeneity in income alone can explain about 62.4% of the rural-urban gap in life expectancy. Heterogeneity in medical insurance coverage alone accounts for 57.7% of the gap in life expectancy between the public and private sectors. Cross-regional heterogeneity in the house price growth rate alone generates a gap in life expectancy of 7 years between tier-three and tier-one cities and explains 44% of the rural-urban gap in life expectancy.

We pay particular attention to housing assets in both the empirical and structural analysis. This is motivated by the fact that housing wealth accounts for 88.4% of the total wealth for old-age homeowners in China, and that housing is the largest contributor to wealth inequality across different tiers of cities due to the highly heterogeneous growth rate of house prices. In the empirical analysis, we identify a significant effect of housing wealth on mortality rates via regression discontinuity. Specifically, we utilize the housing policy implemented in China in 2006 that unexpectedly reduced the required down payment from 30% to 20% for houses sized less than or equal to 90 square meters, as well as the policy implemented in 2008 that decreased the property deed tax from 3% to 1%, also for houses sized less than or equal to 90 square meters. These two policies significantly increased the unit prices for houses smaller than or equal to the 90 square meters cutoff, creating a discontinuity in housing wealth around the cutoff. Based on this wealth discontinuity, we show that the increase in housing wealth cause a decrease in the mortality rate of retiree in our CHARLS sample.[2]

In the structural analysis, we explicitly include the endogenous allocation of financial resources among health investment, housing asset and risk-free asset throughout the retirees' lifetimes, which allows for a two-way causal relationship between housing assets and mortality rates in our model. On the one hand, when individuals are hit by large negative health shocks, they tend to downsize their housing wealth or exit the housing investment market. On the other hand, given a negative house price shock, individuals tend to cut their out-of-pocket health spending, leading to higher mortality rates and lower life expectancy, which is consistent with our empirical findings as well as findings in the literature. The bequest motive plays an important role in the above mechanism. With the mildly strong bequest motive that we find through the simulated method of moments estimation, a reduction in housing assets causes individuals to cut health spending substantially so that the bequest does not decline much. As we show in a counterfactual experiment, a decline in house prices reduces health investment both contemporaneously and in the long run, and it lowers life expectancy and increases the inequality.

We further use the model as a laboratory to assess two policies that can potentially reduce the inequality in life expectancy: a universal decrease in out-of-pocket medical expenses and an equalization of out-of-pocket medical expenses as a share of total expenses. Our counterfactual

[2]Our approach is similar to those in Li et al. (2020) and Fan and Zhou (2025).

experiments show that the universal decrease in out-of-pocket medical expenses encourages more health investment, which leads to higher life expectancy in the long run, with the most significant gain received by rural residents and private sector retirees. The equalization of out-of-pocket medical expenses turns out to be more effective in decreasing life expectancy inequality – it almost completely removes the inequality among urban retirees and significantly decreases the rural-urban gap. This result lends support to the on-going reform aimed to reduce the inequality in the healthcare system in China.[3]

We extend the baseline structural model in two ways to check for robustness of the quantitative results. First, we include housing consumption in health production, allowing for the possibility that better housing is conducive to health. Second, we include locational choices – allowing large city retirees to migrate to smaller cities or the rural area for lower housing costs while still maintain their higher post-retirement income and better medical insurance coverage. We observe extremely low migration rates in our sample of retirees, and we show that the low migration rates are consistent with the hypothesis that larger cities have significantly better amenities.[4] In both extensions, our model well captures the observed inequality in life expectancy, and our quantitative results remain robust.

The rest of this article proceeds as follows. Section 2 provides background information on the evolution of the healthcare system and the housing market in China, and it offers a discussion of the related literature. Section 3 describes some key facts based on the China Health and Retirement Longitudinal Study. In Section 4, we present the life-cycle model of health investment and portfolio choice in retirement. Section 5 discusses exogenous model inputs for estimation. In Section 6, we estimate the model via the simulated method of moments based on a set of moments on heterogeneous mortality rates and home ownership rates. Section 7 uses the estimated model to evaluate the contributing factors of the inequality in life expectancy and conduct counterfactual studies. Section 8 gives extensions and checks for the robustness of our results. Finally, Section 9 provides a summary of the research.

[3]In 2023, many Chinese localities, including Hubei, Sichuan, and Heilongjiang, are implementing health insurance reform for urban employees and retirees, drawing widespread attention (https://www.hsph.harvard.edu/china-health-partnership/2023/02/17/china-health-insurance-protests/). After the reform, contributions by employers into employees' personal accounts will be directly paid to the pooled fund to support the reimbursement of ordinary outpatient medical bills, creating a more equitable system.

[4]Because we focus on older individuals, the Hukou system, which works mainly through employment and educational benefits, is unlikely to play a significant role in locational choice. Still, it is unlikely for retirees to migrate from rural areas to cities, or from smaller cities to larger ones, because such migrants would suffer from higher housing costs without benefiting from higher income or better social insurance. Taking amenities into account, such migration is possible if larger cities have sufficiently better amenities than smaller cities or the rural area, which is also unlikely because of the extremely low migration rate for old-age individuals observed in the data.

2 Background and Literature

Given the importance of the healthcare system and housing market in our study, we present the healthcare system in modern China and offer a discussion of the housing market in this section. We also present a review of related studies towards the end of the section.

2.1 Healthcare in China

The healthcare system in China has gone through a series of reforms in the last decades in order to reduce the inequality of healthcare, some of which are still ongoing. Because many reform details are available in Chinese texts only, we delve into the original materials and summarize them in Appendix A, particularly in Figure A.1, which shows graphically the evolution of the healthcare system since the end of the 1970s.

Large inequality in healthcare coverage still exists after these reforms. As detailed in Appendix A, the current healthcare system in China, for workers and retirees alike, includes two major types: the URRBMI (Urban and Rural Resident Basic Medical Insurance) and the UEBMI (Urban Employee Basic Medical Insurance). The two types offer drastically different coverage. Even within the same type, the coverage differs significantly across regions. This is because the insurance funds are mostly pooled at the prefecture level, and prefectural governments, who are responsible for covering the deficits of pooled insurance funds, are incentivized to provide lower coverage if the prefectures are economically less developed.

The primary forms of inequality are different deductibles, coverage ratios, and annual coverage caps. The coverage ratio, defined as the fraction of medical expenses paid out of the insurance funds after deductibles and before reaching the cap, is typically higher in the UEBMI than in the URRBMI, and it is usually higher in more economically advanced regions. The annual coverage limits of outpatient care and hospitalization, set by regional governments, also tend to be higher in the UEBMI and in more economically developed regions.[5]

As an illustration, Table 1 reports the deductibles, coverage ratios, and annual coverage limits in 2020 for three different groups of retirees enrolled in Beijing URRBMI, Beijing UEBMI and, Suzhou UEBMI, respectively. The coverage is more generous in Beijing than in Suzhou. Within Beijing, the coverage of the UEBMI is more generous than the URRBMI.

Another form of healthcare inequality is the "medicines in the list." The Ministry of Human Resources and Social Security publishes two lists of medicines that should be covered by publicly funded medical insurance: the category-A list and the category-B list. While the category-A list should be strictly implemented in each region, the category-B list can be adjusted at the discretion of the regional governments in accordance with the level of economic development.

[5]By contrast, the Affordable Care Act in the US bans any annual and lifetime coverage caps on essential benefits.

Table 1: Medical Insurance Coverage in 2020

		Beijing URRBMI	Beijing UEBMI	Suzhou UEBMI
Outpatient care	Deductible (yuan)	100-500	1300	400
	Coverage ratio	50-55%	70-90%	70-90%
	Annual coverage cap (yuan)	4,500	20,000	4,800
Hospitalization	Deductible (yuan)	300-1,300	650-1,300	200-600
	Coverage ratio	75-80%	95.5-99.1%	95%
	Annual coverage cap (yuan)	250,000	500,000	350,000

Notes: This table reports the coverage of publicly funded medical insurance. The coverage for Beijing citizens is available from the Beijing Municipal Medical Insurance Bureau, and the coverage for Suzhou citizens is retrieved from the website of the Suzhou municipal government (https://www.suzhou.gov.cn/szsrmzf/zfwj/202003/9abcb56e82aa44ab9302e402ab0ee20f.shtml). The UEBMI mostly covers retirees from the public sector, while the URRBMI mostly covers farmers, migrant workers, and those retired from the private sector.

As a result, more medicines are included in the category-B list in regions where governments face smaller deficits. Health infrastructure, which differs tremendously across regions, also leads to healthcare inequality.

The factors mentioned above are ultimately translated into healthcare inequality across city tiers and sectors of employment. Larger cities can support more generous healthcare packages because governments face laxer budget constraints. The public sector employees and retirees enjoy more generous coverage because they are enrollees of the UEBMI, and a large fraction of government employees and retirees receive additional subsidies. In contrast, a large fraction of the private sector employees and retirees are enrollees of the less generous URRBMI.

We capture the large inequality in healthcare coverage by calculating out-of-pocket medical expenditure as a share of the total medical expenditures, i.e., the OOP share, for individuals in different city tiers and sectors, employing the detailed information reported in CHARLS. As we will show in Table 7, the OOP share exhibits large inequality across cities and sectors.

2.2 Housing Market in China

In our analysis of life expectancy inequality, we explicitly consider housing investment. Housing assets are vitally important for individuals in China. Table 2 shows the levels and compositions of wealth for each of the seven groups we study, where "housing" is the average housing wealth of homeowners within the group. The average total wealth differs considerably across regions, with the wealth of city retirees an order of magnitude higher than that of rural residents, while the difference between the private and public sectors is relatively small. As shown in the table, the average non-housing wealth accounts for less than 10% of the average wealth in each group. It is clear that housing is the largest contributor to wealth inequality across regions in China.

Table 2: Wealth Composition of Retirees in China (10,000 Yuan)

Wealth	*Total*	*Non-housing*	*Housing* (*homeowners*)
Rural	7.54	0.59	6.95
Tier 1, private sector	239.01	5.21	252.92
Tier 2, private sector	96.48	4.33	84.20
Tier 3, private sector	63.74	1.11	51.75
Tier 1, public sector	341.13	2.87	280.96
Tier 2, public sector	112.29	3.17	105.98
Tier 3, public sector	63.95	2.11	52.80

Notes: Authors' calculation based on the CHARLS. "Housing" is the average housing wealth for homeowners within the group.

The dominance of housing in wealth and the large inequality have been shaped by the development of China's real estate market since the early 2000s, when the privatization of the real estate sector started and urbanization began to accelerate. The national average house price index appreciated by a factor of 5 between 2003 and 2017 (Liu and Xiong, 2020), which has led to an extremely high share of housing in total wealth. During the same time period, the house price index experienced an appreciation amounting to elevenfold in Beijing, eightfold in Shenzhen and Guangzhou, and sixfold in Shanghai, as reported in Liu and Xiong (2020). The unusually high growth rates of house prices in these tier-one cities are consistent with the much higher housing wealth of retirees in these cities shown in Table 2. By contrast, the house price index appreciated about threefold in tier-three cities. In other words, the large cross-region wealth inequality in China is attributable to very different house price appreciation rates across different city tiers.

The growth rates of house prices began to slow down gradually after 2018, due to factors such as imbalances between supply and demand, slowing urbanization, slowing GDP growth, and the aging population (Rogoff and Yang, 2024). The growth rates in the second and tier-three cities turned negative in 2022 (Xiong, 2023). Given the critical importance of housing assets, a decline in house prices might significantly impact health investment and life expectancy, which motivates us to conduct a quantitative analysis of the effect of a 30% decline in house prices.

The implementation of the property tax in China is a potential trigger of a large decline in house prices. Thus far, property tax is absent in China except for the so-called pilot program experimented in Shanghai and Chongqing. In April 2023, the Chinese government announced that a national registration system is now in place as a preparation for nationwide property tax.[6] As demonstrated in Zhu and Dale-Johnson (2020) through simulations, the introduction

[6] See https://global.chinadaily.com.cn/a/202304/26/WS64492319a310b6054facff65.html.

of property tax will increase the cost of property holding and reduce the willingness of investors and home buyers to hold properties, especially for those who have multiple properties for investment purposes, thus creating downward pressure on house prices.

Overall, housing assets are the most important assets for the majority of households in China. House prices in different cities experienced different degrees of rise, correction, and gradual stabilization over the past few decades, which led to large heterogeneity in housing assets. In addition, a large decline in house prices is likely in the coming years.

2.3 Literature

We contribute to the literature on the heterogeneity in individual health or life expectancy. Healthcare access varies geographically and could have meaningful impacts on health (Finkelstein et al., 2016, 2021; Goldin et al., 2021; Miller et al., 2021), and the impacts of the healthcare system on health and life expectancy could be heterogeneous across income, wealth, and some other personal characteristics (Chetty et al., 2016b; Montez et al., 2019). All those factors can cause geographical inequality in health, within a country or across countries. Deryugina and Molitor (2021) find that, within the U.S., the top 10 percent of counties have a life expectancy of 81.0 years or more, while the bottom 10 percent have a life expectancy of 74.4 years or less.[7] Several studies have documented life expectancy inequality by income and region in China, e.g., life expectancy between rich and poor (Baeten et al., 2013), between rural and urban areas (Van de Poel et al., 2012), or between and within provinces (Huang and Liu, 2023). In addition, the existing public health literature already explores urban-rural and regional disparities (e.g., western vs. eastern China) (De la Roca, 2017; Zhou et al., 2019). Most of the literature focuses on causes of death with different age distribution patterns contributing differently to the level and direction of urban-rural and sex differences in life expectancy and lifespan disparity (Chen and Canudas-Romo, 2022). Relative to the existing literature, our work provides new insights regarding inequality across city tiers and sectors of employment in China, and we quantitatively explore the relative importance of housing, wealth, income, and medical insurance coverage, based on an estimated dynamic optimization model.[8]

Our modeling strategy is similar to Yogo (2016). While he focuses on how portfolio choices

[7] The resulting inter-decile gap is 6.5 years, which is larger than the gap between the public sector and the private sector retirees at age 60 in China, but smaller than the rural-urban gap in life expectancy that we find for retirees in China.

[8] Our paper differs from previous literature on healthcare and amenity inequality by explicitly analyzing how health inequalities are related to housing wealth, rather than access to healthcare services or amenities. While prior studies may emphasize healthcare availability or environmental factors, our research highlights how disparities in housing assets—such as property ownership, value, and wealth—contribute to health outcomes across different city tiers. This approach offers a distinctive perspective on the socioeconomic determinants of health, highlighting the role of housing wealth in shaping health disparities.

of retirees depend on health status and health investment without considering ex ante heterogeneities, we study the heterogeneities in the mortality rate and life expectancy across different cities and sectors of employment. To better capture the heterogeneities, we construct a model that is distinctive to Yogo (2016) in the following two aspects. First, we allow shocks to house price growth to be mildly persistent rather than purely transitory. Persistent shocks are not only more realistic, but also pose much more risks to the individual's portfolio and hence have very different implications for health investment. Second, wealth is non-homogeneous in our value function due to the persistence of house price shocks. This non-homogeneity allows wealth level itself to be an essential driver of health investment, mortality, and portfolio choice. There is a vast literature that uses similar lifecycle models to study the effects of medical expenses on saving, wealth accumulation, and portfolio choices (De Nardi et al., 2010; Kopecky and Koreshkova, 2014; Cooper and Zhu, 2016; İmrohoroğlu and Zhao, 2018), taking medical expenses exogenously. Our model differs from these studies by including an endogenous health investment decision with heterogeneous medical insurance coverages, which enables us to investigate the socioeconomic factors underlying the observed inequality in life expectancy.

Our paper builds on the vast literature that documents the relationship between financial resources and health. Both income and wealth have strong independent correlations with health. Positive income shocks improve health (Frijters et al., 2005; Lindahl, 2005), while negative wealth shocks due to the stock market fluctuations impair physical and mental health and increase mortality (Schwandt, 2018). Chetty et al. (2016a) provide a comprehensive empirical study of the income gradient of life expectancy in the US and its evolution over time. Many public health researchers have attributed the health-income gradient to a causal effect from income to health (Wilkinson, 1990). This effect is even stronger for poor individuals and retirees. Regarding the causal effect of wealth on health, several recent studies provide empirical evidence that focuses on housing wealth. Tran et al. (2023) show that house price decreases negatively affect the old-age Americans' healthcare utilization based on the 1996–2016 Health and Retirement Study. Also based on the HRS data, Costa-Font and Swartz (2019) find that an increase in housing wealth results in an increase in the utilization of paid home healthcare, nursing home, and unpaid informal care. Similarly, we document significantly negative effects of house prices on mortality rates based on the CHARLS data and the exogenous housing regulations implemented in China in 2006-2008. We contribute to this strand of literature by quantitatively showing how heterogeneity in financial resources leads to inequality in life expectancy, and by analyzing the short-term and long-term heterogeneous effects of a house price shock on health investment and life expectancy in the context of our structural model.

3 Stylized Facts

In this section, we begin by displaying some stylized facts regarding the mortality rate and life expectancy in China, focusing on the heterogeneity across cities and sectors of pre-retirement employment.

3.1 Data

Our empirical study is based on the China Health and Retirement Longitudinal Study (CHARLS), a panel survey designed to study the health and wealth dynamics of Chinese residents ages 45 and older. We focus on individuals aged between 60 and 100 to ensure that all observations are of retirees.[9] Our sample consists of four waves of surveys conducted in 2011, 2013, 2015, and 2018, respectively. After dropping individuals aged below 60 or above 100, the sample includes 13,097 households and 22,326 individuals (63,294 observations in total) in 126 prefectures. There are 4 tier-one cities, 19 tier-two cities, 81 tier-three cities, and 96 rural areas (prefectures) in the sample.

Table 3 reports the summary statistics. As the table indicates, the average biannual mortality in our sample is 6.1%, where mortality is calculated as the fraction of survey respondents who die between the two consecutive survey waves.[10] In the sample, 20.3% of individuals are retirees from the public sector, and 51% of the individuals are female. We define homeowners as individuals who own one or more housing units, and the average home ownership rate is 83.2%. This number is slightly lower than those in related research using the same dataset, e.g., 90% in Fan and Zhou (2025), because we exclude the population younger than 60. It is important to highlight that our sample exclusively includes retirees aged 60 and above, who are much more likely to be homeowners, resulting in a larger housing share of wealth.[11]

Notably, 81.7% of retiree households consist of a married couple, while 17.6% are one-member households, with 46% being male and 54% female. Only 0.7% of households have

[9] Up until the end of 2024, the mandatory retirement age in China is 60 for men, and 55 for women as public servants, or 50 for the rest of the types of workers. There are some exceptions for individuals with a certain standing in the hierarchy. There are only 18 individuals over the age of 100, accounting for just 0.03% of the total sample. We have decided to drop observations of individuals aged above 100, as the small sample size of these oldest retirees is insufficient to construct reliable statistical moments.

[10] This biannual mortality rate is understated because respondents may die within one year after the first of the two consecutive waves of surveys.

[11] Elderly individuals tend to have a larger share of housing wealth in their total wealth because many elderly individuals have owned their homes for a longer duration, often having purchased properties decades ago when prices were lower. Over time, property values have generally appreciated, resulting in a substantial increase in housing wealth. Additionally, as people age, they often adjust their investment strategies to prioritize stability and risk aversion. This may result in a higher concentration of wealth in real estate, as it is considered a "safe" asset compared to more volatile investments like stocks.

three or more members. Overall, the average household size is 1.83. It is important to highlight that the majority of one-member households are widowed rather than divorced or single.[12] The average annual income per person is 12,079 yuan with a large standard deviation, where income is defined as the sum of individual annual labor income, retirement income, self-employment income, agricultural income, and social security income. In the CHARLS data, there are mainly two key components of agricultural income. The first is crop production. Many rural households engage in the cultivation of staple crops such as rice, wheat, corn, and soybeans. The sale of these crops, either directly to markets or through cooperatives, constitutes a significant portion of their income. The second is livestock raising. Animal husbandry is another vital source of income, with families raising pigs, cattle, sheep, and poultry. Products such as meat, eggs, and milk contribute to both household consumption and income generation. The average wealth per person, defined as household wealth divided by household size, is 380,752 yuan in the sample, where wealth is the sum of housing assets, cash, deposits, bonds, stock, and funds.

Table 3: Summary Statistics

	Definition	Mean	Std Dev
Raw age	actual age	68.790	7.101
Age	(actual age − 60)/10	0.879	0.710
Death	dummy equals 1 if the person dies	0.061	0.239
Public sector	equals 1 if the person used to work in public sector	0.203	0.402
Home ownership	equals 1 if the person has at least one house	0.832	0.374
Female	equals 1 if the person is female	0.511	0.500
Income	annual household income per person (1,000 yuan)	12.079	159.888
Wealth	household wealth per person (1,000 yuan)	380.752	3,082.201
Housing share in wealth	share of housing asset in total asset	0.884	0.194
House size	size of housing area (m^2)	117.782	82.367
Housing price	house price per m^2 (1,000 yuan)	4.315	53.137
OOP medical expenditure share	annual OOP medical expense / total income	0.462	0.881
OOP medical expense	annual OOP medical expense (1,000 yuan)	5.893	43.689
Total medical expense	annual total medical expense (1,000 yuan)	8.311	82.472
Number of households		13,097	
Number of individuals		22,326	
Number of observations		63,294	

Notes: This table presents the definition and summary statistics of the main variables in our specification.

As shown in Table 3, housing share in total wealth is 88.4% for homeowners. This is calculated by dividing the reported value of housing assets by the total value of all assets of

[12] The elderly population (born in the 1960s and before) in China generally adheres to traditional and conservative values, resulting in a low prevalence of individuals who are divorced or have never married. This cultural backdrop emphasizes the importance of family and marital relationships, contributing to the small percentage of older adults who are single or divorced.

homeowners. The out-of-pocket medical expense relative to income is 46.2% on average, where the medical expense includes health insurance premiums, hospitalization costs, outpatient costs, prescription drugs, transportation costs, and self-treatment costs. The out-of-pocket medical expenses and total medical expenses are 5,893 yuan and 8,311 yuan on average, respectively.

Note that the CHARLS data does not include any nursing home residents. However, it might not be a serious concern given the low frequency of nursing homes. Roughly 90 percent of China's elderly are cared for by their families, 7 percent receive community care, and 3 percent are in nursing homes, according to the National Health Commission.[13] Cultural factors play a significant role, as traditional family structures often emphasize filial piety, with elderly individuals typically relying on family members for care.

3.2 Mortality Rates

To study the mortality rates of the different groups of individuals in our sample, we begin with the following baseline specifications:

$$Death_{i,t+2} = \beta_1 Age_{it} + \beta_2 Age_{it}^2 + \beta_3 Region_i \times Sector_i + FE_t + \epsilon_{i,t+2}, \tag{1}$$

where $Death_{i,t+2}$ is the death indicator which equals to one if the individual i dies between period t and $t+2$ (two consecutive surveys), Age_{it} is the adjusted individual's age, i.e., $(actual\ age_{it} - 60)/10$, and λ_t is the year fixed effect.[14] The heterogeneity in mortality rate is captured by $Region_i \times Sector_i$, dummies for the seven types of individuals, where rural residents are treated as the reference (omitted) type. Here, $Region_i$ represents three city tiers and the rural region, and $Sector_i$ is an indicator variable equal to one for public sector retirees. Rural residents are not further divided by the sector of employment because the majority of them are in the private sector.

We estimate equation (1) with the conventional probit method and report the results in column (1) in panel A of Table 4. The coefficients of age and age^2 are both positive, capturing the increase in mortality with age. The coefficients of interaction terms between the region and the sector are all negative, indicating a lower mortality rate among city retirees compared to their rural counterparts. The mortality rate is lower in larger cities, and is significantly lower among public sector retirees. Public sector retirees from tier-one cities have the lowest mortality rate, as indicated by the low coefficients for the tier-one public sector dummy.

Next, to identify the effect of housing asset on mortality rates and address the potential identification issue related to omitted variables, we consider two exogenous housing policies

[13] See https://www.channelnewsasia.com/cna-insider/china-ageing-basic-elderly-care-services-families-cope-4641746.

[14] Note our sample consists of 2011, 2013, 2015, and 2018 waves. The additional period lag effect from 2015 to 2018 could be absorbed by the year fixed effect.

Table 4: Mortality Rate

Panel A: Death heterogeneity	(1)		(2)		(3)	
	Baseline		RD		Hazard	
Size > 90			0.315***	(0.097)		
Size − 90			0.002	(0.006)		
(Size > 90) × (Size − 90)			-0.006	(0.008)		
Age	0.082***	(0.024)	0.067	(0.051)	0.325***	(0.042)
Age^2	0.127***	(0.012)	0.128***	(0.025)	0.117***	(0.017)
City: 1st tier (public)	-0.722***	(0.181)	-1.031***	(0.391)	-1.358***	(0.409)
City: 2nd tier (public)	-0.695***	(0.075)	-0.879***	(0.157)	-1.327***	(0.175)
City: 3rd tier (public)	-0.561***	(0.045)	-0.740***	(0.098)	-1.051***	(0.100)
City: 1st tier (private)	-0.489***	(0.102)	-0.587**	(0.251)	-0.867***	(0.219)
City: 2nd tier (private)	-0.404***	(0.046)	-0.412***	(0.132)	-0.804***	(0.096)
City: 3rd tier (private)	-0.224***	(0.026)	-0.374***	(0.057)	-0.443***	(0.051)
Observations	45643		11782		45643	
Year fixed effect	✓		✓		✓	
ln p					7.421***	(0.019)
Panel B: RD estimate for death and housing price						
	Death		ln Housing price			
RD Estimate	0.036***	(0.009)	-0.303***	(0.093)		
Polynomial order	1		1			
Optimal bandwidth	22.647		12.544			
No. of observations (left side)	5971		3179			
No. of observations (right side)	5811		4585			
No. of observations (total)	29751		28415			
Year fixed effect	✓		✓			

Notes: Panel A of this table shows how death probability depends on city tier, sector of pre-retirement employment, and other variables. Columns (1), (2), and (3) present the estimation results of the probit model, RD design, and hazard model, respectively. The unit of observation is an individual-year. The dependent variable is the dummy death. All regressions include year fixed effects. Panel B of this table shows the RD estimates for death and housing prices. The dependent variables in columns (1) and (2) are dummy death and the natural logarithm of housing prices, respectively. All variables are defined in Table 3. ***, **, or * indicates that the estimate coefficient is significant at the 1%, 5%, or 10% level, respectively. Robust standard errors are in parentheses and given below the coefficient estimates.

implemented in China in 2006-2008. The first policy, issued in May 2006 by the State Council and its seven ministries, lowered the down payment ratio from 30% to 20% for housing units sized less than or equal to 90 square meters. The second policy, issued by the Ministry of Finance and the State Administration of Taxation on 1 November 2008, decreased the property deed tax from 3% to 1%, also for houses sized less than or equal to 90 square meters. These policies created a discontinuity in housing wealth around the cutoff size of 90 square meters, providing a quasi-natural experiment that allows us to exploit a regression discontinuity (RD) design framework to identify the health effect of housing wealth in response to the exogenous policy shocks. We consider the following probit specification:

$$\begin{aligned} Death_{i,t+2} &= \alpha_1 \mathbb{1}\{Size_{it} > 90\} + \alpha_2(Size_{it} - 90) + \alpha_3 \mathbb{1}\{Size_{it} > 90\} \times (Size_{it} - 90) \\ &+ \beta_1' Age_{it} + \beta_2' Age_{it}^2 + \beta_3' Region_i \times Sector_i + FE_t' + \epsilon_{i,t+2}', \end{aligned} \tag{2}$$

where $\mathbb{1}$ is the indicator function and $Size_{it}$ is the house size of individual i at period t.[15]

Following Li et al. (2020) and Fan and Zhou (2025), we use the subsample of housing units that were purchased before 2006, the year when the exogenous policies started, for the RD regression, to avoid issues related to housing markets after 2006.[16] In addition, we select the subsample of housing units that are 22.647 square meters below or above the 90 square meters cutoff for a clean identification of the causal effect based on the discontinuity.[17] As a result, the sample size in the RD regression is significantly smaller.

Column (2) of panel A in Table 4 shows the parametric linearized estimation results of equation (2). The coefficient of the dummy for "Size>90" is significantly positive, indicating a higher mortality rate for owners of housing units above the cutoff size. Coefficients of region-sector dummies are larger than the baseline results reported in column (1), implying a larger urban-rural gap for individuals in the subsample. Overall the disparity in mortality rates are quite similar to the baseline results.

Panel B of Table 4 presents the nonparametric RD estimates, with mortality and housing price in columns (1) and (2), respectively. Column (1) shows that individuals with housing units smaller than 90 square meters have a lower mortality rate than their counterparts with larger housing units; and column (2) indicates that housing units smaller than the cutoff of 90 square meters have higher prices than those above the cutoff, due to policy shocks.

Figure 1 graphically shows results related to panel B of Table 4. Panel (a) of the figure shows the relationship between the size of the housing unit (our assignment variable) and the biannual mortality rate. The dots represent the conditional mean values of the biannual mortality rate for each bin, and the lines are the fitted values of the local linear regression with the optimal bandwidth calculated using the Jacob and Ludwig (2012) approach. The vertical line denotes the eligibility cutoff for our focal housing policies. We find a clear decline in the mortality rate below the 90 square meters cutoff in panel (a), indicating that owners of housing units sized

[15] We include more controls for individual characteristics to check for robustness. As shown in Appendix Section B.2, our baseline estimation results are robust.

[16] For instance, property developers are likely to build more houses just below the 90-square-meter cutoff after policies were put in place to take advantage of the higher expected appreciation rate. The two exogenous policies may also have a sorting effect on housing demand.

[17] The optimal bandwidth of the housing size (i.e. 22.647 square meters) is calculated based on Imbens and Kalyanaraman (2012) approach.

just below 90 square meters have a lower mortality rate than owners of housing units sized just above 90 square meters. Panel (b) shows a clear increase in the house price below the cutoff housing size. Overall, figure 1 suggests that the the preferential treatments given to housing units sized below the cutoff of 90 square meters increase housing wealth of the owners of these properties, and thus reduces their mortality rates.

In the baseline and RD estimation above, *Death* as an outcome in a probit model may raise econometric issues, since people can only die once. To address this issue, we adopt the Nelson-Aalen cumulative hazard model to estimate the survival hazard.[18] The Nelson-Aalen method is a nonparametric estimator that is used to estimate the cumulative hazard function, which represents the probability of death accumulating over a specified period of time. This method is quite simple and effective in describing risk patterns without making certain distribution assumptions, making it suitable for application to observable data, such as the CHARLS data.[19]

The results of the hazard estimate of the risk to individual survivorships are reported in column (3) of panel A in Table 4. These results show the same data patterns as those from the baseline estimation, i.e., the lower mortality rate in larger cities and among public sector retirees, indicating the robustness of our baseline probit regression.[20] It should be noted that the coefficients of the hazard model are not directly comparable with coefficients from either the baseline regression or the RD regression, because they represent different concepts, are estimated under different assumptions, and come with different interpretations.

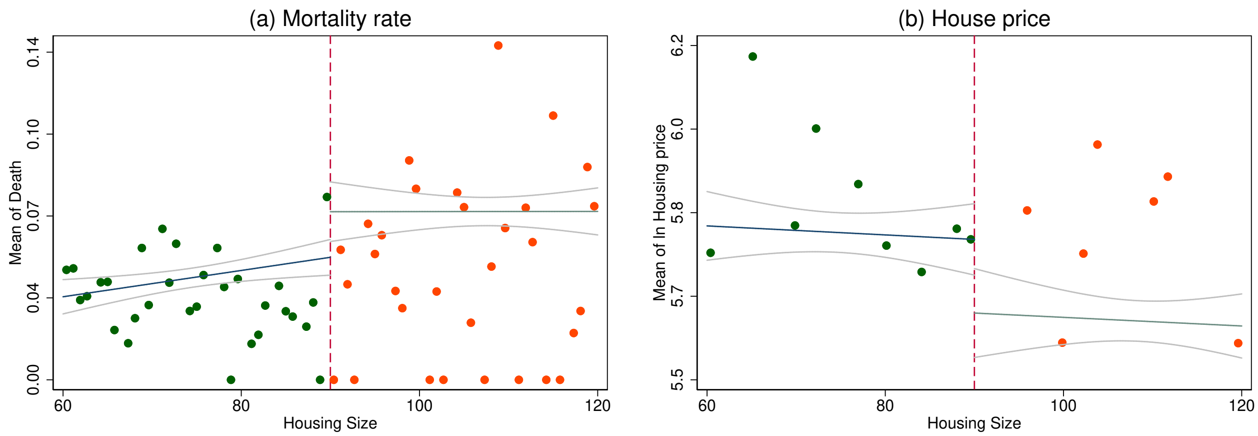
Based on the results in columns (1) and (2) of Table 4, we plot the average age profile of the mortality rate for each of the seven groups in panels (a) and (b) of Figure 2. Panel (c) of Figure 2 shows the cumulative hazard estimates for the average year profile of the mortality rate of each group column (3) of Table 4. It is evident in all the panels that the mortality rate is the highest among rural residents (black solid line) and the lowest in tier one cities, and private sector retirees (solid lines) have higher mortality than public sector retirees (dashed lines).

[18] Survival analysis is a statistical approach that is used to analyze the time until an event, such as death, occurs. In contrast to ordinary descriptive statistics, survival analysis can account for cumulative risk over time and often involves censored data.

[19] Our hazard model analysis focuses on the time it takes for an individual to die. A hazard function consists of two components. The first component is a function of time-varying explanatory variables that affect the level and/or shape of the hazard functions. The second component is a function of the duration of time. It is called the baseline hazard. The hazard is obtained by shifting the baseline hazard as the explanatory variables change. By examining “hazard rates” rather than death dummies, hazard models can avoid death measurement and interpretation problems.

[20] To visualize the estimate variation, we plot the results of the three models in Figure B.1 in the Appendix.

Figure 1: Biannual Mortality Rate and House Price over House Size



Notes: This figure presents the nonparametric RD estimation results, illustrating the differences in mortality rate and housing price across the two sides of the 90 square meters house size threshold. The dots represent conditional mean values of the corresponding variable for each bin. Solid lines represent the fitted values of the local linear regression. The dashed lines indicate the 95% confidence intervals. The vertical line is the cutoff point (90 square meters) in the assignment variable.

3.3 Inequality in Life Expectancy

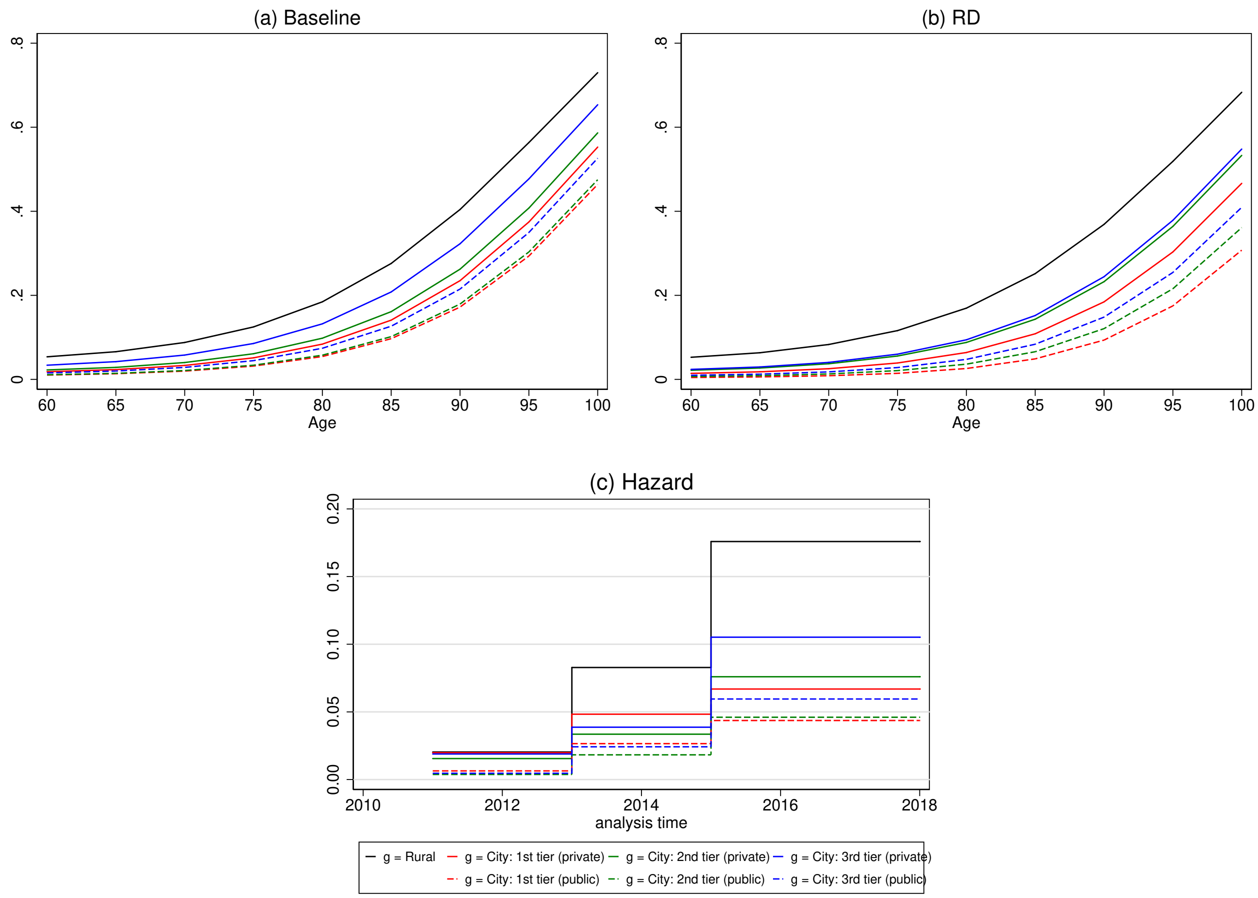
We use the mortality rates by age from the baseline probit and the RD regression, shown in Figure 2, to calculate the life expectancy at age 60 for each of the seven groups.[21] The first step is to divide the biannual rates by two to convert them into annual rates. Next, for a unit measure of people aged 60, we calculate the fraction of people who die between the period t and $t+1$. Specifically, at the beginning of the period t, the percentage of survivors is $\prod_{k=0}^{t-1}(1-death_k)$, where $death_k$ is the annual mortality rate, thus the percentage of people who die between t and $t+1$ is $Life_t = \prod_{k=0}^{t-1}(1-death_k) \times death_t$. Finally, life expectancy at age 60 is

$$Expectancy = \sum_{t=1}^{T} Life_t \times t \tag{3}$$

As shown in the first row of Table 5, based on the baseline probit regression, life expectancy is the lowest among rural individuals (15.54 years), and the highest among the public sector retirees in tier-one cities (27.15 years). The difference in life expectancy between public sector retirees in tier-one cities and rural residents is 11.61 years, which is reported in the "*T1 pub-rural*" column. The "*rural-urban*" column shows the difference in life expectancy between the average of urban retirees and rural residents, which amounts to 8.26 years. Finally, the

[21] The inequality in life expectancy by hazard model is not reported, because the hazard model does not provide the unconditional probability of death at or before a specific age directly.

Figure 2: Biannual Mortality Rates



Notes: This figure presents the average age profile of the mortality rate for each of the seven groups, rural, tier-three cities private sector, tier-two cities private sector, tier-one cities private sector, tier-three cities public sector, tier-two cities public sector, and tier-one cities public sector. Panels (a), (b), and (c) are plotted based on the probit, RD, and hazard specification in columns (1), (2), and (3) of Table 4, respectively.

"*public-private*" column shows the difference between the average of the public sector retirees and the average of the private sector retirees, which is 4.66 years in the data. The second row of the table reports life expectancy based on the RD regression, it shows even larger inequality between urban and rural areas, as well as between the public and private sectors. Nevertheless, Both the baseline and RD specifications present the same patterns of inequality among city tiers and between sectors of pre-retirement employment. These patterns motivate us to develop a structural model to study the socioeconomic factors that potentially contributing to the inequality in life expectancy.

In what follows we prefer to use the mortality rates and life expectancy based on the baseline probit model, rather than those based on the RD estimation or on the hazard model. The RD

Table 5: Inequality in Life Expectancy in the CHARLS Data

	Private sector				Public sector			T1 pub	urban	public
	tier 1	tier 2	tier 3	rural	tier 1	tier 2	tier 3	-rural	-rural	-private
Baseline	23.42	21.96	19.02	15.54	27.15	26.69	24.54	11.61	8.26	4.66
RD	23.64	20.67	19.99	13.99	30.87	28.40	26.21	16.88	10.97	7.06

Notes: This table reports life expectancy at sixty years of age for the seven groups in the data, based on the probit regression and regression of discontinuity (RD). "T1 $pub - rural$" is the difference in life expectancy between public sector retirees in tier-one cities and rural residents. "$rural - urban$" shows the difference in life expectancy between averages of urban retirees and rural residents, and the "$public - private$" shows the difference between averages of public sector retirees and private sector retirees.

estimation is not preferable because it suffers from a large shrinkage of the sample size as a result of using the sub-sample of housing units that are either just below or slightly above the 90 square meters cutoff that were purchased before the housing policies started. The hazard model is not preferable because it does not directly provide the unconditional probability of death by or at a certain age, but focuses on the instantaneous rate of mortality at each point in time.

4 The Model

To understand the above empirical facts, we construct an optimization model in which individuals choose consumption and health investment. We briefly introduce a simple static model to illustrate how health investment depends on income and housing costs. Then, we focus on a fully fledged dynamic model that includes health investment and housing investment to quantitatively study socioeconomic factors that drives the heterogeneity in mortality and life expectancy.

4.1 The Simple Static Model

In the simple static model, an individual with income y allocates the income among the consumption of numeraire goods (C), housing consumption (S), and health investment (H) are specified as follows:

$$\begin{aligned} &\max_{C,S,H} \quad \left[(1-\alpha)(C^{1-\xi}S^{\xi})^{1-1/\eta} + \alpha H^{1-1/\eta}\right]^{\frac{1}{1-1/\eta}} \\ &s.t. \qquad C + qS + H = y, \end{aligned} \tag{4}$$

where $\xi \in (0,1)$ is the utility weight on housing and $\alpha \in (0,1)$ is the utility weight on health. The parameter $\eta \in (0,\infty)$ is the elasticity of substitution between health and the composite of housing and non-housing consumption. We use q to denote the housing cost (i.e., the rental rate of housing). For simplicity, we assume that one unit of income (y) can be converted into one unit of health (H). We will specify a more realistic health production function when we lay out the dynamic model.

Given the Cobb-Douglas preference over housing and non-housing consumption, the optimal allocation satisfies

$$\frac{qS}{C} = \frac{\xi}{1-\xi}. \tag{5}$$

Substituting this optimal allocation rule into the optimization problem above, the problem is simplified into:

$$\begin{aligned} &\max_{C,H} \quad u(C,H) \\ s.t. \quad &\tfrac{C}{1-\xi} + H = y, \end{aligned} \tag{6}$$

where

$$u(C,H) = \left[(1-\alpha)\left(\frac{\xi}{q(1-\xi)}\right)^{\xi(1-1/\eta)} C^{1-1/\eta} + \alpha H^{1-1/\eta}\right]^{\frac{1}{1-1/\eta}}. \tag{7}$$

Solving the above optimization problem yields the following expression for the optimal amount of health investment. Details are provided in Appendix C.

$$H = \frac{y}{\left(\frac{1-\alpha}{\alpha}\right)^{\eta}\left(\frac{1}{\xi^{\xi}(1-\xi)^{1-\xi}}\right)^{1-\eta} q^{\xi(1-\eta)} + 1}. \tag{8}$$

Equation (8) shows that investment in health increases in income and also increases in the cost of housing q if and only if $\eta > 1$, that is, if consumption and health are highly substitutable. This equation implies that residents in larger cities, whose income and housing costs are higher, invest more in health if $\eta > 1$. This result is intuitive: If $\eta > 1$, then health is a substitute for consumption, and larger city residents invest more in health to substitute for the more expensive housing consumption.

For the special case where the elasticity of substitution between consumption and health is unity ($\eta = 1$), we have the following expressions for health investment derived from equation (8):

$$H = \alpha y \qquad , \text{ if } \eta = 1. \tag{9}$$

Thus, health investment does not depend on housing costs when $\eta = 1$, which is because the income effect and substitution effect of a higher housing cost cancel each other. In this case, residents in larger cities invest more in health because of their higher income

For the special case where the substitution elasticity between consumption and health is zero (the Leontief preference), equation (8) gives rise to the following health investment.

$$H = \frac{y}{\frac{q^{\xi}}{\xi^{\xi}(1-\xi)^{1-\xi}} + 1} \quad , \text{ if } \eta = 0\ . \tag{10}$$

Thus, health investment increases with income but decreases with housing costs. In Appendix C we show that when $\eta = 0$, the optimized utility of individuals, denoted $u^{\star}$, has the same expression as H, i.e.,

$$u^{\star} = H \qquad , \text{if } \eta = 0 \ . \tag{11}$$

Imposing the spatial equilibrium condition that individuals living in different cities should have the same level of utilities, equation (11) indicates that health investment is the same across cities when health and consumption have zero substitutability, implying the same life expectancy for individuals living in different cities.

We summarize the above results in the following proposition.

Proposition 1 *In the static model specified in optimization problem (4), health investment is*

(i) increasing in both income and housing cost if $\eta > 1$;

(ii) increasing in income and independent of housing cost if $\eta = 1$;

(iii) increasing in income but decreasing in housing cost if $\eta < 1$;

(iv) independent of income and housing cost if $\eta = 0$ and if the spatial equilibrium condition holds.

The proposition implies that larger city residents should have a higher life expectancy if health and consumption have a high degree of substitutability, and they should have a similar life expectancy as residents in smaller cities or rural areas if the substitutability is near zero. In the data, we observe a lower life expectancy among rural residents and a mild increase of life expectancy in city size, indicating a low degree of substitutability between consumption and health.

4.2 The Dynamic Optimization Model

In this subsection, we extended the simple static model to a dynamic model. One period in our model represents one year. We use t to denote the number of years into retirement, with t ranging between 1 and T, representing age 61-100, respectively. Individuals in the model are categorized into one of the seven groups described earlier, based on their city of residence and sector of pre-retirement employment. Because the dynamic optimization model applies to each group, we do not include the type as a state variable. We will describe the heterogeneity across groups in detail in the subsequent section.

4.2.1 Health Production and Health Shocks

Denote $h_t = log(H_t)$ where H_t is the stock of health for an individual at the beginning of period t. The law of motion of h_t is

$$\begin{aligned} h'_t &= h_t + m_t, & (12)\\ m_t &= \psi \times i_t, & (13)\\ h_{t+1} &= f(h'_t, age), & (14) \end{aligned}$$

where m_t is the additional health as a result of the endogenous health investment, and h'_t is the total amount of health after the health investment.

Equation (13) is the health production function, where $i_t = log(I_t)$ is the logarithm of total health investment in terms of the numeraire, and the parameter $\psi \in (0, 1]$ determines the curvature of the health production function.[22]

The function $h_{t+1} = f(h'_t, age)$ in equation (14) captures the exogenous transition of health between period t and period $t+1$, which we estimate directly from the data. Death is defined as the state in which h_{t+1} is below a threshold level of $\underline{h}$, i.e., $h_{t+1} < \underline{h}$. In this case, the individual dies between period t and $t + 1$.[23]

In terms of timing, the individual observes her health stock h_t at the beginning of period t. If $h_t \geq \underline{h}$, then she chooses to produce m_t amount of additional health, resulting in a total health of h'_t at the beginning of period t, which enters her utility function. Next, between t and $t + 1$, the health depreciates with age and receives random shocks as captured by $f(h'_t, age)$, which results in a health stock of h_{t+1} at the beginning of period $t+1$. If the individual survives (i.e $h_{t+1} \geq \underline{h}$), then she moves on to choose m_{t+1}.

Combining equations (12)-(13) leads to the health that enters the utility function in period t as a function of the existing health at the beginning of period t and the health investment:

$$H'_t = H_t \times I_t^{\psi}. \tag{15}$$

It should be noted that only a fraction of the total health investment is out of pocket, and the remaining is covered by the publicly funded healthcare system. That is, $I_t^{oop} = OOP \times I_t$, where I_t^{oop} is the amount of out-of-pocket health investment, and OOP is the OOP share. The OOP share differs by region and sector of employment. Therefore, individuals choose different

[22] Theoretically, we can model health production as $m_t = log(Q) + \psi \times i_t$, i.e., $M_t = QI^{\psi}$ where Q is a scaling parameter. However, we can not separately identify Q from α in the utility function as shown in equation (7). Therefore, we choose not to include Q in the health production function.

[23] This specification of the exogenous health transition assumes that health shocks are Markovian. As we show in Table B.4, pre-retirement health status has a statistically significant effect on the current health, implying that the Markovian assumption is strong. Relaxing the assumption will significantly increase the computational burden of the dynamic model.

levels of health investment I_t^{oop} not only because of the difference in income and wealth, but also because of the difference in the OOP share.

4.2.2 Financial Market

Housing and bonds are the two types of financial assets available in the model.[24] Bonds are risk-free and perfectly liquid. No mortgage or other borrowing is allowed in the model, as the majority of retirees in China do not have mortgage debt or unsecured debt.

The value of housing at the beginning of period t is $D_t P_t$ where D_t and P_t denote the size and per-unit price of housing, respectively. The growth rate of house prices follows an AR(1) process with a deterministic trend. Thus, housing investment is risky. The return on housing investment comprises rental return and house price appreciation. The rental rate of houses is denoted q_t, which is the housing cost from the renter's perspective.

We separate housing consumption from housing investment in the model, and allow individuals to own housing as an asset on the one hand and obtain housing service through renting on the other hand.[25] Thus, the amount of housing service is generally different from the housing investment for individuals. An individual is defined as a homeowner if she has a positive housing investment. Consistent with the fact that less than 1% of old-age individuals have housing assets outside the city they reside, we assume that individuals own housing assets only in their cities of residence.[26]

We consider three types of friction in the housing market. First, there is an adjustment cost of housing transactions – a homeowner needs to pay a λ fraction of the house value.[27] Second, there is a minimum housing size that differs by city tiers. Third, there is a utility gain for homeowners, i.e., homeowners derive more utility than renters for the same unit of housing, which captures the prestige associated with owning housing assets. As we will show,

[24] Bonds correspond to the following assets in the data: cash, bank deposits, wealth management products, government bonds, and housing funds. Bonds and housing account for 99.8% of the total wealth of retirees in our pooled CHARLS sample.

[25] In our CHARLS sample, 15% of individuals are renters, and about 3% of individuals have multiple condominiums.

[26] Based on the 2017 and 2019 waves of China Household Finance Survey, 0.025% of residents aged 55 or above in non-tier-1 cities have housing investment in tier-1 cities, and only 0.99% of old-age rural residents have housing investment in cities. Thus, very few residents of smaller cities take advantage of the better opportunities in the housing markets of larger cities. We believe this is a result of various barriers, including the often-cited minimum housing size combined with lower income in smaller cities, purchase restrictions imposed by municipal governments, and the high monetary/psychological costs associated with managing a property outside the city of residence. We also show in Table B.5 that, if we exclude individuals with multiple housing assets, we get similar results regarding health transition.

[27] While we assume housing investment involves this selling cost, we assume the rental market involves no transaction cost, i.e., it is cost-free for individuals to adjust the amount of housing consumption.

these frictions generate heterogeneous home ownership rates and have a significant impact on mortality rates.

4.2.3 Optimization Problem

Let $\Omega_t = (D, B, P, q, H)$ represent the current state of an individual at the beginning of a period, where D and B are the stocks of housing assets and risk-free bonds respectively, P is the price of housing asset, q is the housing cost (rental rate of housing), H is the health stock. We omit the time (age) subscript, and use D', B' and I' to denote the choice of housing asset, risk-free bond, and health investment, respectively.

We use ϕ to denote the homeowner's utility gain, and modify the utility function in equation (4) into $\left[(1-\alpha)(C^{1-\xi}((1+\phi)S)^{\xi})^{1-1/\eta} + \alpha H^{1-1/\eta}\right]^{\frac{1}{1-1/\eta}}$. The inclusion of ϕ does not affect the optimal allocation between housing and non-housing consumption shown by equation (5) because of the Cobb-Douglas preference. After some algebra, we obtain the following current utility as a function of consumption C and health H:

$$u = \left[(1-\alpha)\left(\frac{\xi}{q(1-\xi)}\right)^{\xi(1-1/\eta)}(1+\phi)^{\xi(1-1/\eta)}C^{1-1/\eta} + \alpha H^{1-1/\eta}\right]^{\frac{1}{1-1/\eta}}, \tag{16}$$

$$where \quad \phi = 0 \quad for \quad renters.$$

Homeowners Due to the presence of housing transaction costs, an individual may not be a homeowner. If an individual is a homeowner, she chooses between three alternatives: (i) housing adjustment, (ii) no housing adjustment, and (iii) exiting the housing market. This choice is given by:

$$V_t(\Omega) = \max\{V_t^a(\Omega), V_t^n(\Omega), V_t^x(\Omega)\} \tag{17}$$

for all Ω.

In the case of housing adjustment, the value function is:

$$V_t^a(\Omega) = \max_{I',D',B'}\left\{(1-\beta)u^{1-1/\theta} + \beta\left[\left(E_t(1-\nu(\Omega'))V_{t+1}(\Omega')^{1-\gamma}\right)^{\frac{1}{1-\gamma}} + \left(E_t\nu(\Omega')V_b^{1-\gamma}\right)^{\frac{1}{1-\gamma}}\right]^{1-1/\theta}\right\}^{\frac{1}{1-1/\theta}}$$

$$\begin{aligned} s.t. \frac{C}{1-\xi} &= Y - OOP \times I' + (1+r_b)B - B' + (1-\lambda+q)P_tD - P_tD', && (18)\\ H' &= H \times (I')^{\psi}, && (19)\\ P_tD' &\geq \underline{PD}, && (20) \end{aligned}$$

where u is defined by equation (16). Because we assume that housing consumption is derived from renting even for homeowners and it is cost-free to adjust housing consumption, the optimal allocation over housing and non-housing consumption given by equation (5) still holds true in the dynamic model, and we omit housing consumption S from the choice set for simplicity of notation.

The term $\frac{C}{1-\xi}$ in the budget constraint is the total consumption expenditure, including both non-housing and housing consumption, which is clear from equation (5). r_b is the bond return, $\underline{PD}$ is the minimum house value, λ is the selling cost of the house, and q is the rental rate of the owned house, which generates streams of rental income for homeowners. I' is the health investment.

The mortality rate $\nu(\Omega')$ is a function of the next period's state space Ω' because the mortality rate depends on H', which is the health stock the individual chooses based on Ω'. The parameter γ is the coefficient of relative risk aversion, and θ is the elasticity of inter-temporal substitution (EIS). The expectation, denoted E_t, is taken with respect to future health shocks and housing return shocks.

The bequest value V_b is a function of bequeathed wealth $F = (1-\lambda)P_{t+1}D' + (1+r_b)B'$. It has the following functional form:

$$V_b(F) = L^{\frac{1}{1-1/\theta}} \times F, \tag{21}$$

where L determines the strength of bequest motives. This bequest value is stochastic because the house price P_{t+1} is uncertain. The effect of risk aversion on bequest value appears in the parameter γ in the functional equation of $V_t^a(\Omega)$.

In the case where the homeowner chooses not to adjust his or her housing wealth, he or she needs to decide on the health investment and bond purchases for the next period. The value is:

$$V_t^n(\Omega) = \max_{I',B'} \left\{ (1-\beta)u^{1-1/\theta} + \beta \left[\left(E_t(1-\nu(\Omega'))V_{t+1}(\Omega')^{1-\gamma} \right)^{\frac{1}{1-\gamma}} + \left(E_t \nu(\Omega') V_b^{1-\gamma} \right)^{\frac{1}{1-\gamma}} \right]^{1-1/\theta} \right\}^{\frac{1}{1-1/\theta}}$$

$$\begin{aligned} s.t. \qquad \frac{C}{1-\xi} &= Y - OOP \times I' + (1+r_b)B - B' + qP_tD, \\ H' &= H \times (I')^{\psi}, \\ D' &= D. \end{aligned}$$

In the case where the homeowner chooses to exit the housing market, the value is given by

$$V_t^x(\Omega) = \max_{I',B'} \left\{ (1-\beta)u^{1-1/\theta} + \beta \left[\left(E_t(1-\nu(\Omega'))W_{t+1}(\Omega')^{1-\gamma} \right)^{\frac{1}{1-\gamma}} + \left(E_t \nu(\Omega') V_b^{1-\gamma} \right)^{\frac{1}{1-\gamma}} \right]^{1-1/\theta} \right\}^{\frac{1}{1-1/\theta}}$$

$$\begin{aligned} s.t. \qquad \frac{C}{1-\xi} &= Y - OOP \times I' + (1+r_b)B - B' + (1-\lambda+q)P_tD, \\ H' &= H \times (I')^{\psi}, \\ D' &= 0, \end{aligned}$$

where $W_{t+1}(\Omega')$ is the value function for non-homeowners to be specified below.

Non-homeowners An individual who is not currently investing in the housing market can choose to become a homeowner or remain a non-homeowner. The value for this entry decision is:

$$W_t(\Omega) = \max\{W_t^n(\Omega), W_t^e(\Omega)\}, \tag{22}$$

where $W_t^n(\Omega)$, the value of remaining a non-homeowner, is given by

$$W_t^n(\Omega) = \max_{I',B'} \left\{(1-\beta)u^{1-1/\theta} + \beta\left[\left(E_t(1-\nu(\Omega'))W_{t+1}(\Omega')^{1-\gamma}\right)^{\frac{1}{1-\gamma}} + \left(E_t\nu(\Omega')V_b^{1-\gamma}\right)^{\frac{1}{1-\gamma}}\right]^{1-1/\theta}\right\}^{\frac{1}{1-1/\theta}}$$

$$\begin{aligned} s.t. \qquad \frac{C}{1-\xi} &= Y - OOP \times I' + (1+r_b)B - B', \\ H' &= H \times (I')^{\psi}, \\ D' &= 0. \end{aligned}$$

Again, we omit housing consumption S from the choice set for simplicity of notation. As discussed earlier, the optimal allocation between housing and non-housing consumption is given by equation (5), which still holds true in the dynamic model because we assume it is cost-free to adjust housing consumption.

The value of a non-homeowner who chooses to enter the housing investment market is given by:

$$W_t^e(\Omega) = \max_{I',D',B'} \left\{(1-\beta)u^{1-1/\theta} + \beta\left[\left(E_t(1-\nu(\Omega'))V_{t+1}(\Omega')^{1-\gamma}\right)^{\frac{1}{1-\gamma}} + \left(E_t\nu(\Omega')V_b^{1-\gamma}\right)^{\frac{1}{1-\gamma}}\right]^{1-1/\theta}\right\}^{\frac{1}{1-1/\theta}}$$

$$\begin{aligned} s.t. \frac{C}{1-\xi} &= Y - OOP \times I' + (1+r_b)B - B' - P_t D', \\ H' &= H \times (I')^{\psi}, \\ P_t D' &\geq \underline{PD}, \end{aligned}$$

where the continuation value $V_{t+1}(\Omega')$ is the value function of homeowners.

5 Exogenous Model Inputs

The model has a number of exogenous inputs, including the homogeneous stochastic health process, the heterogeneous out-of-pocket medical expenditure, the housing market, income, and the initial distribution of health and wealth. Although income and initial health and wealth are treated as exogenous inputs in our model because we focus on post-retirement decisions, it is noteworthy that they are likely to be affected by the selection induced by pre-retirement migration. For instance, individuals with better education are more likely to be employed in larger cities and receive higher income.

5.1 Health Process

The exogenous component of health is a function of age and lagged health, as shown in equation (14). To estimate this exogenous process, we augment the five self-reported health statuses in CHARLS with "death" as an additional status. The term $Health$ represents health dummies. CHARLS records the self-reported health status, which takes the five values between 1 and 5, with a value of 1 corresponding to very poor health and 5 to very good health. In the regression, we treat health status 3 (i.e., "fair") as the omitted group.[28] Specifically, we use the following vector to denote health categories,

$$h^\star = \{h_0^\star, h_1^\star, h_2^\star, h_3^\star, h_4^\star, h_5^\star\}, \tag{23}$$

where $h_5^\star$ denotes the best health status, and $h_0^\star$ denotes the worst which is death.[29] Given the six statuses, we estimate an ordered probit model, regressing the current health status on age, age-squared, and dummies for the lagged health status, controlling for income, wealth, and year effects. By controlling for income and wealth in the ordered probit regression, the coefficients on lagged health and age effectively capture the exogenous changes in health.

Table 6 reports the estimation results. We find significant coefficients for lagged health dummies where the "fair" status is the omitted group. The negative coefficients for poor and very poor health and the positive coefficients for good and very good health imply a strong serial correlation of health status. The coefficients of age and age-squared are both negative, implying the deterioration of health as one ages. The positive coefficients of income and wealth are consistent with our theoretical prediction that richer individuals invest more in health.

We use the coefficients on age, age-squared, lagged health status, and its interaction with age in Table 6 to estimate the exogenous process of shocks. The positive effects of income and wealth on health are captured by the endogenous health investment in our model, which occurs after the realization of exogenous health shocks.

[28] Self-reported measurements of health might introduce subjective noise for latent health. We check robustness using latent health's projection on its objective components affected by disabilities or diseases. As we show in Tables B.6 and B.7 in Appendix B.5, the self-reported health status is negatively related to various diseases and disabilities, i.e., the subjective self-assessment is in line with more objective health conditions.

[29] The state of death is assigned to individuals who die between two waves of surveys.

Table 6: Health Transition

		lagged Health				lagged Health × Age					
Age	Age^2	Very poor	Poor	Good	Very good	Very poor	Poor	Good	Very good	ln(Income)	ln(Wealth)
-0.050	-0.053	-1.000	-0.656	0.492	0.916	0.0023	-0.0005	-0.067	-0.049	0.009	0.035
(0.021)	(0.014)	(0.029)	(0.016)	(0.020)	(0.029)	(0.036)	(0.020)	(0.026)	(0.037)	(0.002)	(0.004)

Notes: This table reports the ordered probit regression results. The dependent variable is future health status. Robust standard errors are in parentheses. Age is defined as (actual age − 60)/10.

5.2 Out-of-pocket Medical Expenditure

As discussed in Section 2.1, the out-of-pocket share of total health expenditures (the OOP share) features a large disparity between sectors and across regions. To capture the disparity, we regress the OOP share on dummies of the seven groups of individuals, as well as age, age-squared, health dummies, and interaction of health dummies with age, controlling for the year fixed effect.[30]

Table 7 reports the OLS estimation results. Coefficients of region-sector dummies are all negative, indicating a lower OOP share for urban retirees than rural residents, who are the omitted group. Retirees from the public sector enjoy a much lower OOP share than private sector retirees. In addition, the OOP share is lower in larger cities.[31]

Table 7: Heterogeneous Out-of-pocket Expenditure Share

			Private sector			Public sector		
Const.	Age	Age^2	tier 1	tier 2	tier 3	tier 1	tier 2	tier 3
0.653	-0.006	-0.025	-0.16	-0.133	-0.098	-0.288	-0.186	-0.173
(0.008)	(0.009)	(0.005)	(0.022)	(0.012)	(0.008)	(-0.024)	(0.014)	(0.011)

lagged Health				lagged Health ×Age			
Very poor	Poor	Good	Very good	Very poor	Poor	Good	Very good
0.13	0.143	-0.181	-0.263	-0.006	-0.023	0.049	0.046
(0.012)	(0.008)	(0.011)	(0.012)	(0.013)	(0.008)	(0.011)	(0.012)

Notes: This table reports the OLS regression results. The dependent variable is out-of-pocket medical expenditure as a share of the total medical expenditure. Robust standard errors are in parentheses. Age is defined as (actual age − 60)/10.

[30]It is noteworthy that, during our sample period of 2011-2018, the average OOP share in China fell from 40.27% to 35.75% (https://data.worldbank.org/indicator/SH.XPD.OOPC.CH.ZS?locations=CN&view=chart).

[31]For robustness, we re-run regressions using the Tobit model, and we find similar patterns. See Table B.8.

5.3 Housing Market

We assume house price growth is the sum of the deterministic and stochastic components, i.e., the growth rate at time in tier j cities is

$$r^P_{j,t} = \mu_j + \tilde{p}_t,$$

where μ_j is the deterministic component. The stochastic component $\tilde{p}_t$ follows an AR(1) process, i.e., $\tilde{p}_t = \rho\tilde{p}_{t-1} + \epsilon_t$, with the random shock follows $\epsilon_t \sim N(-\frac{\sigma^2}{2}, \sigma^2)$. We set $\rho = 0.15$ and $\sigma = 0.08$ for all cities and the rural area to capture the weak serial correlation and low volatility of house price growth in China.

We use μ_j = 6%, 4%, 2%, and 1% for tier-one, tier-two, tier-three cities, and the rural region, respectively.[32] Fang et al. (2016) find that the average growth rates of real house prices are 13.1%, 10.5%, and 7.9% between 2003-2013 in tier-one, tier-two, and tier-three cities, respectively. However, housing prices in most cities in China have been declining since 2019.

The rental return of houses is calculated based on the rent-to-price ratio. The ratio is generally close to or even below two percent in different regions. Thus, we set the rent-to-price ratio of houses to 2%.

The housing cost, represented by q in equation (16), differs tremendously across regions. In our CHARLS sample, the average monthly rent per square meter is 28.1 Yuan, 14.2 Yuan, and 8.7 Yuan for tier-one, tier-two, and tier-three cities, respectively. The rental rate in rural areas is only about a quarter or one-fifth of the rent in tier-three cities.[33] We normalize the housing cost of rural regions to one, i.e., one unit of housing service for one unit of non-housing consumption, and we set the housing cost of tier-one, tier-two, and tier-three cities to 13, 6.5, and 4, respectively.

We set the minimum house value to 10 times the average income in cities, and set it to the level of average income in the rural regions, to capture the fact that rural residents in China are allotted residential land free of charge, but city residents pay a high house price which mainly is land cost.

5.4 Income

Income is exogenous and deterministic in the structural model, a realistic assumption given our focus on retirees' economic decisions.[34] We regress log income on region-sector dummies and

[32] The underlying assumption is that individuals invest only in housing markets of their own cities or cities of the same tier. In reality a small fraction of wealthy individuals may invest in different tiers of cities.

[33] See `https://research.ke.com/ResearchResults`.

[34] Giles et al. (2012) suggest that China has an informal retirement system, especially in rural areas, where rural residents and individuals in the informal sector rely on family support in old age and tend to have much longer working lives. Thus, the assumption of exogenous and deterministic income could be a bit strong for

age to capture income inequality of the old-age individuals in our CHARLS sample. Table 8 reports the results. As the table shows, income is lower among rural residents (the omitted group in region-sector dummies). Income is significantly higher in larger cities. Within each city tier, income is significantly higher among public sector retirees.

Table 8: Heterogeneous Income

			Private sector			Public sector		
Const.	Age	Age2	tier 1	tier 2	tier 3	tier 1	tier 2	tier 3
7.639	-0.068	-0.04	0.94	0.554	0.43	1.111	0.637	0.498
(0.01)	(0.02)	(0.01)	(0.05)	(0.02)	(0.02)	(0.18)	(0.07)	(0.04)

Notes: This table reports the OLS regression results. The dependent variable is log income. Robust standard errors are in parentheses. Age is defined as (actual age − 60)/10.

5.5 Initial Health and Wealth

For each type of individual, we calculate the joint distribution of health, financial wealth, and housing wealth based on the observations aged 55-65 in our CHARLS sample, and use the distribution as the starting point in the simulations.

Table 9 illustrates the composition of initial wealth per person for the seven groups. The cross-sectional heterogeneity is similar to the patterns observed in Table 2 which reports wealth compositions for all retirees, including those aged above 65. Namely, wealth is higher among larger city residents, and among public sector retirees. The wealth of rural residents is strikingly lower than that of city residents. For each group, housing assets are dominantly important, and home ownership rates are high.

Figure 3 displays the initial distribution of health. As the figure indicates, a larger fraction of retirees in the private sector report very poor health, and a smaller fraction of them report good or very good health. The initial health condition is better among tier-one city residents, irrespective of their pre-retirement sector of employment. Compared to city residents, a significantly large fraction of rural residents report poor or very poor health. Presumably, the inequality in life expectancy is partially driven by the different initial health conditions.

6 Structural Estimation

The model has a set of parameters that we estimate via the simulated method of moments. The set includes 9 parameters, denoted $\Theta = (\beta, \gamma, \theta, L, \alpha, \eta, \psi, \phi, \lambda)$. These parameters are

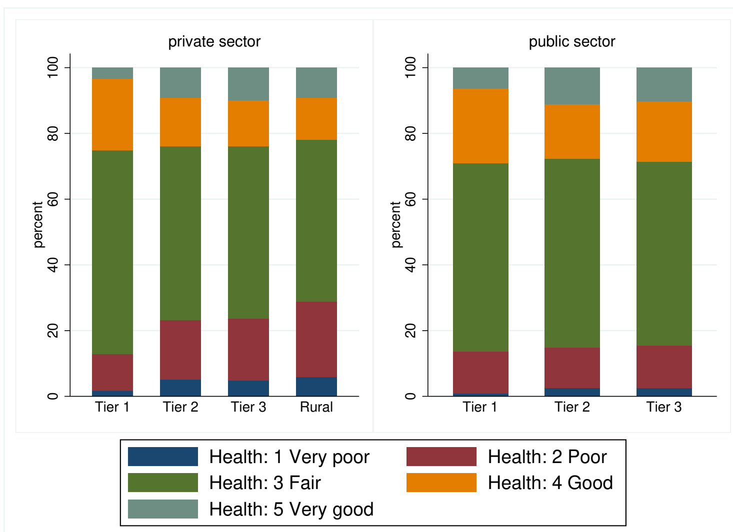
the rural area where healthy individuals are likely to have longer working lives. Nevertheless, we include labor income and monetary transfer from family members in our income measure of rural residents.

Table 9: Initial Wealth Distribution

	Wealth (10,000 yuan)				Home ownership rate
	$Non-housing$		$Housing$ $_{homeowners}$		
	mean	std.	mean	std.	mean
Rural	0.60	(4.30)	6.56	(15.36)	0.955
Tier 1, private sector	2.57	(9.56)	371.29	(1,083.89)	0.685
Tier 2, private sector	1.62	(6.47)	70.75	(378.47)	0.792
Tier 3, private sector	1.07	(4.01)	47.42	(343.72)	0.771
Tier 1, public sector	6.86	(17.40)	410.82	(1,070.73)	0.678
Tier 2, public sector	3.07	(7.43)	115.10	(639.90)	0.855
Tier 3, public sector	1.90	(9.31)	56.48	(341.83)	0.830

Notes: Wealth distribution for retirees aged 55 to 65. The author's calculation is based on the CHARLS. Housing wealth is the average for homeowners within the group.

Figure 3: Initial Health Distribution



Notes: This figure presents the calculation results for the distribution of health status among retirees aged 55 to 65, based on CHARLS data.

identified by minimizing the distance between the moments obtained from the model and their counterparts in the data. We use 18 moments to identify 9 parameters, which leads to an overidentifying restriction of $18 - 9 = 9$.

6.1 Data Moments

To estimate the parameters of our structural model, we choose two sets of moments that summarize the heterogeneous mortality rates and home ownership rates in the data, respectively, each containing 9 moments.

The first set of moments are regression coefficients of the mortality rate on age, age-squared, and six dummies representing retirees from different sectors and city tiers (see column (1) in Table 10). By matching the six dummies, our model generates the heterogeneous mortality rates, the focal point of our study. We transform the actual age in the data into $\frac{age-60}{10}$, and the corresponding squared term is $\left(\frac{age-60}{10}\right)^2$. The transformation increases coefficients on age and age-squared to a scale similar to other coefficients.

The second set of moments is regression coefficients of the home ownership rate, using the same regressors as in the regression of the mortality rate. We choose these moments because we aim to understand the roles of housing investment and housing market frictions in determining life expectancy. In addition, we will examine how a large decline in house prices impacts life expectancy in different regions and sectors.

Table 10: Data Moments

	(1)		(2)	
	Death		Home ownership	
Age	-0.016***	(0.00)	-0.040***	(0.00)
Age square	0.036***	(0.00)	-0.009***	(0.00)
City: 1st tier (private)	-0.048***	(0.01)	-0.204***	(0.02)
City: 2nd tier (private)	-0.041***	(0.00)	-0.129***	(0.01)
City: 3rd tier (private)	-0.026***	(0.00)	-0.152***	(0.00)
City: 1st tier (public)	-0.063***	(0.01)	-0.166***	(0.02)
City: 2nd tier (public)	-0.055***	(0.00)	-0.050***	(0.01)
City: 3rd tier (public)	-0.050***	(0.00)	-0.060***	(0.01)
Constant	0.029***	(0.00)	0.945***	(0.00)
Observations	45643		60261	
R^2	0.052		0.056	

Notes: Data moments used in the Simulated Method of Moments estimation. *Age* is defined as (actual age - 60)/10. Robust standard errors are in parentheses. Significance * .10, ** .05, *** .01.

Table 10 reports the data moments and their standard errors. The coefficients on dummies are all relative to the base group, i.e., old-age rural residents. While we have discussed the heterogeneity in the mortality rate in Section 3, here we briefly discuss the heterogeneity in the home ownership rate. As the table shows, the home ownership rate is higher among retirees in tier-two cities than in tier-three cities. Rural residents enjoy the highest home ownership rate, while retirees in tier-one cities from the private sector have the lowest rate. Within each city tier, public sector retirees enjoy significantly higher home ownership rates. For each group, the home ownership rate declines with age. Our model generates similar heterogeneity in the home ownership rate due to the frictions in the housing market, including the housing adjustment cost, the minimum housing requirement, and the additional utility gained by the homeowners.

6.2 Parameter Estimates

The definitions and estimated values of these parameters are reported in Table 11. The last column of the table reports the standard errors of these estimates. The small standard errors indicate that each parameter is estimated with good precision. Appendix D.1 provides details on the estimation procedure.

Table 11: Model Parameters

Symbol	Definition	Estimate	Std Err
β	discount factor	0.925	0.004
γ	relative risk aversion	3.162	0.096
θ	inter-temporal elasticity of substitution	0.813	0.023
L	bequest motive	1.202	0.052
α	health share in utility	0.468	0.026
η	substitution between health and consumption	0.475	0.013
ψ	curvature in health production	0.640	0.016
ϕ	homeowner's utility gain	0.089	0.003
λ	housing adjustment cost	0.053	0.001

Notes: The estimates of parameters in the structural model and their standard errors.

Our estimate of the elasticity of substitution between health and consumption is $\eta = 0.475$.[35] To match the key facts about asset allocation and health expenditure among American retirees in the Health and Retirement Study, Yogo (2016) chooses an elasticity between health and consumption of 0.7. Thus, both studies find that health and consumption are complements rather than substitutes. As a result, the high housing costs in large cities squeeze out health investments. This housing cost effect has been illustrated in the simple model and summarized in Proposition 1.

The curvature of the health production function is $\psi = 0.64$, implying a positive but mild income and wealth gradient in health investment. Because residents of larger cities tend to

[35] Here, we assume a symmetric elasticity across individuals. See Anderson and Zhang (2022) and Hu and Zhang (2021) for the role of income in the heterogeneous estimates of substitution elasticity.

earn higher incomes and accumulate more wealth, particularly through housing investment, they are more likely to invest in health. However, this income and wealth channel is partially counteracted by the housing cost channel. With two channels combined, health investment increases in city size in the data as well as in our model.[36]

The estimated utility weight on health (i.e., health share) is $\alpha = 0.468$. In simulation exercises, we find that a larger α increases health investment and lowers mortality rates, and increases the inequality in life expectancy.

Our estimates for the discount factor, the risk aversion, and the EIS all fall in the conventional ranges. It is informative to compare our estimates to those in Calvet et al. (2023) based on structural estimations using a panel of Swedish households. Our discount factor of 0.925 is equivalent to a time preference rate of $-log(0.925) = 7.8\%$, which is larger than the mean time preference rate of 5.21% reported in Calvet et al. (2023). Our estimated risk aversion and EIS are 3.163 and 0.813, lower than the estimated mean values of 7.57 and 0.96 reported in Calvet et al. (2023).

The estimated housing transaction cost is $\lambda = 0.054$, i.e., 5.4% of the house value. The cost is interpreted as a combination of monetary costs and psychological costs. This cost makes housing adjustment lumpy, which is consistent with the empirical findings that retirees rarely downsize their houses even in older age (Venti and Wise, 2004). As we will show in the counterfactual simulation, home ownership rates increase when we set housing transactions to zero, because in this case, homeowners downsize their houses rather than becoming renters in response to a negative health shock. The homeowner's utility gain is $\phi = 0.089$. In other words, the same housing unit provides 8.9% more subjective utility if it is owner-occupied rather than rented. This subjective utility gain is identified by matching the home ownership rate from the model with that in the data.

The estimated bequest motive is $L = 1.202$, indicating a mildly strong bequest motive, which is consistent with the China Household Finance Survey results (Yang and Gan, 2020). Similarly modeling bequest, Gomes and Michaelides (2005) uses a larger bequest motive parameter to match the wealth accumulation profiles observed in the US data. In the context of our model, a stronger bequest motive reduces health investment, thereby lowering life expectancy to a level that is below what we observe in the data.

[36] In an unreported experiment, we set $\eta = 1.5$ and re-simulate the model. We find that retirees in tier-one cities substitute out housing consumption and increase their health investment, while retirees in tier-three cities and rural residents decrease their health investment. As a result, the life expectancy of tier-one city retirees increases by 6.05 years in the private sector and by 4.04 years in the public sector, while the life expectancy of rural residents decreases by 2.01 years.

6.3 Model Moments

We obtain model moments by running the regression of the mortality rate and the home ownership rate based on the simulated data, using the same regression specification as with the data moments.

Table 12: Targeted Moments: Model vs. Data

				Private sector			Public sector		
	const	$\frac{age-60}{10}$	$\left(\frac{age-60}{10}\right)^2$	tier 1	tier 2	tier 3	tier 1	tier 2	tier 3
Mortality rate									
Data	0.029	-0.016	0.036	-0.048	-0.041	-0.026	-0.060	-0.055	-0.050
Model	0.039	-0.007	0.022	-0.047	-0.044	-0.022	-0.073	-0.060	-0.050
Home ownership									
Data	0.945	-0.040	-0.009	-0.204	-0.129	-0.152	-0.166	-0.050	-0.060
Model	0.882	-0.042	0.023	-0.230	-0.120	-0.141	-0.321	-0.141	-0.156

Notes: Moments from the CHARLS and the simulated data generated from the structural model.

Table 12 reports the model moments and their corresponding data moments. As the table shows, our model matches fairly well with the data, particularly in terms of heterogeneity across regions and sectors. The model effectively captures the lower mortality rates in larger cities compared to small cities or rural areas, as well as in the public sector compared to the private sector. As in the data, the mortality rate in each tier of cities is significantly lower than in rural areas.

The home ownership rates of the different groups are also matched fairly well. The home ownership rate of each group of urban retirees is lower than that of their rural counterparts. Relative to other urban retirees, tier-one city retirees have significantly lower home ownership rates. Home ownership rate is slightly lower in tier-three cities than in tier-two cities. All these salient features in the data are matched in our model. However, our model generates lower home ownership rates among retirees in the public sector than in the private sector, which is counterfactual.

The model also well matches the within-group averages in life expectancy and in home ownership rate, as shown in Table 13. Here, the life expectancy is calculated with equation (3) based on the heterogeneous mortality generated from the model, and the home ownership rate is a simple average of all individuals within the group. For each group, the model generates the average life expectancy at 60 and home ownership rates that are well aligned with the data counterpart, except that home ownership rates from the model are a bit high among rural residents and private sector retirees in tier-three cities, and it is 12% below the home ownership rate in the data among tier-one city public sector retirees.

Table 13: Model vs. Data – Levels

	Private sector				Public sector		
	Tier 1	Tier 2	Tier 3	Rural	Tier 1	Tier 2	Tier 3
Life expectancy							
Data	23.42	21.96	19.02	15.54	27.15	26.69	24.54
Model	24.06	23.59	18.30	14.16	27.22	25.78	24.46
Home ownership							
Data	0.61	0.69	0.66	0.82	0.65	0.77	0.76
Model	0.65	0.75	0.77	0.92	0.53	0.72	0.75

Notes: This table reports the average life expectancy and home ownership rate for each group in the data as well as in the estimated model.

In addition, we examine how medical expenditures differ among the seven groups. Table 14 reports the total medical expenditures and OOP expenditures by groups, both in the data and in the model. Here, we normalize the expenditures by the average income of all individuals in the seven groups to conceptualize the economic burden of medical expenses while keeping the numbers comparable between groups. As the first row of the table shows, the total medical expenditures are 0.60 and 0.46 for retirees in tier-one and tier-two cities in the private sector in the data, that is, the expenditures are 60% and 46% of the average income of the individuals in our CHARLS sample.

Total medical expenditure is higher in larger cities and the lowest in rural areas, which is consistent with the cross-region inequality in life expectancy. The total medical expenditure is higher among the public sector retirees, consistent with the between-sector inequality in life expectancy. Regarding OOP expenditures, it is clear in the data that rural residents spend less out-of-pocket on medical care, while the differences between city tiers and sectors are small. Our model captures these data features of medical expenditures, although we do not target these statistics in parameter estimation.

6.4 Parameters and Moments

Our structural parameters are estimated based on the minimum distance between the simulated moments and data moments. In this subsection, we discuss the relationship between parameter values and simulated moments to gain an understanding of the source of identification.[37] Specifically, we increase each estimated parameter by 1% one at a time, and calculate the corre-

[37] We are grateful to an anonymous referee for suggesting that we conduct the analysis of the relationship between parameters and moments.

Table 14: Model vs. Data – Medical Expenditures

	Private sector				Public sector		
	tier 1	tier 2	tier 3	rural	tier 1	tier 2	tier 3
Medical exp. (total)							
Data	0.60	0.46	0.48	0.19	0.92	0.67	0.58
Model	0.70	0.65	0.47	0.15	1.05	0.81	0.56
Medical exp. (OOP)							
Data	0.23	0.22	0.23	0.11	0.29	0.28	0.27
Model	0.16	0.17	0.15	0.08	0.16	0.16	0.12

Notes: This table reports the averages of total medical expenditures and out-of-pocket medical expenditures for each group in the data, as well as in the estimated model. The expenditures are normalized by the average income of all individuals.

sponding percentage changes of all the moments.[38] For more straightforward interpretations of the sensitivity of moments with respect to parameter, we convert the changes of model moments into the changes of life expectancy and home ownership rates by groups.

The elasticities are reported in Table D.1 in the appendix. Here we briefly discuss the elasticities of life expectancy with respect to parameters. The elasticity of life expectancy to β is significantly negative. On the one hand, the higher β tends to increase health investment due to the higher value of future health. On the other hand, it tends to decrease health investment due to the higher value of future consumption and bequest. The reported elasticities indicate that the latter channel dominates the former. As an additional check, we set the bequest motive L to zero, and re-calculate the elasticities with respect to β, and we find that the elasticities are slightly positive. Thus, the bequest motive is particularly important in determining the role of β health investment. The elasticity of life expectancy with respect to γ is mildly positive, because more risk aversion leads to more health investment.[39] A higher θ implies more tolerance for inter-temporal variation in consumption and health, which reduces health investment and life expectancy. A stronger bequest motive (i.e., larger L) is associated with lower life expectancy due to less health investment, and with more housing investment. A higher share of health in the utility function (larger α) clearly leads to higher life expectancy, and a higher substitutability between health and consumption (larger η) is generally associated with lower life expectancy

[38] An alternative approach is to calculate the sensitivity of parameters with respect to moments. As shown in Andrews et al. (2017), the matrix that measures the sensitivity of moments to parameters is the right inverse of the matrix that measures the sensitivity of estimated parameters with respect to moments. Our sensitivity analysis follows recent articles that conduct structural estimation, e.g. Morten (2019) and Ampudia et al. (2024).

[39] More risk aversion also leads to less risky investment, hence a lower home ownership rate.

because individuals substitute out health, which is costly to produce due to the large curvature, for more consumption. In addition, it is clear in the table that a higher η leads to more inequality in life expectancy, which is consistent with our discussion about proposition 1. With a larger ψ, it is less costly to produce health with the numeraire, which increases life expectancy. A larger utility gain for homeowners (i.e., larger ϕ) leads to higher life expectancy because most of the individuals are homeowners. Finally, a higher housing transaction cost is associated with slightly lower life expectancy, as it makesa homeowners financially worse off.

6.5 Housing Market Frictions

Our model captures three types of housing market frictions: the adjustment cost, the minimum housing size, and the home owner's utility gain. To understand their roles in determining life expectancy, we remove one type of friction at a time and examine the resulting life expectancy and home ownership rates. Results are reported in Table 15.

Table 15: Housing Market Frictions

	Private sector				Public sector		
	tier 1	tier 2	tier 3	rural	tier 1	tier 2	tier 3
Life expectancy at 60							
Model (benchmark)	24.06	23.59	18.30	14.16	27.22	25.78	24.46
Housing adjustment cost=0	29.88	26.64	19.08	14.38	31.04	28.64	24.95
Minimum housing=0	19.28	19.62	17.62	14.48	25.08	25.54	23.42
Homeowner's utility gain=0	24.03	23.73	18.42	14.17	27.04	26.09	24.48
Home Ownership Rate							
Model (benchmark)	0.648	0.753	0.768	0.920	0.534	0.724	0.751
Housing adjustment cost=0	0.808	0.912	0.823	0.923	0.831	0.908	0.826
Minimum housing=0	0.931	0.934	0.975	0.977	0.782	0.915	0.964
Homeowner's utility gain=0	0.501	0.729	0.764	0.912	0.450	0.668	0.746

Notes: This table reports life expectancy and home ownership rates when one housing market frictions are removed at a time.

Compared to the benchmark case where the housing adjustment cost is $\lambda = 0.054$, both the life expectancy and the home ownership rate are higher for each group when we set $\lambda = 0$. As noted in the literature, the adjustment cost makes the adjustment lumpy. In the context of our model, individuals economize on housing adjustment costs either by suppressing medical expenditures or exiting the housing market to finance medical expenditures. The former reduces life expectancy and the latter decreases home ownership rates. These effects are removed when the adjustment cost is set to zero.

The impacts of removing adjustment costs are unequal, most significant in tier-one cities and least significant in rural areas, which widens the rural-urban gap in life expectancy. The removal of adjustment costs has a greater impact in larger cities because the Yuan amount of housing adjustment costs is higher in larger cities where housing values are higher, increasing home ownership rates more. This, in turn, generates an even larger housing wealth effect in larger cities, further increasing life expectancy in these cities.

Setting the minimum housing size to zero (i.e., $\underline{DP} = 0$) significantly increases the home ownership rate, and it decreases life expectancy except for the rural group, as shown in Table 15. The removal of minimum housing size removes a large entry barrier, thus increasing home ownership rates and generating more housing wealth effect. However, home ownership comes with adjustment costs and the need to economize on health expenditures in order to avoid adjustment costs. As a result, life expectancy is decreased in cities, especially in tier-one and tier-two cities, where home ownership rates are low in the benchmark model. However, life expectancy increases slightly in rural areas, indicating a stronger housing wealth effect relative to the costs associated with home ownership.

Setting the homeowner's utility gain ϕ to zero decreases home ownership rates, especially in tier-one cities. As shown in the initial wealth distribution (Table 9), tier-one city retirees own significantly more housing wealth than other groups, so they need to economize more on health expenditures in order to keep their home ownership status and avoid adjustment costs. With the removal of the homeowner's utility gain, they have significantly less incentive to own homes, which has two effects. Firstly, it reduces the need to economize on health expenditure, thereby increasing life expectancy. Secondly, it decreases the housing wealth effect, which lowers health expenditure and life expectancy. Because of these two opposing effects, setting the homeowner's utility gain to zero has a marginal impact on life expectancy.

7 Life Expectancy Inequality

This section turns to a key question in our study – inequality in life expectancy. We begin with analyzing the quantitative importance of the socioeconomic factors included in our model in determining the inequality. Next, we gain further understanding of health investment and life expectancy by conducting counterfactual analyses.

7.1 Driving Forces of Life Expectancy Inequality

To assess the contributing role of each of the six heterogeneous socioeconomic factors introduced in Section 5, we maintain the heterogeneity of only one factor at a time, while disabling the heterogeneity of all other factors. This approach allows us to gauge how much of the inequality in life expectancy can be driven by one single heterogeneous socioeconomic factor.

We use rural residents as the base group, turning off heterogeneity by imposing the socioeconomic factors of rural residents on other groups. By design, this controlled experiment changes the life expectancy of all the groups except the base group, i.e., the rural group. There is a caveat in interpreting the results of these experiments – the results will be different if we use a different base group.

We begin with the heterogeneous initial health, i.e., the within-group distribution of health status at age 60, which differs across groups as illustrated in Figure 3, turning off the remaining heterogeneity. As shown in the second row of Table 16, the heterogeneity in initial health contributes only marginally to the inequality in life expectancy. With all the other heterogeneity turned off, the life expectancy of urban retirees is only 0.11 years higher than that of the rural group. Evidently, even though some groups of urban residents are healthier on average at retirement, this initial difference has a very small effect on the overall inequality in life expectancy.

Table 16: Contributing Factors of Inequality in Life Expectancy

	Private sector				Public sector			T1 pub	urban	public
	tier 1	tier 2	tier 3	rural	tier 1	tier 2	tier 3	-rural	-rural	-private
(1) Model (benchmark)	24.06	23.59	18.30	14.16	27.22	25.78	24.46	13.07	9.74	3.84
(2) Hetero initial health	14.31	14.26	14.23	14.16	14.27	14.25	14.27	0.11	0.11	-0.01
(3) Hetero initial wealth	17.09	16.71	15.13	14.16	18.12	17.51	15.49	3.97	2.52	0.73
(4) Hetero income	24.16	17.94	17.05	14.16	25.99	18.66	17.63	11.83	6.08	1.04
(5) Hetero housing cost	12.35	12.67	12.79	14.16	12.35	12.67	12.79	-1.81	-1.56	0.00
(6) Hetero income & housing cost	15.35	14.02	14.21	14.16	17.62	14.49	14.52	3.47	0.88	1.02
(7) Hetero housing inv. market	21.97	18.52	14.91	14.16	21.97	18.52	14.91	7.82	4.31	0.00
(8) Hetero OOP medical cost	17.86	17.05	16.32	14.16	21.17	18.54	18.18	7.01	4.03	2.22

Notes: This table reports life expectancy at sixty years of age for the seven groups in the benchmark model and from the experiments. In the row of "Hetero initial health", groups differ only in the health distribution at retirement. Other rows are similarly defined. "T1 $pub - rural$" is the difference in life expectancy between public sector retirees in tier-one cities and rural residents."$rural - urban$" shows the difference in life expectancy between the averages of urban retirees and the rural residents, and the "$public - private$" shows the difference between the average of the public sector retirees and the average of the private sector retirees.

Next, we turn to the heterogeneous initial wealth. As reported earlier in Table 9, urban residents, especially those of large cities, are significantly wealthier than rural residents at retirement. The third row of Table 16 indicates that this initial wealth inequality is translated into noteworthy inequality in life expectancy. For instance, it leads to a gap in life expectancy of about 4 years between rural residents and tier-one city retirees from the public sector. In larger cities, retirees tend to live longer partly because they are wealthier at the time of retirement. Public sector retirees live 0.73 years longer than private sector retirees in this controlled experiment, reflecting the fact that they are wealthier at retirement.

Income heterogeneity turns out to be the most important driver of inequality in life expectancy. As shown in the fourth row of Table 16, solely driven by income heterogeneity, the difference between tier-one city public sector retirees and rural residents is 11.83 years, while the difference is 13.7 years in the benchmark model where all types of heterogeneity exist. The average rural-urban gap is 6.08 years, which is 62% of the gap of 9.74 years in the benchmark model. The income heterogeneity also leads to a gap of about one year between the public and the private sectors.

In the heterogeneous housing cost experiment, life expectancy is highest among rural residents and lowest in tier-one cities. The rural-urban gap is non-trivial – 1.56 years on average. As we demonstrate in the simple static model, the effect of housing costs on health investment depends critically on the elasticity of substitution between consumption and health in the utility function. Our estimated elasticity of $\eta = 0.475$ implies it is not optimal for large city residents to take better health as a substitute for the costly housing consumption. Thus, everything else being equal, they invest less in health to support housing consumption, which in turn lowers their life expectancy.

We also conduct an experiment where both income and housing costs are heterogeneous, while the remaining heterogeneity is turned off. This is motivated by the urban economics theory that higher incomes in larger cities is a compensation for the higher housing costs in a spatial equilibrium. As shown in the sixth row of Table 16, on average, city residents live 0.88 years longer than rural residents at age sixty, indicating their income slightly overcompensates the high housing costs once life expectancy is taken into account in the context of a spatial equilibrium. The overcompensation is more significant among tier-one city residents who outlive rural residents by 3.47 years. Tier-two city residents are slightly outlived by tier-three city residents, indicating that their housing costs are undercompensated.

When the housing investment market is the only source of heterogeneity, tier-one city residents outlive rural residents by 7.82 years, indicating a large wealth effect of house price appreciation on life expectancy. The rural-urban gap is also substantial — 4.31 years, which is 44% of the rural-urban gap of 9.74 in the benchmark model. The house price appreciation rate is significantly higher in tier-one cities than in tier-three cities, resulting in a gap of more than 7 years in life expectancy. The significant role played by the heterogeneous housing investment market is hardly surprising, given the dominant importance of housing in total wealth in China and the substantial cross-regional difference in house price appreciation.

Lastly, as shown in the eighth row, when the OOP share in total medical expenditure is the only source of heterogeneity, tier-one city retirees from the public sector, the most advantaged group in terms of OOP share, outlive rural residents, the most disadvantaged group, by 7.01 years. On average, the rural-urban gap is 4.03 years. Thus, we conclude that rural residents' poor medical insurance coverage is an important determinant of their low life expectancy. Public sector retirees outlive their private sector counterparts by 2.22 years, accounting for 57.7% of the 3.84-year gap in the benchmark model. This suggests that better medical insurance coverage in the public sector is the most significant determinant of the public-private gap.

7.2 Counterfactual Analysis

Using the estimated model, we conduct three counterfactual experiments. The first experiment, motivated by the ongoing predicament in the Chinese housing markets, assesses the heterogeneous impacts of a 30% decline in house prices on on medical expenditures and life expectancy.[40] The second and third experiments assess two policies designed to increase the level of insurance coverage and to decrease inequality, namely, a more generous coverage of publicly funded medical insurance and an equalization of medical insurance coverage to the level enjoyed by retirees of the public sector of a tier one city.

7.2.1 Medical Expenditures

This subsection reports the responses in medical expenditures to each of the three experimental changes. The reactions depend on the state variables of each individual. Because individuals are distributed in state space, their responses are highly heterogeneous. We aggregate these responses based on the distribution of individuals in the state space and report the average responses of the seven groups.

We report both the contemporaneous and long-term effects. To compute the contemporaneous effects, we use the distribution of individuals prior to the experimental changes. For the long-term effects, we re-simulate the economy to obtain the new distribution of individuals in the state space, which captures the long-term effect of individuals' re-optimization. Essentially, the long-term effects reflect the new economy where all the pre-experiment retirees have died and left the economy.[41]

Table 17 reports the percentage changes in total medical expenditures and OOP medical expenditures. As the table shows, the decline in house prices has a large negative effect on medical expenditures for each group. This is a typical (negative) housing wealth effect.[42] The large effect is not surprising given the concentration of wealth in the housing market among the individuals we study. The effect is strongest among rural residents: total medical expenditures and OOP expenditures are contemporaneously decreased by 60. 6% and 52. 42%, reflecting

[40]See the Bloomberg report regarding China's housing market decline: https://fortune.com/2023/08/17/china-home-sales-worse-than-official-data-real-estate-crisis/.

[41]The new distribution depends on the distribution of health and wealth at the initial age, i.e., age sixty. We use the same initial distribution as in the benchmark model, then simulate forward to generate a new distribution for individuals at each age.

[42]We assume that the decline in house price does not affect the rental market, which is consistent with the recent rental market performance in China. According to data released by the National Bureau of Statistics, the average annual decline rate in 2024 in rents is less than 8% of the house price depreciation rate.

Table 17: Percentage Changes in Medical Expenditures

	Private sector				Public sector		
	tier 1	tier 2	tier 3	rural	tier 1	tier 2	tier 3
House price decline (30%)							
Total medical exp. *contempo.*	-33.52	-35.46	-28.51	-60.60	-22.48	-26.08	-15.16
long-term	-8.43	-12.47	-12.88	-44.64	-2.49	-10.99	-10.06
OOP medical exp. *contempo.*	-29.86	-31.30	-26.06	-52.42	-18.46	-22.37	-12.49
long-term	-7.85	-9.81	-10.29	-36.66	-2.63	-8.71	-5.39
OOP **share decline** (30%)							
Total medical exp. *contempo.*	106.67	114.44	57.73	201.87	82.79	90.32	110.67
long-term	23.96	27.35	16.56	87.61	5.48	25.26	22.37
OOP medical exp. *contempo.*	44.47	47.26	7.96	92.59	27.47	35.54	45.57
long-term	-14.24	-12.58	-20.66	21.79	-24.46	-13.60	-15.32
OOP **share equalization**							
Total medical exp. *contempo.*	104.92	143.06	136.02	665.94	0.00	55.26	95.60
long-term	29.08	30.95	35.70	264.60	0.00	16.51	19.49
OOP medical exp. *contempo.*	39.64	44.06	18.78	178.38	0.00	19.27	34.51
long-term	-15.06	-24.37	-31.03	34.25	0.00	-14.13	-15.85

Notes: This table reports the percentage changes of medical expenditures in response to each of the three experimental changes. *contempo.* represents the contemporaneos changes.

the fact that rural residents have the highest home ownership rate among the seven groups. A comparison between contemporaneous and long-term effects reveals that the negative impacts of a drop in house prices are mitigated in the long term, and the mitigation is significant. For instance, the total medical expenditures of tier-one private sector retirees drop by 33.52% contemporaneously, but decrease by 8.43% in the long term. The significantly mitigated long-term effects indicate that individuals partly rebuild their wealth through savings after they suffer the 30% loss in housing wealth.

The decline of the OOP share by 30% effectively lowers the price of medical expenditure, which tilts the allocation of resources towards health. As a result, the medical contemporaneous expenses increase drastically. The increases are most significant among the rural group, the group that faces the highest OOP share and spends the least on health prior to the experimental change.

The decline of the OOP share has quite different long-term impacts relative to the contemporaneous effects. For total medical expenditures, the drastic contemporaneous increase is significantly mitigated in the long term. For the OOP expenditure, the drastic contemporaneous increase is reversed, except for the rural group, which spends significantly less on health than the other groups prior to the experiment. The contrast between the contemporaneous and the long-term effects clearly indicates the improvement in health status, which reduces medical expenditures in the long run.

The third experiment, i.e., equalizing the OOP share to the level of tier-one city public sector retirees who have the lowest OOP share, is designed to assess further the role played by the unequal OOP share in shaping life expectancy inequality. As the bottom block of Table 17 shows, each group of individuals significantly increases their contemporaneous total medical expenditures as well as the OOP expenditures, except the tier-one city public sector group, whose OOP share remains unchanged. The effects are stronger among groups whose pre-experiment OOP share is higher, i.e., private sector retirees in tier-two and tier-three cities. The effects are the strongest among the rural residents, the group that faces the highest OOP share prior to the experimental change. The contemporaneous increase in total medical expenditure among the rural group is a staggering 665.94%, reflecting the large pre-experiment gap in the OOP share between the rural group and the tier-one city public sector retirees.

The effects of the equalization of the OOP share on total medical expenditures are also significantly mitigated in the long term. For the OOP medical expenditure, the effects of equalization are again reversed except for the rural group.

7.2.2 Life Expectancy

Table 18 reports the long-term changes in life expectancy after the experimental changes. We do not report the contemporaneous effect because it is zero by construction – changes in medical

Table 18: Changes in Life Expectancy (years)

	Private sector				Public sector		
	tier 1	tier 2	tier 3	rural	tier 1	tier 2	tier 3
House price decline (30%)	-0.81	-2.77	-1.94	-0.88	-0.09	-1.37	-3.22
Renters	0	0	0	0	0	0	0
Owners	-1.30	-3.22	-2.24	-0.97	-0.15	-1.57	-3.71
$L = 0$	-0.004	0.005	-0.118	-0.429	0.000	-0.010	0.002
OOP share decline (30%)	1.40	1.59	4.92	2.61	1.14	1.58	1.58
OOP share equalization	2.36	3.51	7.16	7.01	0.00	1.83	1.77

Notes: This table reports the long-term changes in life expectancy in response to each of the three experimental changes. The "$L = 0$" row reports the effects of the house price decline on life expectancy when the bequest motive is set to zero.

expenditures do not affect the contemporaneous mortality.

As the table indicates, the drop in house prices reduces life expectancy for each of the seven groups, and the effects are stronger among tier-two and tier-three retirees, ranging between 1.37 and 3.22 years. The impacts are the mildest among tier-one city retirees, as they are groups in better financial conditions, and their home ownership rates are the lowest. The effects on the rural group are relatively mild, a 0.88-year decline, although rural residents cut the medical expenditures the most. This is a result of the non-linearity in health transition – an individual's health stock in our model is a combination of the exogenous transition and the endogenous medical expenditures. When medical costs are near zero, the exogenous transition is the key determinant of health, and further cutting the endogenous expenditures decreases health only marginally.

The decline in house prices should have heterogeneous effects on renters and homeowners. Intuitively, for individuals who are renters before the price shock, the impact on health investment and life expectancy should be zero for those who continue to rent throughout their lifetime, and be positive for those who become owners because of the decline in house prices. As reported in the second row of table 18, the house price decline has zero long-run effects on renters in each of the seven groups. The third row reports the effects on individuals who are owners before the price shock. Not surprisingly, the effects on owners are stronger than the effects on all old-age individuals reported in the first row.[43]

As we discussed in the section 6, the bequest motive plays an important role in our model.[44]

[43] We thank an anonymous referee for suggesting that we split the old-age individuals into renters and homeowners to uncover the heterogeneous effects.

[44] As we show in table B.9 in the Appendix based on the CHARLS data, a closer relationship with children have a mildly positive association with the mortality rate, which is consistent with our theory that the bequest

Given the mildly strong bequest motive, individuals are likely to cut health investment and increase savings in response to a decline in house prices, so that the planned inheritance will not decline much. To assess the quantitative importance of this channel, we set the bequest motive to zero (i.e., setting $L = 0$) and redo the counterfactual experiment. We expect that, without bequest motives, the decline in house prices should have a smaller effect on life expectancy. Consistent with our expectation, the decline in house prices has a significantly weaker impact on life expectancy when the bequest motive is turned off, as shown in the fourth row of the table. The drop in house prices even has a slight positive effect in some regions, because the lower house price allows some low-wealth individuals to enter the housing market. It still has a relatively large effect on residents in the rural areas where the home ownership rate is the highest.

The decline in OOP share by 30% leads to nontrivial increases in life expectancy. The most significant effect, an increase of 4.92 years, is observed among tier-three city private sector retirees. Within each city tier, private sector retirees gain more than their public sector counterparts, which is because their pre-experiment OOP share is larger. The life expectancy of the rural group increases by 2.61 years.

The effects of equalization by imposing the OOP share of the tier-one city public sector retirees on the other groups are more significant. For private sector retirees, the life expectancy is increased by 2.36-7.16 years. Life expectancy of public sector retirees increases by 1.83 years in tier-two cities and 1.77 years in tier-three cities. The gain is larger among retirees in the private sector simply because their OOP share is cut more to reach the level of tier-one city public sector retirees. The life expectancy of rural residents increases by 7.01 years.

In addition, we examine how the inequality in life expectancy is changed in these experiments. As shown in Table 19, the house price decline narrows the rural-urban gap, although it increases the gap between the rural group and the tier-one city public sector retirees. The decline in house prices widens the public-private gap from 3.84 years in the benchmark model to 4.12 years. It also significantly widens the gap between tier-one and tier-three cities. In general, the drop in house prices leads to more unequal life expectancy across urban groups, because wealthier individuals, especially tier-one city public sector retirees, are able to better mitigate the impact of the house price drop on medical expenditures.

The universal decline of the OOP share by 30% narrows both the rural-urban gap and the public-private gap. It also narrows the gap between city tiers. The heterogeneous effects of a universal decline in the OOP share result from the diminishing marginal product of health investment, which is captured by the curvature parameter ψ in our health production function.

The equalized OOP share also narrows the between-group gaps in life expectancy, and the effects are significantly stronger than the universal decline in the OOP share. It nearly

motive shifts an individual's financial resources from health investment toward wealth accumulation.

Table 19: Inequality in Life Expectancy

	Private sector				Public sector			T1 pub	urban	public
	tier 1	tier 2	tier 3	rural	tier 1	tier 2	tier 3	-rural	-rural	-private
Model (benchmark)	24.06	23.59	18.30	14.16	27.22	25.78	24.46	13.07	9.74	3.84
House price decline	23.25	20.80	16.33	13.29	27.14	24.36	21.23	13.85	8.90	4.12
OOP share decline	25.47	25.17	23.21	16.77	28.36	27.36	26.05	11.59	9.17	2.64
OOP share equal.	26.43	27.10	25.46	21.17	27.22	27.61	26.23	6.06	5.51	0.69

Notes: This table reports life expectancy at sixty years of age for the seven groups in the benchmark model and from the experiments. "T1 $pub - rural$" is the difference in life expectancy between public sector retirees in tier-one cities and rural residents."$rural - urban$" shows the difference in life expectancy between the averages of urban retirees and the rural residents, and the "$public - private$" shows the difference between the average of the public sector retirees and the average of the private sector retirees.

eliminates the public-private gap and brings the gap between city tiers below one year. It also narrows the rural-urban gap from 9.74 years to 5.51 years.[45] The remaining gap indicates rural residents' disadvantageous position in income and wealth takes a toll on their life expectancy.

The last two experiments have important implications for policies designed to reduce inequality in life expectancy. A universal decline in the *OOP* share can reduce the inequality without receiving push-backs from the public sector retirees or employees who are enjoying more generous medical insurance coverage. However, inequality remains large under this type of policy. An equalized *OOP* share can almost eliminate the inequality in life expectancy among urban residents, and it is also an effective policy to reduce the rural-urban gap. If the policy goal is to also eliminate the rural-urban gap, then rural residents need to be further subsidized.

8 Extensions and Robustness

We have studied heterogeneous life expectancy among old-age individuals in China in the context of the benchmark model. In this section, we consider several extensions of the model to gain further insight.

8.1 Housing in Health Production

Our benchmark model assumes that health production has only one input, i.e., the monetary input. In reality, the housing condition is closely related to health condition and life expectancy.

[45] It is noteworthy that the life expectancy is 21.17 years among rural residents after imposing the *OOP* share of tier-one city public sector retirees on rural residents, which is identical to the life expectancy of tier-one city public sector retirees in the case of *OOP* share heterogeneity reported in Table 16.

On the one hand, better housing improves health conditions and reduces mortality. On the other hand, individuals in poor health may require additional housing, such as an extra room for a nursing care professional or a close relative. As we show in table B.4 in the appendix, housing size is positively associated with health even after we control for wealth and income.

To account for the direct effects of housing on health, we extend the benchmark model by including housing in the health production function. Specifically, we modify equation (15) into

$$H_t' = H_t \times I_t^{\psi} \times S_t^{\omega}, \tag{24}$$

where S_t is the size of the housing at age t. The elasticity of health with respect to housing, ω, captures the direct effect of housing on health.

To quantitatively assess the direct effect of housing on health outcome and life expectancy, we re-estimate the structural parameters in the extended model, including ω, based on the same set of moments shown in Table 10. Table 20 reports the estimated parameters and their standard errors. To facilitate the comparison of the extended model with the benchmark model, the table also reports parameter values from the benchmark model.

Table 20: Parameters of the Extended Model

	β	γ	θ	L	α	η	ψ	ϕ	λ	ω
Benchmark	0.925	3.162	0.813	1.202	0.468	0.475	0.640	0.089	0.053	n.a
Extension	0.912	3.165	0.788	1.118	0.491	0.433	0.675	0.115	0.030	0.089
Std Err	(0.003)	(0.105)	(0.035)	(0.035)	(0.018)	(0.028)	(0.027)	(0.010)	(0.001)	(0.014)

Notes: The estimated parameters in the extended model with housing in the health production function. ω is the elasticity of health w.r.t. housing. The first row reports parameter estimates from the benchmark model.

As the table shows, the estimated ω is 0.089. Thus, holding the monetary input constant, health stock increases by 0.089% if housing consumption increases by 1%. It is noteworthy that η, the substitutability between health and consumption, is smaller in the extended model than the benchmark model. Intuitively, the inclusion of housing in the health production (ω) favors high-income individuals who consume more housing, therefore it tends to increase the inequality in mortality rate. Thus, to match the mortality rate moments, a smaller η is needed to counter the effect of ω. The remaining parameters are quite similar to those estimated from the benchmark model.

We also compare the ratio of housing to nonhousing consumption in the benchmark model and the extended model, and find that the ratio is 3%-8% higher in the extended model. This result is intuitive – with housing in health production, individuals optimally choose to consume more housing.

Table 21 reports the life expectancy from both the benchmark model and the extended model. Overall, life expectancy is very similar between the benchmark model and the extended model. More importantly, the between-group inequality is also similar.

Table 21: Life Expectancy: Benchmark VS Extension

	Private sector				Public sector		
	Tier 1	Tier 2	Tier 3	Rural	Tier 1	Tier 2	Tier 3
Benchmark	24.06	23.59	18.30	14.16	27.22	25.78	24.46
Extension	24.39	22.68	20.00	14.52	28.36	26.62	24.69

Notes: Life expectancy from the benchmark model and the extended model with housing as an input in the health production function.

We draw two conclusions from the analysis of the extended model. First, including housing in the health production changes the parameter estimates slightly and leads to a higher ratio of housing to nonhousing consumption. In particular, the estimated substitutability between consumption and health (η) becomes smaller. Second, our results from the benchmark model regarding life expectancy inequality are robust to the inclusion of housing in health production.

8.2 Locational Choice and City Amenities

One of the fundamental insights in urban economics is the spatial equilibrium in which larger cities offer higher income to compensate for the higher housing cost. The spatial equilibrium is achieved through inter-city migrations. We do not include the choice of inter-city migration for retirees in our benchmark model, because most retirees in China continue to reside in the areas where they worked. Nevertheless, given that housing is cheaper in smaller cities and the rural area, and that post-retirement income and medical insurance coverage are not affected by migration, it seems puzzling that we do not observe large-scale downward migrations, i.e., migration of retirees from larger cities to smaller cities or the rural area.[46] The plausible explanation is that larger cities offer better amenities that outweigh the benefits of cheaper housing in smaller cities and the rural area. The amenities include access to better medical services, recreational facilities, parks and other public goods.

To evaluate the amenities provided by different tiers of cities, we extend the baseline model to: (i) include amenities specific to city tiers, using A_1, A_2, A_3 to denote the amenity in tier 1, tier 2 and tier 3 cities respectively while normalizing the rural amenity to one; and (ii) allow for a one-time location choice for individuals throughout their old-age lives. For instance, individuals in tier-one cities can choose to migrate permanently to the rural area where they pay a significantly lower housing cost while keeping their higher income, lower OOP costs, and better housing investment return in tier-one cities.

Amenities are modeled as utility multipliers. Specifically, for residents in tier i cities, the

[46]As shown in figure B.4 in the appendix, in each city, less than 1% of old age residents are in-migrants from outside the city.

utility and the bequest value are defined by

$$u_i = A_i \left[(1-\alpha) \left(\frac{\xi}{q(1-\xi)} \right)^{\xi(1-1/\eta)} (1+\phi)^{\xi(1-1/\eta)} C^{1-1/\eta} + \alpha H^{1-1/\eta} \right]^{\frac{1}{1-1/\eta}}, \quad (25)$$

$$V_{i,b}(F) = (A_i L)^{\frac{1}{1-1/\theta}} \times F. \quad (26)$$

It is noteworthy that u_i in the above equation is the same as the benchmark utility defined in equation (16) if $A_i = 1$.

The specification of equation25 implies that amenities are neutral on consumption and health, i.e., the better amenity increases the utility level without affecting the allocation of financial resources between health, consumption, and bequest. As a result, amenities affect the inequality in life expectancy only through cross-city migrations of individuals. An alternative specification is to assume that $A_i = 1$ is multiplicative to health, so that the better amenity induces more health investment at the cost of less consumption. We choose not to follow this alternative specification for two reasons. First of all, there is no empirical or theoretical support for the alternative specification as far as we know. Secondly, the benchmark model already include multiple channels affecting the allocation between health and consumption.

Let i and j denote the origin and destination of migration respectively where i and j are elements in the set of 4 regions $\{tier_1, tier_2, tier_3, rural\}$. The value of a resident in region i migrating to region j at age t is $V_t^{i,j}(\Omega)$. In the special case of $i = j$, $V_t^{i,j}(\Omega)$ is the same as $V_t(\Omega)$ defined in equation (17), except that u is replaced by u_i in the dynamic programming problems that describe $V_t(\Omega)$,

To solve for $V_t^{i,j}(\Omega)$ for cases where $j \neq i$, we use all the exogenous processes in region i, except that we use housing costs in region j and the utility function u_j, which includes the amenity in region j. Individuals make migration decisions by comparing $V_t^{i,i}(\Omega)$ and $V_t^{i,j}(\Omega)$. If $V_t^{i,j}(\Omega) > V_t^{i,i}(\Omega)$, then the individual will be better off by migrating from region i to region j in the state of Ω.

To identify amenities A_1, A_2, A_3 that prevent downward migration, we begin by setting A_1, A_2, A_3 to zero, which causes all the city residents to migrate to the rural area where housing is the cheapest. Next, we increase the amenities gradually until the downward migrations become zero, and the resulting A_1, A_2, A_3, reported in table 22, are amenities in larger cities that exactly counterbalance the benefits of cheaper housing in smaller cities or the rural area.

As table 22 shows, amenities in tier one, tier two, and tier three cities increase the utility of their residents by a factor of 1.828, 1.608, and 1.520, respectively. Because we normalize the amenity in rural areas to 1, these city amenities can be interpreted as multipliers relative to the rural area. The table indicates that cities in China provide remarkably better amenities than rural areas, and that the amenities in tier one cities are significantly better than those in tier two and tier three cities.

Table 22: Amenity Values

Symbol	Definition	Value
A_1	amenity in tier 1 cities	1.83
A_2	amenity in tier 2 cities	1.61
A_3	amenity in tier 3 cities	1.52

Notes: Amenity values of cities. Rural amenity value is normalized to 1.

As we discussed earlier, these amenities affect inequality in life expectancy only if they induces cross-city migration. Given the the near-zero migration in the data and the zero migration from the model, the estimated amenities do not change our quantative results from the benchmark model.

9 Conclusion

We have presented data on heterogeneous mortality rates among retirees from different sectors in different tiers of cities, as well as rural residents. Because of the heterogeneous mortality rates, life expectancy is higher among public sector retirees, and it is higher in tier-one cities and lowest among rural residents. These salient data features are endogenously generated in our dynamic model, which incorporates endogenous health investment and housing investment, as well as cross-sectional heterogeneity in terms of health and wealth at retirement, post-retirement income, housing costs, housing investment markets, and out-of-pocket medical expenditures.

Based on the structurally estimated model, we show that the most important contributor to the overall inequality in life expectancy is the heterogeneity in post-retirement income. Heterogeneity in the out-of-pocket medical expenditures explains a large fraction of the inequality between the private sector and the public sector. Heterogeneity in housing investment return is an important driver of the rural-urban gap in life expectancy, as well as the inequality in life expectancy between different tiers of cities.

Our results indicate that larger city residents tend to invest more in health due to their higher income and larger wealth accumulation on the one hand. Still, they tend to invest less in health because of the higher housing costs, on the other hand. The former effect tends to be stronger in China, as retirees in larger cities live longer in the data as well as in our model. We also show that larger cities provide significantly better amenities than smaller cities and rural areas.

Counterfactual experiments show that a drop in house prices harms life expectancy, and the effect is stronger among retirees in tier-two and tier-three cities. The drop in house prices tends to increase the inequality in life expectancy among urban retirees. A universal decline in the out-of-pocket share in total medical expenditures increases total medical spending significantly, but it tends to lower the out-of-pocket costs in the long term. The decline in the out-of-pocket share increases life expectancy significantly – a 30% decline increases life expectancy by 4.92 years among private sector retirees in tier-three cities. It also reduces the inequality in life expectancy because private sector retirees and rural residents gain more from the smaller out-of-pocket share. Finally, the equalization of medical insurance coverage between groups has a large effect on life expectancy, both in terms of level and inequality. It nearly eliminates the inequality among urban retirees and narrows the rural-urban gap in life expectancy by nearly 50%.

Our results are based on a model in which the publicly funded healthcare is exogenous. It should be interesting to extend our current model such that the publicly funded healthcare is endogenous, funded by the tax revenue. Such a framework would be suitable for a quantitative study of the welfare effects of the publicly funded healthcare system. Another interesting extension of our study is to include pre-retirement health decisions, including the choice of time investment in health. The allocation of time between health investment and work could be particularly important in light of the rising incidents of work-related diseases and deaths.[47]

The inequality in life expectancy studied in our paper has important implications for the pricing of insurance products such as life insurance and annuities. Since the pricing of these products is contingent on life expectancy, a natural question to ask is whether pricing should also be contingent on city tiers and sectors of employment in China. We leave the explorations to future studies.

While we have focused on cross-region and between-sector inequality in life expectancy, it is also noteworthy that inequality among individuals with different skill levels and educational attainments is important. As we discussed, because of the selection effect of migration, retirees in larger cities tend to be more educated, which partly explains the higher income in larger cities that we use as an input in our dynamic model. In other words, inequality among different skill groups is partly reflected in our cross-region inequality. Nevertheless, it is interesting to conduct an independent study that focuses on the association between skill levels and life expectancy inequality.

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[47]See the report of the World Health Organization: https://www.who.int/news/item/17-05-2021-long-working-hours-increasing-deaths-from-heart-disease-and-stroke-who-ilo.

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A Background: Evolution of Healthcare System

We summarize the evolution of the healthcare system in China in Figure A.1. As the figure illustrates, China's healthcare system consisted of three types of schemes in the pre-reform era. The first type was the Free Medical Service available to government employees and retirees, a non-contributory scheme that covers almost 100 percent of medical costs. The second type was the Labour Medical Insurance Scheme for employees and retirees of the state-owned and collectively owned enterprises. Because it was mostly funded by the enterprises with limited subsidy from regional governments, the coverage of the Labour Medical Insurance Scheme differed by region, province, and enterprise, and it was much less generous compared with the Free Medical Service. The third type was the Rural Co-op Medical Scheme, which provided basic coverage to rural residents.[48] There existed a small fraction of self-employed or unemployed urban residents who received no medical insurance coverage. Overall, this healthcare system in the pre-reform era featured large inequality among the three types.

While this basic structure remained largely unchanged until the end of the 1990s, inequality in healthcare coverage increased significantly during the same period. This is because a large fraction of urban residents lost their Labour Medical Insurance due to the privatization of small state-owned and collectively-owned enterprises, and because the majority of rural residents dropped out of the Rural Co-op Medical Scheme.[49] The Urban Private sector grew tremendously during this period of time, but employees in the private firms and the self-employed were still completely excluded from the publicly funded healthcare system.

As shown in Figure A.1, in 1998, the Chinese government started to merge the Free Medical Service and the Labour Medical Insurance Scheme into one single insurance plan for all the employed urban residents, namely, the Urban Employee Basic Medical Insurance (UEBMI).[50] This is a contributory scheme that typically requires 6% contributions from employers and 2% contributions from employees, while the contribution percentages are subject to the discretion of regional governments. The UEBMI funds are mostly administered at the prefecture level, while the goal set by the central government is to administer the funds at the provincial level.[51] The reform is still on-going as government employees still receive various subsidies that are not

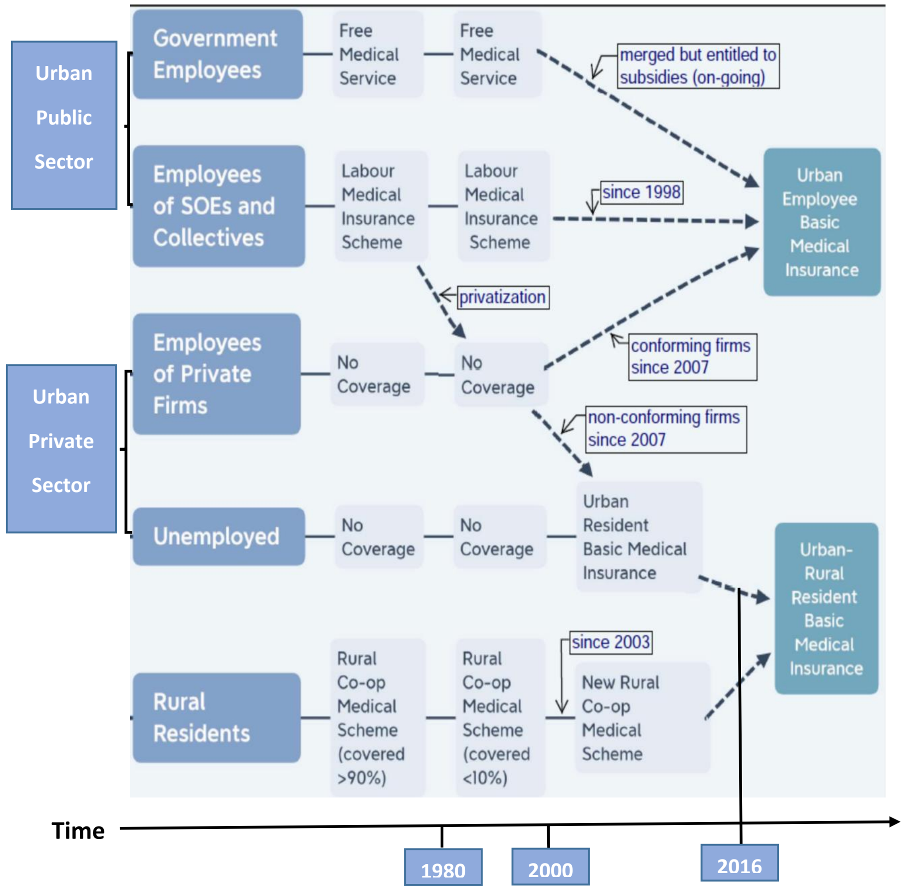
[48] The Rural Co-op Medical scheme consisted of three tiers of medical facilities: village health stations, township health centers, and county hospitals. A village health station was funded by the village administration and by premiums paid by villagers. Township and county hospitals were funded by subsidies from the corresponding regional governments and revenues generated by the services they provided. See Liu et al. (1995).

[49] Transition of the healthcare system in rural China up to 1990s is well described in Liu et al. (1995), and the transition in urban China in the same period of time is discussed in Grogan (1995).

[50] A decisive document is *Decision of the State Council on Establishing a Basic Medical Insurance System for Urban Employees* issued by the State Council in 1998 (https://www.gov.cn/banshi/2005-08/04/content_20256.htm).

[51] https://www.gov.cn/zhengce/content/2021-06/17/content_5618799.htm.

Figure A.1: Evolution Healthcare System in China



Note: The figure illustrates the evolution of the healthcare system in China.

accessible to ordinary UEBMI enrollees.[52]

In principle, private sector employees should also enroll in the UEBMI. However, in reality, many small private enterprises choose not to conform to the governmental policy.[53] As a result these private sector employees were uninsured until 2007, when the State Council commenced the Urban Residence Basic Medical Insurance (URBMI).[54] The URBMI provides coverage to unemployed urban residents as well as minors and the elderly. It is jointly funded by the central

[52]As stated explicitly in the document jointly issued to provincial governments in 2000 by the Ministry of Labour and Social Security and the Ministry of Finance, government civil servants should receive healthcare subsidies in addition to the coverage offered by UEBMI (https://www.gov.cn/gongbao/content/2000/content_60249.htm).

[53]Private sector employers tended to use loopholes or outright evasion to avoid making contributions for their employees until the recent few years.

[54]The commencement of the URBMI was marked by the issuance of *Guiding Opinions on Carrying out the Pilot Program of Basic Medical Insurance System for Urban Residents* (https://www.gov.cn/gongbao/content/2007/content_719882.htm).

government through earmarked transfers, the regional government, and the premium payments of enrollees. A large fraction of private sector employees not covered by the UEBMI choose to enroll in the URBMI.

Another major achievement in healthcare reform is the establishment of the New Rural Co-op Medical Scheme (NRCMS) which provides coverage for rural residents, jointly funded by the central government, regional governments, and the premium payments of enrollees. The NRCMS started in 2003.[55] Within 10 years, the NRCMS covered 99% of rural residents in China.[56]

Since 2016, the central government has been integrate URBMI and NRCMS into Urban and Rural Resident Basic Medical Insurance (URRBMI). As Figure A.1 indicates, after integration, the current healthcare system in China includes two major types: the URRBMI and the UEBMI, applicable to both non-retirees and retirees.

[55] The inception of the NRCMS is the issuance of *Opinions of the Ministry of Health, the Ministry of Finance and the Ministry of Agriculture on the Establishment of a New Rural Cooperative Medical System* (https://www.gov.cn/zwgk/2005-08/12/content_21850.htm).

[56] https://www.gov.cn/xinwen/2014-05/26/content_2686847.htm

B Robustness

B.1 City Tiers

Table B.1 shows lists of tier-one, tier-two, and tier-three cities.

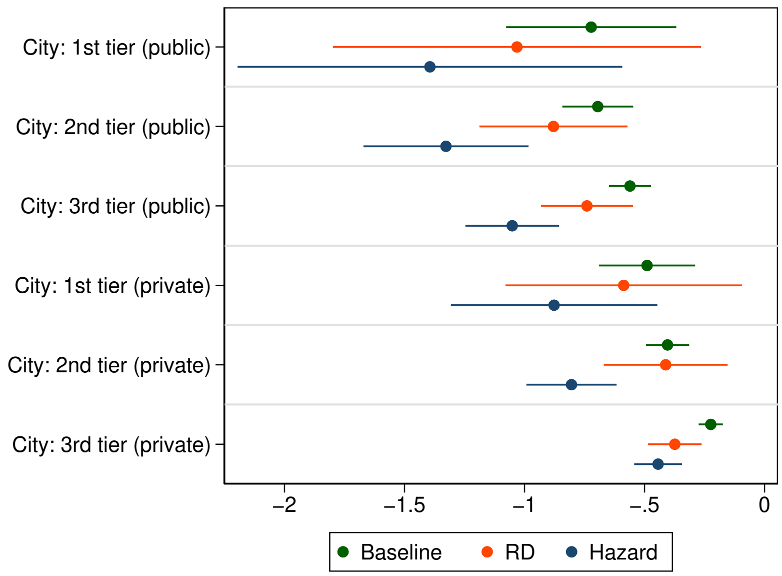
Table B.1: City List

province	city	tier	province	city	tier	province	city	tier
Shanghai	Shanghai	1	Yunnan	Lincang	3	Jiangsu	Taizhou	3
Beijing	Beijing	1	Yunnan	Lijiang	3	Jiangsu	Yancheng	3
Guangdong	Shenzhen	1	Yunnan	Baoshan	3	Jiangsu	Lianyungang	3
Guangdong	Guangzhou	1	Yunnan	Zhaotong	3	Jiangxi	Shangrao	3
Tianjin	Tianjin	2	Neimenggu	Xingan	3	Jiangxi	Jiujiang	3
Yunnan	Kunming	2	Neimenggu	Hulunbeidong	3	Jiangxi	Jian	3
Sichuan	Chengdong	2	Neimenggu	Huhehaote	3	Jiangxi	Jingdezhen	3
Shandong	Jinan	2	Neimenggu	Chifeng	3	Jiangxi	Ganzhou	3
Shandong	Qingdao	2	Neimenggu	Xilinguole	3	Hebei	Cangzhou	3
Guangdong	Foshan	2	Jilin	Jilin	3	Henan	Xinyang	3
Guangxi	Nanning	2	Jilin	Siping	3	Henan	Zhoukou	3
Jiangsu	Suzhou	2	Sichuan	Liangshan	3	Henan	Luoyang	3
Jiangxi	Nanchang	2	Sichuan	Yibin	3	Henan	Puyang	3
Hebei	Shijiazhuang	2	Sichuan	Meishan	3	Henan	Jiaozuo	3
Henan	Zhengzhou	2	Sichuan	Mianyang	3	Zhejiang	Taizhou	3
Zhejiang	Ningbo	2	Sichuan	Ziyang	3	Zhejiang	Jiaxing	3
Zhejiang	Hangzhou	2	Anhui	Bozhou	3	Zhejiang	Huzhou	3
Hunan	Changsha	2	Anhui	Liuan	3	Hubei	Dongshi	3
Fujian	Fuzhou	2	Anhui	Suzhou	3	Hubei	Jingmen	3
Liaoning	Dalian	2	Anhui	Chaohu	3	Hubei	Xiangfan	3
Zhongqing	Zhongqing	2	Anhui	Huainan	3	Hubei	Huanggang	3
Heilongjiang	Hadongbin	2	Shandong	Linyi	3	Hunan	Loudi	3
Heilongjiang	Hadongbin	2	Shandong	Weihai	3	Hunan	Yueyang	3
			Shandong	Dezhou	3	Hunan	Changde	3
			Shandong	Zaozhuang	3	Hunan	Yiyang	3
			Shandong	Weifang	3	Hunan	Shaoyang	3
			Shandong	Liaocheng	3	Gansu	Lanzhou	3
			Shanxi	Linfen	3	Gansu	Dingxi	3
			Shanxi	Xinzhou	3	Gansu	Zhangye	3
			Shanxi	Yuncheng	3	Fujian	Zhangzhou	3
			Guangdong	Jiangmen	3	Guizhou	Qiandongnan	3
			Guangdong	Qingyuan	3	Guizhou	Qiannan	3
			Guangdong	Chaozhou	3	Liaoning	Benxi	3
			Guangdong	Maoming	3	Liaoning	Jinzhou	3
			Guangxi	Guilin	3	Liaoning	Anshan	3
			Guangxi	Yulin	3	Shanxi	Baoji	3
			Xinjiang	Akesu	3	Shanxi	Yulin	3
			Jiangsu	Suqian	3	Shanxi	Hanzhong	3
			Jiangsu	Xuzhou	3	Heilongjiang	Jiamusi	3
			Jiangsu	Yangzhou	3	Heilongjiang	Jixi	3
						Heilongjiang	Qiqihadong	3

B.2 Additional Controls

To visualize the estimate difference across models, we plot the three sets of results in Figure B.1. The estimation results of the RD design and hazard method are quite similar to our baseline results, and even more statistically and economically significant, which justifies the robustness of our baseline regression.

Figure B.1: Mortality Rate Inequality



We have checked robustness by including more controls for individual characteristics in the baseline regressions. Specifically, we have added female, higher education, and non-agricultural hukou dummy variables for each individual. The results are reported in column (1) of Table B.2 and panel (1) of Figure B.2. Furthermore, the RD results are reported in column (1) of Table B.3 and panel (1) of Figure B.3. All individual characteristics significantly affect the death probability intuitively. The coefficients of group-specific retiree dummies are more negative, implying even larger cross-group life expectancy inequality when controlling for early-life economic conditions. RD regressions with additional controls also suggest our baseline results are quite robust. The coefficients of group-specific retiree dummies are quite close to our baseline results, suggesting robustness.

In rural China, informal retirement relies on family support and longer (agricultural) work lives, which complicates rural-urban comparisons (Giles et al., 2012). We have added robustness checks of mortality rate heterogeneity by including labor supply and informal insurance factors in the baseline and RD regressions. First, we use the number of months of agricultural work in the year to measure the ongoing labor supply for each rural individual. Second, the money transfer from their child(ren) in the year has been added to control for the potential family support effect for rural elderly. The results are reported in column (2) and panel (2). Rural elderly typically engage in longer periods of agricultural work, which is associated with additional food or meat, reducing the likelihood of mortality. Family support, such as money transfers from children, does not significantly reduce mortality among the rural elderly, possibly due to modernization and migration of younger family members. Importantly, the coefficients of urban retiree dummies are more negative and imply even larger rural-urban life expectancy inequality, controlling for labor supply and informal insurance in rural areas. RD regressions with additional controls also suggest our baseline results are quite robust.

Early-life health and environmental factors influence health outcomes, with these relationships reflecting characteristics and circumstances from before retirement. We have added robustness checks of mortality rate heterogeneity by including pre-retirement income in our related regressions. We use the log value of the monthly income immediately preceding retirement to measure the pre-retirement economic conditions for each rural individual. The results are reported in column (3) and panel (3). Pre-retirement income significantly reduces the post-retirement death probability with a persistent effect. Higher income before retirement often leads to healthier lifestyles and more effective management of health conditions, thereby sustaining the positive impact on longevity. The coefficients of group-specific retiree dummies are more negative, implying even larger cross-group life expectancy inequality when controlling for early-life economic conditions.

Non-investment determinants, such as genetics and local sanitation, play a significant role in influencing the mortality risk of the elderly. Genetics can predispose individuals to certain health conditions or resilience against diseases, directly impacting their longevity. These factors, often beyond personal control, underscore the importance of external influences on aging and survival. We use a dummy variable of whether the retiree's father (or mother) is still alive to measure the paternal (maternal) longevity genes. The results are reported in column (4) and panel (4). It turns out to be insignificant, either for paternal or maternal longevity genes. Genetic factors may be less influential for individuals under 80 (the majority of our sample), but become significant for those over 90 years old. In younger elderly populations, lifestyle, healthcare, and environmental factors may play a larger role in mortality, while genetic predispositions for longevity may only manifest their effects in the oldest age groups. The coefficients of group-specific retiree dummies are quite close to our baseline results, suggesting robustness.

We have also checked the housing investment effect in the baseline regression. We use dummy variables of whether the house has bath facility, elevator, flushable toilet, or natural gas to measure the housing improvement. The results are reported in column (6) and panel (6). Only the bath facility significantly reduces the elderly's death probability. Because bath facility improves hygiene, reduce the risk of infections, and enhance overall health and well-being. In contrast, elevators, flushable toilets, or natural gas may not have as direct an impact on health outcomes or mortality. These amenities, while contributing to comfort and convenience, may not adequately address the primary health risks faced by retirees, such as infections or hygiene-related issues, which proper bathing facilities can more effectively mitigate. The coefficients of group-specific retiree dummies are quite close to our baseline results, implying robustness.

Figure B.2: Robustness with Additional Controls

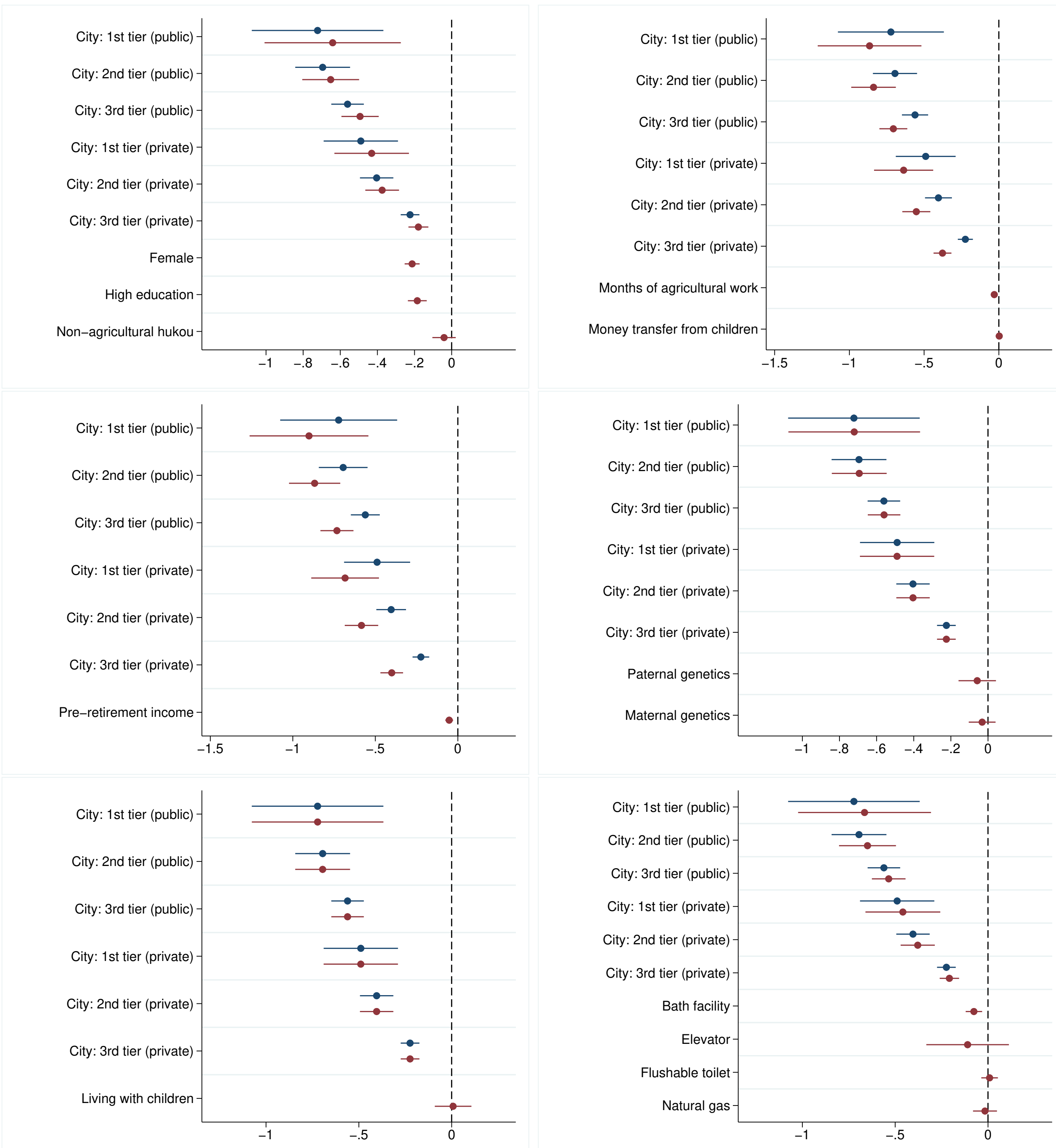


Table B.2: Robustness with Additional Controls

	(1) Death	(2) Death	(3) Death	(4) Death	(5) Death	(6) Death
Age	0.032	0.050**	0.237***	0.074***	0.082***	0.072***
	(0.025)	(0.025)	(0.034)	(0.024)	(0.024)	(0.024)
Age^2	0.143***	0.126***	0.070***	0.128***	0.127***	0.129***
	(0.012)	(0.013)	(0.016)	(0.012)	(0.012)	(0.012)
City: 1st tier (public)	-0.641***	-0.865***	-0.902***	-0.720***	-0.722***	-0.665***
	(0.187)	(0.177)	(0.184)	(0.181)	(0.181)	(0.183)
City: 2nd tier (public)	-0.652***	-0.838***	-0.868***	-0.693***	-0.695***	-0.649***
	(0.078)	(0.076)	(0.079)	(0.075)	(0.075)	(0.078)
City: 3rd tier (public)	-0.493***	-0.706***	-0.733***	-0.560***	-0.561***	-0.535***
	(0.051)	(0.048)	(0.051)	(0.045)	(0.045)	(0.046)
City: 1st tier (private)	-0.431***	-0.637***	-0.683***	-0.490***	-0.489***	-0.459***
	(0.102)	(0.101)	(0.105)	(0.102)	(0.102)	(0.103)
City: 2nd tier (private)	-0.374***	-0.552***	-0.584***	-0.404***	-0.404***	-0.379***
	(0.046)	(0.048)	(0.052)	(0.046)	(0.046)	(0.047)
City: 3rd tier (private)	-0.179***	-0.377***	-0.401***	-0.224***	-0.224***	-0.208***
	(0.027)	(0.031)	(0.035)	(0.026)	(0.026)	(0.027)
Female	-0.213***					
	(0.021)					
High education	-0.185***					
	(0.026)					
Non-agricultural hukou	-0.041					
	(0.032)					
Months of agricultural work		-0.031***				
		(0.003)				
Money transfer from children		0.003				
		(0.004)				
Pre-retirement income			-0.052***			
			(0.012)			
Paternal genetics				-0.058		
				(0.051)		
Maternal genetics				-0.031		
				(0.037)		
Living with children					0.008	
					(0.050)	
Bath facility						-0.076***
						(0.023)
Elevator						-0.110
						(0.113)
Flushable toilet						0.009
						(0.023)
Natural gas						-0.016
						(0.033)
Observations	45643	37535	24234	45643	45643	45643
Year fixed effect	✓	✓	✓	✓	✓	✓

Notes: This table shows how the mortality rate depends on the city tier, the sector of pre-retirement employment, and additional control variables. The unit of observation is an individual-year. All regressions include year fixed effects. ***, **, or * indicates that the estimate coefficient is significant at the 1%, 5%, or 10% level, respectively.

Figure B.3: Robustness with Additional Controls: RD

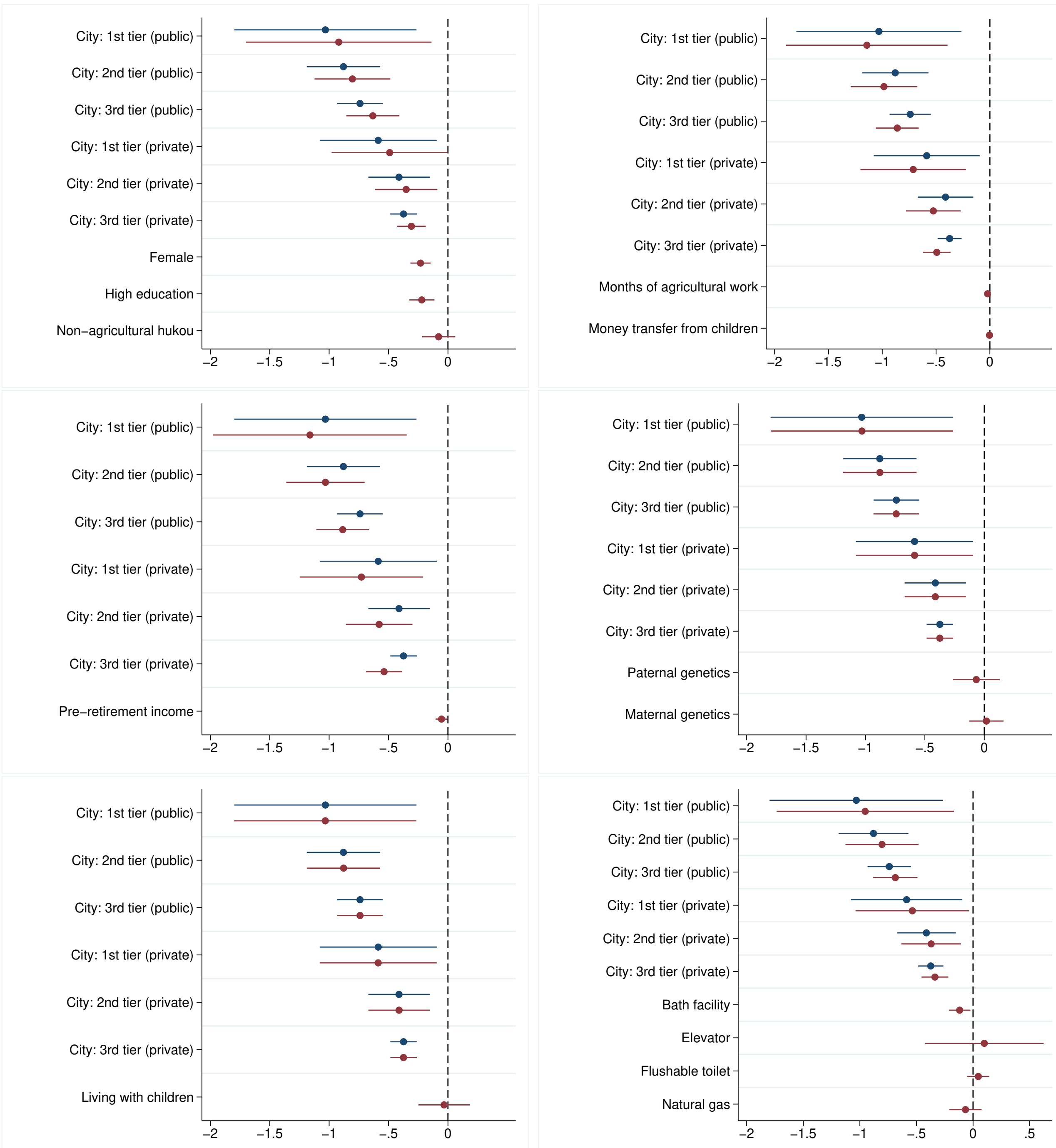


Table B.3: Robustness with Additional Controls: RD

	(1) Death	(2) Death	(3) Death	(4) Death	(5) Death	(6) Death
Size > 90	0.314***	0.272***	0.514***	0.316***	0.315***	0.314***
	(0.098)	(0.100)	(0.155)	(0.097)	(0.097)	(0.097)
Size − 90	0.002	0.000	-0.002	0.002	0.002	0.002
	(0.006)	(0.006)	(0.010)	(0.006)	(0.006)	(0.006)
(Size > 90) × (Size − 90)	-0.006	-0.004	-0.005	-0.006	-0.006	-0.006
	(0.008)	(0.008)	(0.012)	(0.008)	(0.008)	(0.008)
Age	0.015	0.030	0.238***	0.064	0.067	0.058
	(0.053)	(0.054)	(0.079)	(0.052)	(0.051)	(0.051)
Age^2	0.144***	0.125***	0.085**	0.129***	0.128***	0.131***
	(0.026)	(0.027)	(0.037)	(0.025)	(0.025)	(0.025)
City: 1st tier (public)	-0.919**	-1.143***	-1.161***	-1.030***	-1.032***	-0.952**
	(0.398)	(0.383)	(0.415)	(0.392)	(0.391)	(0.400)
City: 2nd tier (public)	-0.804***	-0.984***	-1.031***	-0.879***	-0.878***	-0.804***
	(0.163)	(0.158)	(0.168)	(0.157)	(0.157)	(0.165)
City: 3rd tier (public)	-0.632***	-0.860***	-0.886***	-0.741***	-0.740***	-0.687***
	(0.114)	(0.102)	(0.113)	(0.098)	(0.098)	(0.100)
City: 1st tier (private)	-0.490**	-0.712***	-0.728***	-0.587**	-0.587**	-0.536**
	(0.250)	(0.250)	(0.265)	(0.251)	(0.251)	(0.256)
City: 2nd tier (private)	-0.351***	-0.525***	-0.579***	-0.412***	-0.411***	-0.370***
	(0.134)	(0.129)	(0.143)	(0.132)	(0.132)	(0.135)
City: 3rd tier (private)	-0.307***	-0.494***	-0.538***	-0.374***	-0.374***	-0.337***
	(0.062)	(0.065)	(0.077)	(0.057)	(0.057)	(0.060)
Female	-0.231***					
	(0.043)					
High education	-0.220***					
	(0.054)					
Non-agricultural hukou	-0.079					
	(0.071)					
Months of agricultural work		-0.021***				
		(0.006)				
Money transfer from children		-0.003				
		(0.007)				
Pre-retirement income			-0.054**			
			(0.025)			
Paternal genetics				-0.067		
				(0.100)		
Maternal genetics				0.018		
				(0.073)		
Living with children					-0.033	
					(0.110)	
Bath facility						-0.118**
						(0.048)
Elevator						0.100
						(0.268)
Flushable toilet						0.047
						(0.050)
Natural gas						-0.067
						(0.073)
Observations	11782	9611	6105	11782	11782	11782
Year fixed effect	✓	✓	✓	✓	✓	✓

Notes: This table shows how the mortality rate depends on the city tier, the sector of pre-retirement employment, and additional control variables using the RD approach. ***, **, or * indicates that the estimate coefficient is significant at the 1%, 5%, or 10% level, respectively.

B.3 Health Transition & Housing Size

Table B.4 shows the relationship between health transition and housing size. The larger housing size is associated with better health. The table also reports the persistent effect of pre-retirement health on current health.

Table B.4: Health Transition

	(1) Health status		(2) Health status		(3) Health status	
Age	-0.045***	(0.016)	-0.045***	(0.016)	-0.129**	(0.059)
Age^2	-0.065***	(0.009)	-0.061***	(0.009)	0.080	(0.064)
Health: 1 Very poor	-1.032***	(0.026)	-1.021***	(0.027)	-0.793***	(0.049)
Health: 2 Poor	-0.656***	(0.015)	-0.648***	(0.015)	-0.542***	(0.029)
Health: 4 Good	0.505***	(0.017)	0.501***	(0.017)	0.362***	(0.033)
Health: 5 Very good	0.879***	(0.021)	0.880***	(0.021)	0.699***	(0.038)
Health: 1 Very poor × Age	0.033	(0.028)	0.027	(0.029)	-0.027	(0.088)
Health: 2 Poor × Age	0.003	(0.016)	0.002	(0.016)	-0.119**	(0.051)
Health: 4 Good × Age	-0.075***	(0.019)	-0.069***	(0.019)	-0.080	(0.056)
Health: 5 Very good × Age	-0.072***	(0.024)	-0.072***	(0.025)	-0.058	(0.066)
ln Income			0.011***	(0.002)		
ln Wealth			0.008***	(0.001)		
House size			0.006*	(0.003)		
Initial health: 1 Very poor					-0.403***	(0.046)
Initial health: 2 Poor					-0.266***	(0.024)
Initial health: 4 Good					0.207***	(0.025)
Initial health: 5 Very good					0.314***	(0.036)
cut1	-1.932***	(0.015)	-1.764***	(0.025)	-2.014***	(0.026)
cut2	-1.557***	(0.014)	-1.389***	(0.024)	-1.605***	(0.024)
cut3	-0.754***	(0.012)	-0.585***	(0.023)	-0.787***	(0.021)
cut4	0.727***	(0.012)	0.899***	(0.024)	0.763***	(0.021)
cut5	1.312***	(0.014)	1.483***	(0.024)	1.342***	(0.023)
Observations	39893		39466		22201	
Year fixed effect	✓		✓		✓	

Notes: This table reports the ordered probit regression results to show how the health transition depends on lagged health, initial health, age, age square, income, wealth, and house size. The unit of observation is an individual-year. The dependent variable is health status. All regressions include year fixed effects. All variables are defined in Table 3. ***, **, or * indicates that the estimate coefficient is significant at the 1%, 5%, or 10% level, respectively. Robust standard errors are in parentheses and given below the coefficient estimates.

B.4 One House or None: Cross-City Housing Investment

There is concern that this paper does not consider the potential investments made by retirees from smaller cities in larger-city housing. If retirees in smaller cities can invest in housing in larger cities, they should be able to benefit from excess returns. However, we could not directly observe the cross-city housing investment. To address this concern, compared to our main specification in Table 4, we focus only on households that have only one house or none. In other words, it is almost impossible for households with one house or none to make the investment in housing between cities. Table B.5 reports the results of our main specification with the subsample of households with only one house or none, which is quite consistent with the main results in Table 4.

Table B.5: Mortality Rate (Subsample): One House or None

	(1) Baseline		(2) RD	
Size > 90			0.3549***	(0.0993)
Size − 90			-0.0011	(0.0061)
(Size > 90) × (Size − 90)			-0.0032	(0.0077)
Age	0.0896***	(0.0242)	0.0614	(0.0523)
Age^2	0.1241***	(0.0117)	0.1308***	(0.0257)
City: 1st tier (public)	-0.6830***	(0.1840)	-0.9902**	(0.4001)
City: 2nd tier (public)	-0.6781***	(0.0770)	-0.8464***	(0.1587)
City: 3rd tier (public)	-0.5436***	(0.0454)	-0.7368***	(0.1009)
City: 1st tier (private)	-0.4712***	(0.1053)	-0.5395**	(0.2554)
City: 2nd tier (private)	-0.3866***	(0.0471)	-0.3997***	(0.1375)
City: 3rd tier (private)	-0.2129***	(0.0263)	-0.3745***	(0.0586)
Constant	-1.9584***	(0.0241)	-2.3089***	(0.0980)
Observations	43331		11204	
Year fixed effect	✓		✓	

Notes: This table shows how the mortality rate depends on the city tier, the sector of pre-retirement employment, and other variables. Compared to our main specification in Table 4, this paper focuses only on households that have only one house or none. Columns (1), (2), and (3) present the estimation results of the probit model, RD design, and hazard model, respectively. The unit of observation is an individual-year. The dependent variable is the dummy death. All regressions include year fixed effects. All variables are defined in Table 3. ***, **, or * indicates that the estimate coefficient is significant at the 1%, 5%, or 10% level, respectively. Robust standard errors are in parentheses and given below the coefficient estimates.

B.5 Self-reported Health Status

The self-reported measurement of health is not an unsatisfactory proxy for latent health. The literature construct indeces based on selected health metrics among the elderly to provide a more objective assessment of aging health. We borrow this idea to project the latent health by keeping its objective components affected by disabilities or diseases and eliminating the subjective components measured by errors. Specifically, we run an ordered probit regression of self-reported health status on various diseases and disabilities. Table B.6 reports the results of the validation check. The diseases and disabilities all show significantly negative correlations with self-reported health status, indicating good reliability and validity of the self-reported health status. Then we re-estimate the health transition regression using projected health measures. Specifically, we run an ordered probit regression model to estimate how future projected health status depends on current projected health status. The results in Table B.7 are quite consistent with our baseline results.

Table B.6: Health Validation Checks

	(1) Health status		(2) Health status		(3) Health status	
Age					-0.089***	(0.014)
Age^2					-0.002	(0.008)
Physical Disabilities	-0.424***	(0.030)	-0.374***	(0.031)	-0.369***	(0.031)
Brain Damage/Mental Retardation	-0.614***	(0.033)	-0.521***	(0.034)	-0.522***	(0.034)
Vision Problem	-0.335***	(0.024)	-0.288***	(0.024)	-0.265***	(0.024)
Hearing Problem	-0.258***	(0.021)	-0.207***	(0.021)	-0.173***	(0.022)
Speech Impediment	-0.513***	(0.088)	-0.493***	(0.086)	-0.486***	(0.087)
Hypertension			-0.110***	(0.019)	-0.098***	(0.019)
Dyslipidemia			-0.104***	(0.025)	-0.115***	(0.025)
Disabetes or High Blood Sugar			-0.212***	(0.032)	-0.214***	(0.032)
Cancer or Malignant Tumor			-0.562***	(0.077)	-0.563***	(0.077)
Chronic Lung Diseases			-0.230***	(0.026)	-0.216***	(0.027)
Liver Disease			-0.245***	(0.037)	-0.255***	(0.037)
Heart Problems			-0.347***	(0.024)	-0.342***	(0.024)
Stroke			-0.446***	(0.039)	-0.424***	(0.039)
Kidney Diease			-0.309***	(0.031)	-0.313***	(0.031)
Emotional, Nervous, or Psychiatric Problems			-0.249***	(0.069)	-0.262***	(0.069)
Memory-Related Disease			-0.346***	(0.058)	-0.304***	(0.058)
Arthritis or Rheumatism			-0.225***	(0.018)	-0.228***	(0.018)
Asthma			-0.320***	(0.043)	-0.300***	(0.043)
cut1	-1.584***	(0.014)	-1.962***	(0.017)	-1.981***	(0.017)
cut2	-0.577***	(0.012)	-0.920***	(0.015)	-0.936***	(0.015)
cut3	0.839***	(0.012)	0.535***	(0.014)	0.523***	(0.015)
cut4	1.448***	(0.013)	1.154***	(0.015)	1.144***	(0.015)
Observations	40685		40685		40685	
Year fixed effect	✓		✓		✓	

Notes: This table reports the ordered probit regression model to estimate how self-reported health status depends on disabilities, diseases, and other variables. The unit of observation is an individual-year. The dependent variable is health status. All regressions include year fixed effects. All variables are defined in Table 3. ***, **, or * indicates that the estimate coefficient is significant at the 1%, 5%, or 10% level, respectively. Robust standard errors are in parentheses and given below the coefficient estimates.

Table B.7: Health Transition with Projected Measures

	(1)		(2)	
	Future reported health		Future projected health	
Age	-0.045***	(0.017)	-0.120***	(0.018)
Age^2	-0.065***	(0.011)	-0.007	(0.012)
Health: 1 Very poor	-1.032***	(0.025)		
Health: 2 Poor	-0.656***	(0.014)		
Health: 4 Good	0.505***	(0.017)		
Health: 5 Very good	0.879***	(0.026)		
Health: 1 Very poor × Age	0.033	(0.029)		
Health: 2 Poor × Age	0.003	(0.017)		
Health: 4 Good × Age	-0.075***	(0.022)		
Health: 5 Very good × Age	-0.072**	(0.032)		
Projected health: 1 Very poor			-0.528***	(0.025)
Projected health: 2 Poor			-0.420***	(0.014)
Projected health: 4 Good			1.304***	(0.022)
Projected health: 5 Very good			1.283***	(0.024)
Projected health: 1 Very poor × Age			-0.395***	(0.026)
Projected health: 2 Poor × Age			-0.325***	(0.020)
Projected health: 4 Good × Age			-0.043	(0.028)
Projected health: 5 Very good × Age			-0.037	(0.031)
cut1	-1.932***	(0.015)	-1.944***	(0.016)
cut2	-1.557***	(0.013)	-1.724***	(0.015)
cut3	-0.754***	(0.011)	-0.802***	(0.012)
cut4	0.727***	(0.012)	0.963***	(0.014)
cut5	1.312***	(0.013)	1.722***	(0.018)
Observations	39893		40381	
Year fixed effect	✓		✓	

Notes: This table reports the ordered probit regression model to estimate how future disease-projected health status depends on current health status, and other variables. The unit of observation is an individual-year. The dependent variable is health status. All regressions include year fixed effects. All variables are defined in Table 3. ***, **, or * indicates that the estimate coefficient is significant at the 1%, 5%, or 10% level, respectively. Robust standard errors are in parentheses and given below the coefficient estimates.

B.6 Out-of-pocket Share (Tobit)

Our baseline regression estimates *OOP* share by OLS. For robustness, we rerun regressions using the Tobit model. Table B.8 reports the results. Again, retirees from the public sector enjoy a much lower *OOP* share than the other groups.

Table B.8: Out-of-pocket Expenditure Share: Tobit

	(1)		(2)		(3)	
	OOP share		OOP share		OOP share	
Age	-0.038	(0.034)	-0.026	(0.033)	-0.125***	(0.042)
Age^2	-0.089***	(0.018)	-0.083***	(0.018)	-0.046**	(0.023)
Health: 1 Very poor	0.503***	(0.050)	0.396***	(0.050)	0.316***	(0.059)
Health: 2 Poor	0.584***	(0.033)	0.503***	(0.032)	0.440***	(0.038)
Health: 4 Good	-0.813***	(0.044)	-0.760***	(0.043)	-0.754***	(0.050)
Health: 5 Very good	-1.138***	(0.054)	-1.128***	(0.053)	-1.065***	(0.064)
Health: 1 Very poor × Age	0.011	(0.051)	0.000	(0.050)	-0.024	(0.064)
Health: 2 Poor × Age	-0.067**	(0.032)	-0.079**	(0.032)	-0.041	(0.040)
Health: 4 Good × Age	0.224***	(0.044)	0.199***	(0.043)	0.161***	(0.055)
Health: 5 Very good × Age	0.187***	(0.056)	0.198***	(0.055)	0.203***	(0.070)
City: 1st tier (private)			-0.570***	(0.084)	-0.584***	(0.109)
City: 2nd tier (private)			-0.503***	(0.047)	-0.425***	(0.060)
City: 3rd tier (private)			-0.369***	(0.031)	-0.251***	(0.039)
City: 1st tier (public)			-0.975***	(0.105)	-1.010***	(0.139)
City: 2nd tier (public)			-0.691***	(0.057)	-0.637***	(0.068)
City: 3rd tier (public)			-0.634***	(0.043)	-0.544***	(0.052)
ln Income					-0.002	(0.005)
ln Wealth					-0.051***	(0.009)
Housing share					-0.122	(0.078)
Constant	0.817***	(0.031)	1.085***	(0.033)	1.732***	(0.117)
Observations	19111		19111		12509	
Year fixed effect	✓		✓		✓	
var(e.shareofp)	2.127***	(0.055)	2.043***	(0.053)	1.917***	(0.061)

Notes: This table reports the Tobit regression model to estimate how the out-of-pocket expenditure share depends on health status, age, and its interaction with health status, and other variables. The unit of observation is an individual-year. The dependent variable is health status. All regressions include year fixed effects. All variables are defined in Table 3. ***, **, or * indicates that the estimate coefficient is significant at the 1%, 5%, or 10% level, respectively. Robust standard errors are in parentheses and given below the coefficient estimates.

B.7 Bequest

Table B.9 reports our main specification considering the bequest motive of the retirees. In our sample, only 0.9% of the elderly have no children, or all their children have already died. In this case, the vast majority of retirees have at least one successor. However, we could observe the retirees' bequest motive directly from the CHARLS data since it does not have a question directly related to it. We used the degree of their satisfaction with the relationship with their children as a proxy to measure the willingness of retirees to save for the bequest. Both the results of the baseline and the RD estimate show that retirees with higher bequest motives are associated with a higher mortality rate only when they live in the first-tier city, while these effects are not significant in the third-tier city and not that significant for the second-tier city.

Table B.9: Bequest: Satisfied Relationship with Children

	(1) Baseline		(2) RD	
Size > 90			0.316***	(0.097)
Size − 90			0.002	(0.006)
(Size > 90) × (Size − 90)			-0.006	(0.008)
Age	0.085***	(0.024)	0.069	(0.051)
Age^2	0.124***	(0.012)	0.127***	(0.025)
City: 1st tier (public)	-4.409***	(0.093)	-4.714***	(0.135)
City: 2nd tier (public)	-0.569***	(0.159)	-0.593*	(0.314)
City: 3rd tier (public)	-0.551***	(0.104)	-0.660***	(0.204)
City: 1st tier (private)	-4.224***	(0.061)	-4.428***	(0.104)
City: 2nd tier (private)	-0.558***	(0.121)	-0.325	(0.341)
City: 3rd tier (private)	-0.187***	(0.063)	-0.286**	(0.128)
City: 1st tier (public) × Good relation with children	3.891***	(0.203)	3.883***	(0.407)
City: 2nd tier (public) × Good relation with children	-0.071	(0.179)	-0.295	(0.359)
City: 3rd tier (public) × Good relation with children	0.076	(0.112)	-0.031	(0.226)
City: 1st tier (private) × Good relation with children	3.924***	(0.118)	4.037***	(0.272)
City: 2nd tier (private) × Good relation with children	0.268**	(0.127)	-0.035	(0.364)
City: 3rd tier (private) × Good relation with children	0.041	(0.062)	-0.038	(0.131)
Constant	-2.039***	(0.042)	-2.304***	(0.118)
Observations	45643		11782	
Year fixed effect	✓		✓	

Notes: This table shows how mortality rate depends on the interaction between good relations with children and city tier, sector of pre-retirement employment, and other variables. Columns (1), (2), and (3) present the estimation results of the probit model and RD design, respectively. The unit of observation is an individual-year. The dependent variable is the dummy death. All regressions include year fixed effects. All variables are defined in Table 3. ***, **, or * indicates that the estimate coefficient is significant at the 1%, 5%, or 10% level, respectively. Robust standard errors are in parentheses and given below the coefficient estimates.

B.8 Health Change and Future Housing

Table B.10 reports the relationship between health deterioration and future housing. Columns (1) and (2) show that health deterioration is associated with a lower level of future home ownership and housing wealth. Column (3) indicates that health deterioration is associated with a larger future house size.

Table B.10: Health Change and Future Housing

	(1)		(2)		(3)	
	Future home ownership		Future housing wealth		Future house size	
Health deterioration	-0.126***	(0.020)	-0.365***	(0.055)	0.029***	(0.008)
Age	-0.384***	(0.020)	-1.200***	(0.059)	-0.065***	(0.009)
Age^2	0.045***	(0.010)	0.069**	(0.034)	-0.017***	(0.005)
City: 1st tier (public)	-0.465***	(0.090)	1.117***	(0.400)	-0.412***	(0.042)
City: 2nd tier (public)	-0.043	(0.042)	1.677***	(0.122)	-0.118***	(0.015)
City: 3rd tier (public)	-0.104***	(0.028)	1.094***	(0.080)	-0.111***	(0.010)
City: 1st tier (private)	-0.367***	(0.066)	0.580**	(0.285)	-0.453***	(0.031)
City: 2nd tier (private)	-0.224***	(0.030)	0.429***	(0.103)	-0.140***	(0.017)
City: 3rd tier (private)	-0.317***	(0.019)	0.025	(0.062)	-0.024***	(0.008)
Constant	1.528***	(0.023)	9.486***	(0.054)	4.570***	(0.009)
Observations	39821		36398		35873	
Year fixed effect	✓		✓		✓	
R^2			0.062		0.035	

Notes: This table shows the relationship between health deterioration and future housing. The unit of observation is an individual-year. The dependent variables in columns (1)-(3) are future home ownership, future housing wealth, and future house size, respectively. All regressions include year fixed effects. All variables are defined in Table 3. ***, **, or * indicates that the estimate coefficient is significant at the 1%, 5%, or 10% level, respectively. Robust standard errors are in parentheses and given below the coefficient estimates.

B.9 Migration

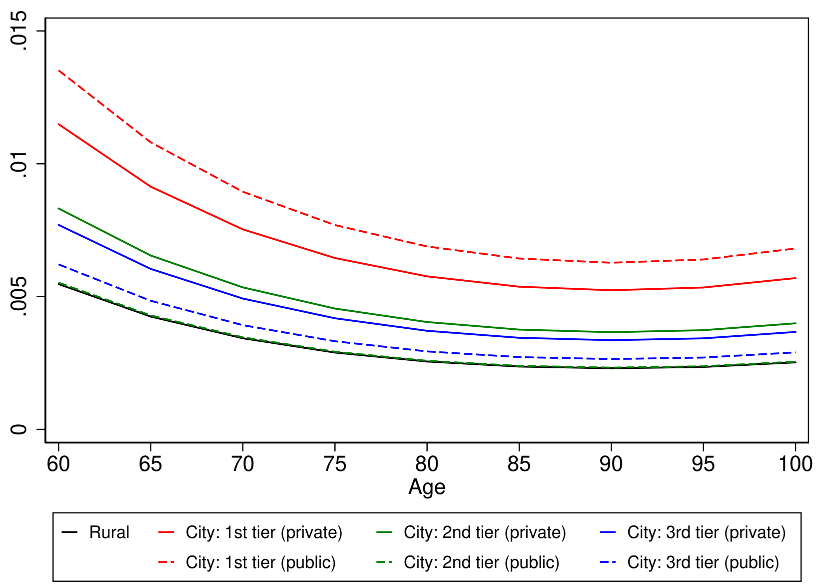
One potential concern is that our estimate may be biased by the selection to migrate to large cities. Given the hukou policy, only highly educated or senior individuals can get hukou in bigger cities, leading to positive selection on factors. Despite restrictions, China has a large migration. However, we focus on retirees. In our sample, the average immigrant shares in 1st, 2nd, 3rd cities, and rural area are just 0.97%, 0.73%, 0.73%, and 0.55%, respectively. Table B.11 reports the estimate for the odds of in-migrants, and Figure B.4 plots the average age profile of the odds of in-migrants for each of the seven groups based on the estimation.

Table B.11: Probit: In-migrants

	(1) In-migrant	
Age	-0.249***	(0.050)
Age^2	0.046	(0.030)
City: 1st tier (public)	0.377**	(0.190)
City: 2nd tier (public)	0.004	(0.111)
City: 3rd tier (public)	0.051	(0.071)
City: 1st tier (private)	0.308*	(0.162)
City: 2nd tier (private)	0.169**	(0.075)
City: 3rd tier (private)	0.138***	(0.049)
Constant	-3.152***	(0.077)
Observations	63294	
Year fixed effect	✓	

Notes: This table shows the probit estimation results of how migration depends on the city tier, sector of pre-retirement employment, and other variables. The unit of observation is an individual-year. The dependent variable is the dummy for in-migrant or not. All regressions include year fixed effects. All variables are defined in Table 3. ***, **, or * indicates that the estimate coefficient is significant at the 1%, 5%, or 10% level, respectively. Robust standard errors are in parentheses and given below the coefficient estimates.

Figure B.4: Odds of In-migrants



Notes: This figure presents the average age profile of the odds of seven types of retirees.

C Details on the Model

The appendix shows details on the derivations of results from the static model in Section 4.1.

C.1 Health Investment

In the optimization problem given by equations (6)-(7) in Section 4.1, the optimal allocation between consumption and health investment satisfies

$$(1-\xi) = \frac{u_H}{u_C}, \tag{27}$$

where u_H and u_C are the marginal utility of health and consumption, respectively. Using the utility function given by equation (7), we have the following expressions for the marginal utilities:

$$\begin{aligned}
u_C &= (1-\alpha)\left(\frac{\xi}{(1-\xi)q}\right)^{\xi(1-\frac{1}{\eta})} C^{-\frac{1}{\eta}} \left[(1-\alpha)\left(\frac{\xi}{q(1-\xi)}\right)^{\xi(1-1/\eta)} C^{1-1/\eta} + \alpha H^{1-1/\eta}\right]^{\frac{1}{\eta-1}}, \\
u_H &= \alpha H^{-\frac{1}{\eta}} \left[(1-\alpha)\left(\frac{\xi}{q(1-\xi)}\right)^{\xi(1-1/\eta)} C^{1-1/\eta} + \alpha H^{1-1/\eta}\right]^{\frac{1}{\eta-1}}.
\end{aligned}$$

Thus, we have

$$\frac{u_H}{u_C} = \frac{\alpha H^{-\frac{1}{\eta}}}{(1-\alpha)\left(\frac{\xi}{(1-\xi)q}\right)^{\xi(1-\frac{1}{\eta})} C^{-\frac{1}{\eta}}}. \tag{28}$$

Substitute equation (28) into equation (27), we obtain

$$(1-\xi) = \frac{\alpha}{1-\alpha}\left(\frac{q(1-\xi)}{\xi}\right)^{\xi(1-\frac{1}{\eta})}\left(\frac{C}{H}\right)^{\frac{1}{\eta}},$$

which is equivalent to

$$\frac{C}{H} = \left((1-\xi)\frac{1-\alpha}{\alpha}\right)^{\eta}\left(\frac{\xi}{1-\xi}\frac{1}{q}\right)^{\xi(\eta-1)}. \tag{29}$$

We substitute out C in equation (29) using the budget constraint of $C = (1-\xi)(y-H)$. After rearrangement, we obtain

$$H = \frac{y}{\left(\frac{1-\alpha}{\alpha}\right)^{\eta}\left(\frac{1}{\xi^{\xi}(1-\xi)^{1-\xi}}\right)^{1-\eta} q^{\xi(1-\eta)} + 1},$$

which is equation (8) in the main text.

C.2 Optimized Utility

Next, we derived the optimized utility (i.e., the indirect utility) in the static model. The utility function given by equation (7) can be written into

$$u(C,H) = \left[(1-\alpha)\left(\frac{\xi}{q(1-\xi)}\right)^{\xi(1-1/\eta)}\left(\frac{C}{H}\right)^{1-1/\eta}+\alpha\right]^{\frac{1}{1-1/\eta}} H,$$

which becomes the following after substituting out $\frac{C}{H}$ with the necessary condition of optimization given by equation (29)

$$u(C,H) = \left[(1-\alpha)\left(\frac{1-\alpha}{\alpha}\xi^{\xi}(1-\xi)^{1-\xi}\right)^{\eta-1}\left(\frac{1}{q}\right)^{\xi(\eta-1)}+\alpha\right]^{\frac{1}{1-1/\eta}} H. \tag{30}$$

When η approaches zero, the term in brackets of equation (30) becomes one because it is raised to the power of zero, thus

$$u^{\star} = \lim_{\eta\to 0} u(C^{\star},H^{\star}) = H^{\star}, \tag{31}$$

where we use $C^{\star}$ and $H^{\star}$ to denoted optimal consumption and health investment, and $u^{\star}$ is the optimized utility. Note that the optimal health investment when $\eta = 0$ is given by equation (10).

Given the spatial equilibrium condition that $u^{\star}$ should be the same across regions, equation (31) indicates $H^{\star}$ should also be the same across regions.

D Details on the Structural Analysis

D.1 Details on Model Computation and Estimation

This appendix describes the computation and estimation of the structural model that generates the results reported in Section 6.

The model is computed recursively through backward induction, starting from the bequest function. In each period, we search over the grid of state space to find the maximum of the value function and the corresponding policy functions. The policy functions are saved and used in the simulation.

For the grid of state space, we use 60 grid points for the bond and 90 grid points for the housing asset, and we use 5 grid points for health stock, which correspond to the five health statuses. We discretize the stochastic house price process using 3 states. Given that we have 7 groups in the model, overall, the grid space is $60 \times 90 \times 5 \times 3 \times 7$. The model is solved with Fortran parallel computing.

The structural parameters are estimated via the simulated method of moments. In total, there are 9 structural parameters, and the total number of moments is 18, corresponding to the regression coefficients reported in columns (1) and (2) of Table 10.

Given a set of parameters, we solve for policy functions and simulate the model to generate artificial data on health, death, home ownership, and portfolio composition. Then, we run regressions based on the simulated data to obtain the coefficients, naming them the simulated moments. The distance between the model and data is calculated as the Euclidean norm of the simulated moments and the data moments, which are coefficients in Table 10. We use the inverse of the variance of moments as the weighting matrix. Thus, moments with smaller variances receive more weight. We search for the parameters that minimize the distance using the Simplex algorithm.

D.2 Elasticities of Life Expectancy and Home Ownership Rate to Parameters

Each row in table D.1 reports the percentage changes of life expectancy or home ownership rates in response to a 1% increase in one of the parameter values.

Table D.1: Elasticities of Life Expectancy and Home Ownership Rate to Parameters

		Private sector				Public sector		
		tier 1	tier 2	tier 3	rural	tier 1	tier 2	tier 3
β	Life Expectancy	-14.03	-16.21	-13.79	-8.56	-10.00	-13.83	-18.07
	Home Ownership	0.46	-4.48	-1.12	-0.47	8.38	-6.42	-0.33
γ	Life Expectancy	0.93	1.08	1.34	0.55	0.57	0.95	-0.07
	Home Ownership	-0.50	-0.24	-0.32	0.01	-1.75	-1.77	0.00
θ	Life Expectancy	-1.54	-1.78	-1.58	-0.52	-1.51	-1.24	-1.86
	Home Ownership	-0.69	0.82	-0.08	0.00	1.96	-0.95	0.43
L	Life Expectancy	-0.61	-0.55	-1.10	-0.10	-0.60	-0.54	-1.14
	Home Ownership	-0.29	0.87	0.17	0.00	2.29	-0.86	0.37
α	Life Expectancy	0.98	0.99	0.57	0.35	0.79	0.75	0.91
	Home Ownership	-0.33	0.43	0.40	0.01	-0.65	-1.28	-0.20
η	Life Expectancy	-0.08	-0.36	-0.34	-0.26	0.25	-0.28	-0.02
	Home Ownership	-0.61	0.28	0.03	-0.02	1.44	0.18	0.12
ψ	Life Expectancy	0.23	0.18	0.95	0.12	0.44	0.19	0.45
	Home Ownership	-1.23	1.24	-0.31	-0.04	2.26	-1.65	-0.08
ϕ	Life Expectancy	0.04	0.15	0.23	0.01	0.16	-0.06	0.06
	Home Ownership	0.16	0.42	-0.22	0.01	-0.26	0.43	0.00
λ	Life Expectancy	-0.11	0.05	-0.03	-0.05	-0.03	-0.10	-0.15
	Home Ownership	-0.27	0.40	0.28	-0.01	-0.43	-0.34	0.11

Notes: The percentage changes of life expectancy and home ownership rate in response to a 1% increase in a parameter.