Essays on the Dynamics of Residential Sorting, Health, and Environmental Quality

by

Sophie-Marie Mathes

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Graduate Supervisory Committee:

Nicolai V Kuminoff, Co-Chair
Alvin D Murphy, Co-Chair
Alexander Bick
Kelly C Bishop
Jonathan Ketcham

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ABSTRACT

My dissertation combines the notion of residential sorting from Tiebout (1956) with Grossman's (1972) concept of a health production function to develop a new empirical framework for investigating what individuals' residential location choices reveal about their valuation of amenities, the welfare effects of climate change, the forces underlying environmental justice, and the value of a statistical life. Location choices are affected by age, health, and financial constraints, and by exposure to local amenities that affect people's health and longevity. Chapter 1 previews how I formalize this idea and investigate its empirical implications in three interrelated essays.

Chapter 2 investigates interactions between health, the environment, and income. Seniors tend to move at higher rates after being diagnosed with new chronic medical conditions. While seniors generally tend to move to locations with less polluted air, those who have been diagnosed with respiratory conditions move to relatively more polluted locations. This counterintuitive pattern is reconciled by documenting that new diagnoses bring about increases in medical expenditures, thereby limiting disposable income that can be spent on housing. Relatively cheaper places tend to be more polluted, and higher exposure to pollution leaves seniors more vulnerable to future health shocks.

In Chapter 3, I combine information about housing prices with estimates of location-specific effects on mortality to estimate the Value of a Statistical Life (VSL) for seniors - one of the most important statistics used to evaluate policies affecting mortality. Since local amenities correlate with causal mortality effects, but also provide utility independently, the difficulty in controlling for local amenities implies that my VSL estimates are best interpreted as bounds.

Chapter 4 builds a new structural framework for evaluating spatially heterogeneous changes to local amenities. I estimate a dynamic model of location choice with a sample of 5.5 million seniors from 2001-2013. Their average annual willingness-to-pay to avoid future climate change in the United States under a “business as usual” scenario ranges from $962 for older, sicker groups who are more vulnerable to climate change’s negative effects on health to -$1,894 for younger, healthier groups, who value warmer winters and are relatively resilient.

DEDICATION

To my parents, my sisters, and to Juan.

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Chapter 1

INTRODUCTION

My research investigates the dynamic interactions between residential location choices and health among senior citizens in the United States, how these dynamics can create and widen disparities in pollution exposure and health outcomes between socioeconomic groups, and what can be learned from these dynamics about the Value of a Statistical Life among different demographic groups.

I am focused on problems related to human health, migration, and climate change. The studies that form this dissertation investigate these problems using cutting-edge empirical methods that improve the way that economic ideas such as dynamic optimization can be used to rigorously analyze individual behavior to improve current understanding of how individuals make decisions when facing tradeoffs between private good consumption, their own health, and their access to local public goods. This information can be used to evaluate the distributional effects of policies that target individuals' decision-making behavior in order to achieve outcomes that policy-makers deem to be beneficial to society.

In Chapter 2 I start from the observation that seniors who have been diagnosed with chronic respiratory conditions are more likely to move to places with relatively higher levels of ambient air pollution, compared to movers who have not been diagnosed with respiratory conditions. I attribute this counterintuitive finding to a combination of dynamic interactions between health, wealth, and residential sorting that can create an "Illness Poverty Amenity Trap". Results show that the onset of new chronic medical conditions increases out-of pocket medical expenditure, and can trigger people to move due to their lower disposable income and the loss of physical and cognitive skills. Since more polluted neighborhoods tend to be cheaper in terms of housing costs, sicker and poorer individuals become more likely to move there following negative shocks to their health, and hence to their disposable income. The higher pollution levels in their new neighborhoods make them even more vulnerable to future health shocks. The economic implications of illness-poverty-amenity traps for U.S. senior citizens are potentially large, when their residential location choices can mitigate or exacerbate disparities in pollution exposure and health outcomes.

This research on air pollution can in principle be extended to investigate whether similar phenomenona arise with respect to forms of water and land pollution. For example, pollution of ground water in rural areas on well water and pollution of fresh water bodies that feed public water systems may contribute to negative health outcomes. Similarly, the removal of pollutants, for example through Superfund cleanups of hazardous waste sites has potential to reverse this cycle. However, the scope for reversal also depends on the extent to which cleanups are capitalized into property values and trigger gentrification that may prompt sicker and poorer renters to move away from the improved areas. Understanding the dynamic interactions between pollution, health, and residential sorting among senior citizens is especially important for the United States because people over 65 are the fastest growing age group. My results suggest there is more to be learned about which demographic groups are most at risk from negative effects of climate change in areas that will grow to be more prone to extreme weather and natural disasters.

In Chapter 3 I estimate the Value of a Statistical Life (VSL) for senior citizens based on the amounts they implicitly pay for statistical life extension through residential housing prices. Recent research has shown that there is large spatial heterogeneity in longevity across the US. These differences stem from underlying differences in health among the population in different locations, but also from causal effects that locations appear to have on their citizens' mortality. In the spirit of the Rosen-Roback sorting model, differences in longevity across locations can be expected to be reflected in differences in the cost of living, such that the total utility values across locations equalize. Thus, I combine estimates of local causal mortality effects with information on the cost of housing to estimate the VSL from these joint differences in mortality and housing cost. Results suggest that the VSL declines in age, in line with previous literature (Aldy and Viscusi, 2008; Ketcham *et al.*, 2020). The estimated lower and upper bounds cover VSL estimates from the literature, yet span relatively wide intervals, which future research could usefully aim to refine.

Chapter 4 combines the ideas of Grossman health investment and Tiebout sorting. Put simply, one's residential location can have a causal effect on one's health and mortality, making the choice of where to live a form of investment in future health that individuals may consider when they sort into neighborhoods. I investigate this link using data provided by the Center for Medicare and Medicaid Services (CMS), that gives me information on the evolving residential locations and health of over 5 million seniors between 2001 and 2013. I estimate a dynamic discrete choice model of residential location choices made by forward-looking individuals and use the estimates to analyze the distributional welfare implications of future climate change for the United States under a "business as usual" scenario. I find that older and sicker individuals will bear the largest burden of climate change, while relatively younger and healthier seniors may in fact benefit from warmer climates in part because they are relatively mobile. My analytical framework can be adapted to investigate the winners and losers from changes in pollution of air, or water, or land.

Chapter 2

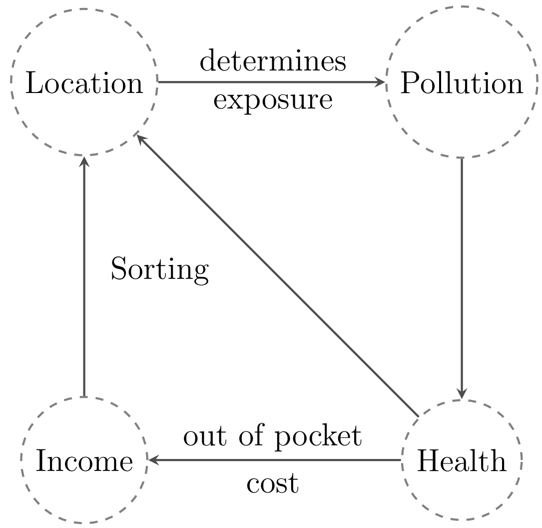
ENVIRONMENTAL JUSTICE FOR SENIORS: EVIDENCE FROM MEDICARE ADMINISTRATIVE RECORDS

In this essay, I investigate the post-retirement dynamics of residential sorting, pollution exposure and health among US senior citizens.[1] My findings are consistent with a "pollution poverty" trap. Figure 2.1 summarizes the key mechanisms. The trap results from the fact that it more expensive to live in neighborhoods with better amenities like clean air, mild climate, and high-quality health care. Lower-income seniors are more likely to choose to live in less expensive neighborhoods with worse environmental conditions. Elevated pollution exposure increases their risk of negative health shocks. Health shocks increase their out-of-pocket medical costs and reduce their physical and cognitive skills. Declines in health and disposable income can motivate seniors to move. And movers who face growing medical bills and declining health may optimally choose to move to more polluted neighborhoods, perpetuating the vicious cycle shown in Figure 2.1.

It is especially important to investigate disparities in pollution exposure among seniors. Seniors are the fastest growing age group in the US, predicted to account for 20 percent of the population by 2030. They are also the most vulnerable age group to the health effects of air pollution and heat stress. For instance, the EPA attributes 78 percent of all premature deaths avoided by its air pollution regulations to people over age 65 (IEc, 2011). Further, annual taxpayer-financed Medicare spending exceeds $600 billion.

[1] This essay has emerged from joint work with Nicolai Kuminoff and Jonathan Ketcham.

Figure 2.1: Illustration of the Pollution Poverty Trap



I first develop a novel model of Tiebout sorting that incorporates health and medical spending. Then I test its predictions using 13 years of administrative records on more than 5 million seniors. My work connects the literatures on environmental justice (Banzhaf *et al.*, 2019), poverty traps (Becker and Tomes, 1979; Chetty and Hendren, 2018), residential sorting (Kuminoff *et al.*, 2013), and measuring the effects of residential location on health (Deryugina and Molitor, 2018; Finkelstein *et al.*, 2018). The conceptual framework combines a Tiebout-style (Tiebout, 1956) model of residential sorting with a Grossman-style (Grossman, 1972) health production function. Flow utility depends on consumption of housing and other private goods, the stock of health, and an index of neighborhood amenities (e.g. air pollution, climate, and health care quality). The health stock evolves as a stochastic function of past health, neighborhood quality, and medical expenditures. Seniors solve a repeated static optimization problem. Each period they realize their health, incur medical costs, and then choose where to live the following period. The model allows me to characterize the dynamics of residential sorting and health when seniors value amenities that affect their health but do not fully know their own health production functions (e.g. they may dislike air pollution, but not know precisely how their exposures affect their risk of a fatal heart attack). This model allows me to consider how current health may affect residential choice through two channels. First, it may constrain the amount of income that can spent on housing by requiring out-of-pocket medical costs. Second, it may affect seniors' marginal rates of substitution between public and private goods. Residential locations affect future health via local environmental quality. A single-crossing assumption allows me to make predictions about sorting behavior.

Specifically, I assume that the slope of the indirect indifference curve in price-amenity space is increasing in income conditional on health and in health conditional on income. Intuitively, a healthier person will have a higher marginal willingness-to-pay for local public goods, conditional on income, because being healthy enhances their ability to engage in complementary activities such as outdoor recreation. The single-crossing assumption disciplines the model in a way that allows me to make testable predictions about the dynamics of sorting and health. First, it implies that lower income seniors will sort themselves into lower amenity areas, causing their health to decline faster and causing them to spend more on health care. Second, health shocks will tend to increase medical spending and migration rates. Finally, lower income migrants will tend to move to lower amenity areas.

I test these predictions using administrative records for a 10 percent random panel sample of U.S. senior citizens from 2001-2013. I observe each person's age, gender, and race; their evolving health measured by diagnoses for more than 30 chronic medical conditions; their annual medical expenses; whether they receive Medicaid subsidies (a proxy for low wealth); their precise residential locations each year; and their death dates. Consistent with model predictions I find that: (1) lower-income seniors become sicker and die sooner, (2) lower-income seniors have higher medical costs, (3) morbidities linked to air pollution and heat stress substantially increase medical costs and migration, and (4) conditional on moving, lower-income seniors tend to move to neighborhoods with higher fine-particulate matter air pollution. These findings suggest that the pollution poverty trap works against the EPA's environmental justice goal of reducing pollution disparities across different socioeconomic groups. For instance, my findings show that the average move during the 2000's widened the income-$PM_{2.5}$ gap by 17 percent of its start-of-decade level among seniors.

2.1 Related Literature

This study connects on several distinct literatures. The conceptual framework built here models a poverty trap, where the channel that sustains inequality in income is the interaction of health and the environment. Lower income individuals sort into lower amenity locations, in line with theory formalized by the Tiebout sorting literature. Lower amenity neighborhoods in turn tend to be more polluted and to have less favorable effects on health, which has been documented in empirical studies. Negative health shocks finally bring about expenditure shocks that reduce disposable income and constrain location choices even further. Since this work investigates systematic differential exposure to pollution for individuals of different means, it forms part of the literature in Environmental Justice (EJ). The EJ literature aims to quantify the extent of and understand the ways in which some groups are disproportionately exposed to environmental disamenities.

2.1.1 Poverty Traps

There is a large economic literature on poverty traps starting with a seminal paper by Becker and Tomes (1979) that shows how income inequality may persist for multiple generations.[2] In their model differences in luck for an initial generation can affect future generations through investments in the human capital of their offspring. Initial income inequality can persist when borrowing is constrained. Specifically, if borrowing constraints limit parents' investments in their children's human capital this can transmit income inequality from the first generation to the second generation, effectively establishing an intergenerational poverty trap (Loury, 1981; Galor and Zeira, 1993).

Poverty traps can also arise from residential sorting and neighborhood spillovers such as peer effects in schools. If wealthier and more highly educated parents tend to choose to live in similar neighborhoods where (1) public education spending is determined at the local level and (2) the neighborhood composition generates spillover effects (e.g. higher school spending, peer effects in schools), then income inequality can persist over many generations (Benabou, 1994; Durlauf, 1996). In the earlier models of intergenerational poverty traps like Galor and Zeira (1993), income inequality is not persistent in the long run because the intergenerational transmission of inequality is not perfect; in the models of Benabou (1994) and Durlauf (1996) income inequality can persist. In recent work, Durlauf and Seshadri (2018) show how increases in cross-sectional inequality lead to lower social mobility across generations. The key channel for these intergenerational poverty traps is the production technology of human capital, together with a borrowing constraint.

Poverty trap dynamics may also occur within a single generation. Sizeable neighborhood-level effects on children's future incomes have been confirmed empirically (Chetty and Hendren, 2018). A recent example of an intragenerational poverty trap, arising from differences in pollution exposure, is Isen *et al.* (2017). They show that differences in pollution exposure in utero cause significant income differences among workers in

[2] For an overview of this literature see the Handbook chapter Azariadis and Stachurski (2005).

their early 30's. This paper will add to the literature by investigating the potential empirical importance of poverty traps late in life.

2.1.2 *Tiebout Sorting*

The seminal sorting paper by Tiebout (1956) envisions individuals choosing the community that offers their most preferred bundle of local public goods (Tiebout sorting). A large body of research has since formalized spatial equilibria (Epple *et al.*, 1993; Epple and Platt, 1998; Epple and Sieg, 1999) used them to estimate the valuation of consumers for public goods (Bayer *et al.*, 2009; Hamilton and Phaneuf, 2015), and simulated the welfare effects of changes in public good provision at the community level (Sieg *et al.*, 2004; Tra, 2010). A comprehensive review of the literature on residential sorting is provided in Kuminoff *et al.* (2013).

The economic magnitude of Tiebout sorting is an open research question. Rhode and Strumpf (2003) argue that if individuals sort into communities primarily based on their preferences for public good provision, a decline in the cost of moving should augment Tiebout sorting and therefore lead to more pronounced heterogeneity in public good provision across communities. However, they find no strong evidence that the historic decrease in mobility cost over the past century would have increased the heterogeneity in public good provision across communities. On the other hand, Banzhaf and Walsh (2008) find evidence that community sizes and community income distributions respond to exogenous changes in public goods in ways that are consistent with Tiebout sorting. A common feature of sorting models is heterogeneity among individuals along dimensions like income, wealth, and tastes, which then systematically affect decision-making. This paper will add to this research question by gauging to what extent changes in individual health translate into observable moves, and whether these moves and the accompanying changes in pollution exposure reinforce initial differences in health.

2.1.3 The Effect of Neighborhoods on Health

Locally determined factors like air quality, health care, and climate affect human health. Ambient air pollution has been shown to increase all-cause mortality (Pope III *et al.*, 2002; Deryugina *et al.*, 2019), cognitive performance (Zhang *et al.*, 2018), and the risk of dementia (Underwood, 2017; Bishop *et al.*, 2018). For an overview over empirical evidence of how pollution affects human health see Graff Zivin and Neidell (2013). Beyond that, recent empirical evidence has shown that the location of residence has a causal effect on mortality (Deryugina and Molitor, 2018; Finkelstein *et al.*, 2018).

2.1.4 Environmental Justice

Environmental justice is a political mandate for more equitable distribution of exposure to environmental quality among the population. Residential sorting by income and taste can make this goal harder to achieve. Depro *et al.* (2015) show that when individuals re-sort following policy changes that affect public good provision, costs and benefits of the policies may be distributed differently among the population than intended by the policy-maker. A recent comprehensive review can be found in Banzhaf *et al.* (2019). It is known that pollution negatively affects health, and that people sort differently based on individual-level heterogeneity like income and health status. These insights open the door to acknowledging that when an adverse health shock affects income, future location decisions might be constrained - and sorting into cheaper, more polluted places endangers health even further.

2.2 Data

I use data on Medicare beneficiaries to identify the effect of health shocks on medical expenditures, on the propensity to move, and the relative changes in pollution exposure among movers. All US citizens age 65 and above are eligible for Medicare benefits. The US Centers for Medicare and Medicaid Services (CMS) maintains a national database of beneficiaries' administrative records, including information on their residential address histories, medical claims, and demographics. I link these records to develop a novel individual-level panel database on residential location, health, and exposure to air pollution.

I start with a random 10 percent sample from the universe of Medicare beneficiaries who were at least 65 years old in 2000. I then add random 10 percent samples of all new 65-year-old Medicare beneficiaries each year from 2001 to 2011. Then, I drop people who ever enrolled in Medicare Advantage plans, which replace traditional Medicare with a managed care plan, due to insufficient information on the medical expenditures and the chronic illnesses of Medicare Advantage enrollees. I drop people who cannot be matched to a precise residential location at any point during the period 2000 to 2013 at which they are still alive. This includes addresses that are post-office boxes or incomplete address records. These cuts are essential to ensure that I observe where each person lives each year since entering my sample, their air pollution exposure, their annual medical expenditures, and their diagnoses with chronic illnesses.

The sample consists of 5.9 million individuals whom are observed for a total of 50.9 million person-years. Approximately 44 percent of these individuals are male and 86 percent are white. The mean age of the initial sample in year 2000 is 74.8. Once an individual enters the sample, they are tracked through the end of 2013 or until they die. Approximately 56 percent of individuals survive through the end of 2013. For those who die, the mean age at death is 82.

CMS uses information from the US Social Security Administration to track Medicare beneficiaries' residential addresses. I obtain ZIP+4 Codes (also referred to as nine-digit ZIP Codes) for each individual's sequence of home addresses from 2000 to 2013. ZIP+4 Codes are close to street addresses in terms of spatial precision: each code corresponds to a single mail delivery segment such as one floor of an apartment building or one side of a street on a city block. The US includes more than 34 million ZIP+4 Codes, or about one for every four households.

Migration patterns of the individuals in my sample are similar to those reported by the Census Bureau for individuals aged 65 and above. 82 percent of individuals live in the same ZIP+4 throughout my study period. Of the 18 percent of people who move between ZIP+4 Codes at least once, 9 percent move between counties and 5 percent move between states.[3] I use this information to measure each individual's long term exposure to air pollution, accounting for migration.[4] Annual air pollution is measured at the geographical centroid of each ZIP+4 code, focusing on $PM_{2.5}$ commonly believed to have the most pernicious effects on human health among the six criteria air pollutants regulated by the Environmental Protection Agency (EPA). Air pollution at each ZIP+4 centroid is interpolated with inverse squared distance weighting of all surrounding monitors, following the methodology outlined in Bishop *et al.* (2018).

[3]Among those who ever move between ZIP+4 Codes 77 percent move once during our study period, 17 percent move twice, 4 percent move three times and 1 precent move four or more times.

[4]It is not possible to identify people with more than one residence ("snowbirds") because only the residential address on record with the CMS is observed. However, Jeffery (2015) estimates that seasonal migrants only account for 2 percent to 4.1 percent of the Medicare population based on addresses on Medicare claims for primary care and emergency room visits.

Figure 2.2: Average Residential Concentration of $PM_{2.5}$ by Year

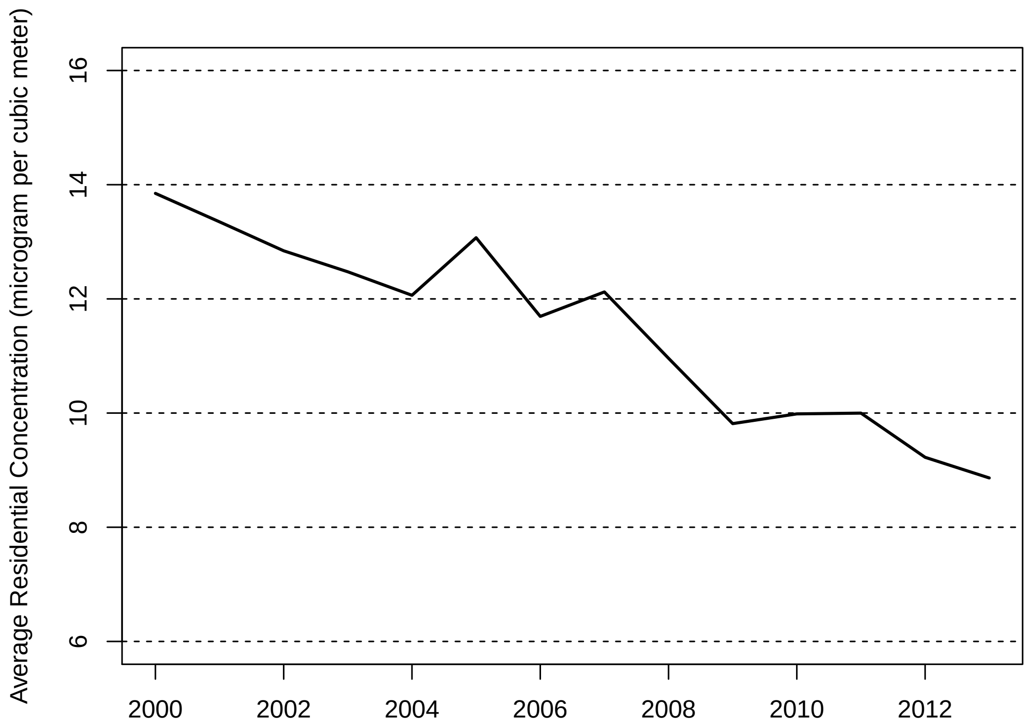


Figure 2.2 shows the annual average concentrations of fine particulate matter based on place of residence for the study sample of Medicare beneficiaries. Exposure to air pollution declined remarkably during the 2000s. Annual average residential exposure to PM2.5 declined from about 14 microgram per cubic meter in 2000 to below 9 microgram per cubic meter in 2013.

These annual histories of exposure are the most comprehensive data to date to measure how air pollution affects seniors' health. Still, it should be noted that the constructed histories may embed measurement error because it is infeasible to fully control for factors such as avoidance behavior, the location and duration of activities taking place outside of the home, variation in indoor air penetration or variation in respiration due to health and physical activity.

Information on the income of seniors comes from the Medicare Current Beneficiary

Survey. This is a rolling panel that surveys a randomly drawn sample of individuals for four consecutive years, as long as they are alive, even if they move into or out of long-term care facilitates. If they become incapacitated (e.g. due to Alzheimer's disease) then a caregiver answers the survey for them. It is possible to connect 14,511 individuals from the CMS random sample to the MCBS respondents with valid income data. Information on income is given in bins of width \$5,000.

2.3 Conceptual Framework

In the model environment, seniors are assumed to maximize utility by choosing a residential location j, which determines the level of public good consumption; private consumption and consumption of housing. The model environment is a repeated static decision problem. Each period t, seniors choose how much of their disposable income to allocate to private good consumption b, public good consumption g, and housing consumption q, given their disposable income y and current state of health h. Equations (2.1) and (2.2) show the constrained utility maximization problem. The current state of health may affect the marginal rate of substitution between private and public goods. Disposable income is the difference between permanent income y_i, such as social security and pension income, and medical expenditures m that are assumed to be an increasing function of the current state of health.[5]

$$\max_{j,b,q} u(b, q, g_{jt}; h_{it}) \tag{2.1}$$

$$y_i - m(h_{it}) = \hat{y}_i = b + p_{jt}q \tag{2.2}$$

The indirect per-period utility function is derived by expressing optimal consumption quantities for housing and other private goods as function of local public goods, hous-

[5]It is assumed that a worse state of health demands higher medical expenditures. This assumption is supported by the data.

ing prices, disposable income and health status. The public good g_{jt} is interpreted as a composite index of ambient environmental quality (e.g. pollution, climate, outdoor recreation opportunities) and other local amenities (e.g. crime, quality of local health care). This consumption bundle may directly affect utility in period t and, as explained below, it may also affect utility in future periods by modifying an individual's health stock. For convenience, I henceforth refer to the composite public good as "environmental quality".

$$v(g_{jt}, p_{jt}, \hat{y}_i, h_{it}) = u\left(\hat{y}_i - pq(g_{jt}, p_{jt}, \hat{y}_i, h_{it}), q(g_{jt}, p_{jt}, \hat{y}_i, h_{it}), g_{jt}, h_{it}\right) \tag{2.3}$$

Assume that there is a finite number of locations j, that differ in their environmental quality g. Assume furthermore that the slopes of indifference curves in the (p, g) space are monotonically decreasing in income y and monotonically increasing in health h, i.e. that

$$\frac{\partial\left(\frac{\partial g}{\partial p}\right)}{\partial y} < 0 \quad \wedge \quad \frac{\partial\left(\frac{\partial g}{\partial p}\right)}{\partial h} < 0 \tag{2.4}$$

This is a single crossing condition (SCC) that formalizes the notion that as income increases, individuals become less price-sensitive and relatively more sensitive to environmental quality, conditional on health; analogously, when health is better, meaning that h is higher, individuals are less price-sensitive and relatively more sensitive to differences in environmental quality, conditional on income. The idea is that when health is very good, individuals are able to enjoy nice amenities. When health is very poor individuals are less able to enjoy environmental quality, e.g. because they are confined to stay in bed. Put differently, this condition implies that as income increases, the marginal willingness to pay (MWTP) for environmental quality increases, holding health constant. On the other hand, a negative health shock decreases the MWTP for environmental quality, holding income constant. Imposing (2.4) results in three equilibrium characteristics: (1) The equilibrium housing prices across locations will mirror the ranking by environmental quality g. (2) Conditional on health, the communities will be perfectly stratified by income. (3) Higher income individuals will inhabit the locations with higher environmental quality. In other words, conditions (2) and (3) mean that among the individuals with the same state of health $\bar{h}$, those of the highest income will inhabit the highest amenity community up until the individual $(\bar{y}_1, \bar{h})$ who is just indifferent between the more expensive, higher quality, and the second most expensive community with the second highest level of environmental quality. Everyone with health $\bar{h}$ and income higher than $\bar{y}_1$ will choose community 1. Next there is a second highest income level $\bar{y}_2$ such that everyone with health $\bar{h}$ and income between $\bar{y}_1$ and $\bar{y}_2$ will choose community 2, and so on until community J. The stratification in h, conditional on income $\bar{y}$, will work analogously. A proof of these results can be found in Epple and Sieg (1999). Modelling health explicitly as an individual-level variable that affects preferences is a departure from prior literature which imposed a SCC using a vaguer concept of preferences (Epple and Platt, 1998; Sieg *et al.*, 2002, 2004). Banzhaf and Walsh (2013) have used a similar framework modelling preferences for racial composition of neighborhoods.

Over time, an individual's health is assumed to evolve as a stochastic function of their past health status and their past exposure to environmental quality. In Equation (2.5) ε represents the stochastic component of health; e.g. whether an individual suffers a non-fatal heart attack or stroke.

$$h_{it} = f(h_{i,t-1}, g_{j,t-1}, \varepsilon_{j,t-1}) \tag{2.5}$$

Exposure to lower environmental quality is assumed to cause the health stock to deteriorate faster, all else constant. This assumption is supported by the large literature cited earlier linking air pollution to negative health outcomes.

Understood through the lens of the model, the following hypothesized mechanisms are jointly sufficient to create a pollution-poverty trap. (1) Lower income seniors live in locations with lower environmental quality (2) Health shocks increase medical spending. (3) In the aggregate, lower income seniors spend more on health care. (4) Following a bad health shock, and realizing the accompanying expenditure shock, individuals move at higher rates than individuals who do not realize a bad health shock. (5) Individuals who have suffered a bad health shock and move, move to low amenity places.

Strictly speaking, (2) is a testable assumption of the model. Hypothesis (3) results from lower income individuals living in lower quality neighborhoods and thus experiencing relatively more bad health shocks. (5) jointly results from a bad health shock's effect on preferences and the fact that a bad health shock is accompanied by an expenditure shock.

2.4 Results

The empirical strategy is a combination of direct nonparametric tests of model hypotheses and regression based analysis. I use a difference-in-differences approach to estimate the effect of a new diagnosis of a chronic medical condition on out-of-pocket medical expenditures and on the propensity to move in the following year.

Since hypotheses (1), (3), and (5) describe features of a spatial equilibrium, I will present descriptive statistics. Hypotheses (2) and (4) contain claims about underlying mechanisms, therefore I will test them with a difference-in-differences estimation. To test hypothesis (2), the year-to-year changes in out of pocket medical expenditures m_{it} are regressed on year-to-year changes in the diagnosis status d_{cit} of a vector of 27 chronic conditions c, controlling for individual demographics age and gender x_i.

$$\Delta\, m_{it} = \beta_c\, \Delta d_{cit} + \beta_x\, x_i + \varepsilon_{it} \tag{2.6}$$

Using the full vector of 27 chronic conditions allows the different chronic conditions to have differential intensities of impact. For hypothesis (4), I estimate the impact of a change in diagnosis status d_{cit} on an indicator for whether the individual moves $move_{it}$ in a linear probability model.

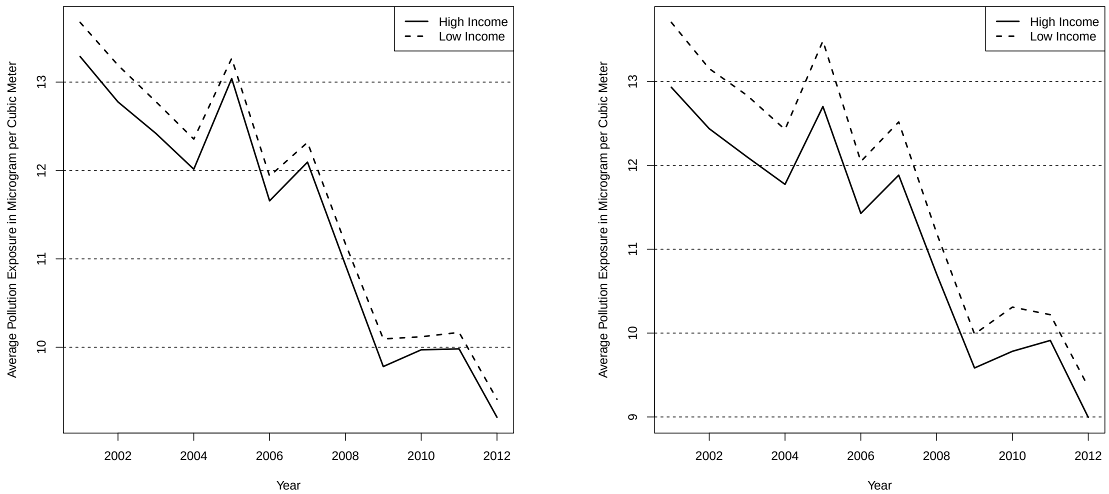
$$move_{it} = \beta_c \, \Delta d_{cit} + \beta_x \, x_i + \varepsilon_{it} \tag{2.7}$$

Both equations are estimated for each year from 2001 to 2012.

2.4.1 Hypothesis 1: Lower Income Seniors Live in Lower-Amenity Areas

Figure 2.3 highlights the gap in exposure to ambient air pollution between high and low income groups. The CMS data does not contain direct information on individual income. Therefore, the left panel measures high and low income status using Medicaid eligibility as a proxy. The right panel uses individual annual income for the small subset of individuals who are part of the Medicare Current Beneficiary Survey (MCBS). The dashed line shows the average exposure to $PM_{2.5}$ for the low-income group, defined as individuals with an annual income of less than \$15,000. The solid line shows the average exposure to pollution among the high-income group, defined as individuals with an annual income higher than \$30,000. In every year observed in the sample, the average exposure to air pollution is higher for low income individuals. Empirical research has shown that exposure to pollution has adverse effects on health and mortality. Consistent with this and the fact that lower income seniors live in lower-amenity areas, Figure 2.4 shows that lower income seniors die at higher rates. The left panel shows the share of surviving individuals of the initial cohorts that were 65, 80, and 95 years old in 2001, by income status. Out of those who were 65 years old in 2001 and of low income status, less than 60 percent were still alive in 2012. Out of those who were 65 years old and belonged to the high income group, almost

Figure 2.3: Average Pollution Exposure by Income



Notes: Low Income - has been eligible for Medicaid at least once during the study period, High Income - never been eligible for Medicaid.

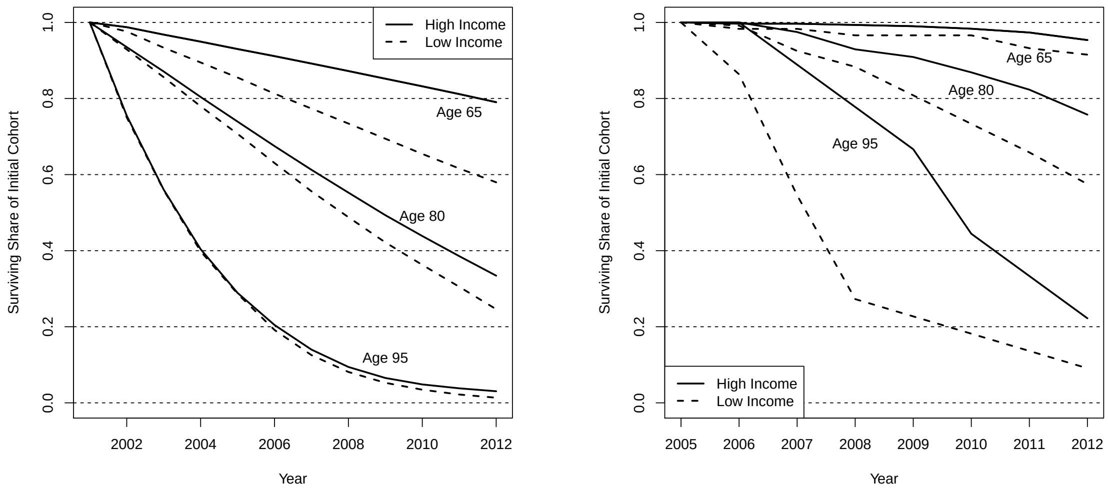
Notes: MCBS ($N = 9,931$) subsample. Low Income - less than \$15,000 per year, High Income - more than \$30,000 per year

80 percent were still alive in 2012. The right panel shows the survival rates for the subsample in the MCBS. Since the MCBS started in 2005, only individuals who were alive in 2005 are part of the sample. The lines show the analogous surviving shares of the cohorts initially alive in 2005.

2.4.2 Hypothesis 2: Health Shocks Increase Medical Spending

Figure 2.5 shows the impact of a new chronic illness on annual out of pocket medical spending. Every single condition significantly increases out of pocket medical spending. Lung cancer, diagnosed in 2001, increases out of pocket medical spending by \$2,706, making this the most expensive condition in terms of out of pocket spending. Eight of the 27 chronic conditions studied here increase out of pocket spending by over \$1,000 per year in 2001. COPD checks out at \$615 additional spending per year, and asthma at \$404. Especially for low income households, this can imply a

Figure 2.4: Survival Rates by Income



Notes: Low Income - has been eligible for Medicaid at least once during the study period, High Income - never been eligible for Medicaid.

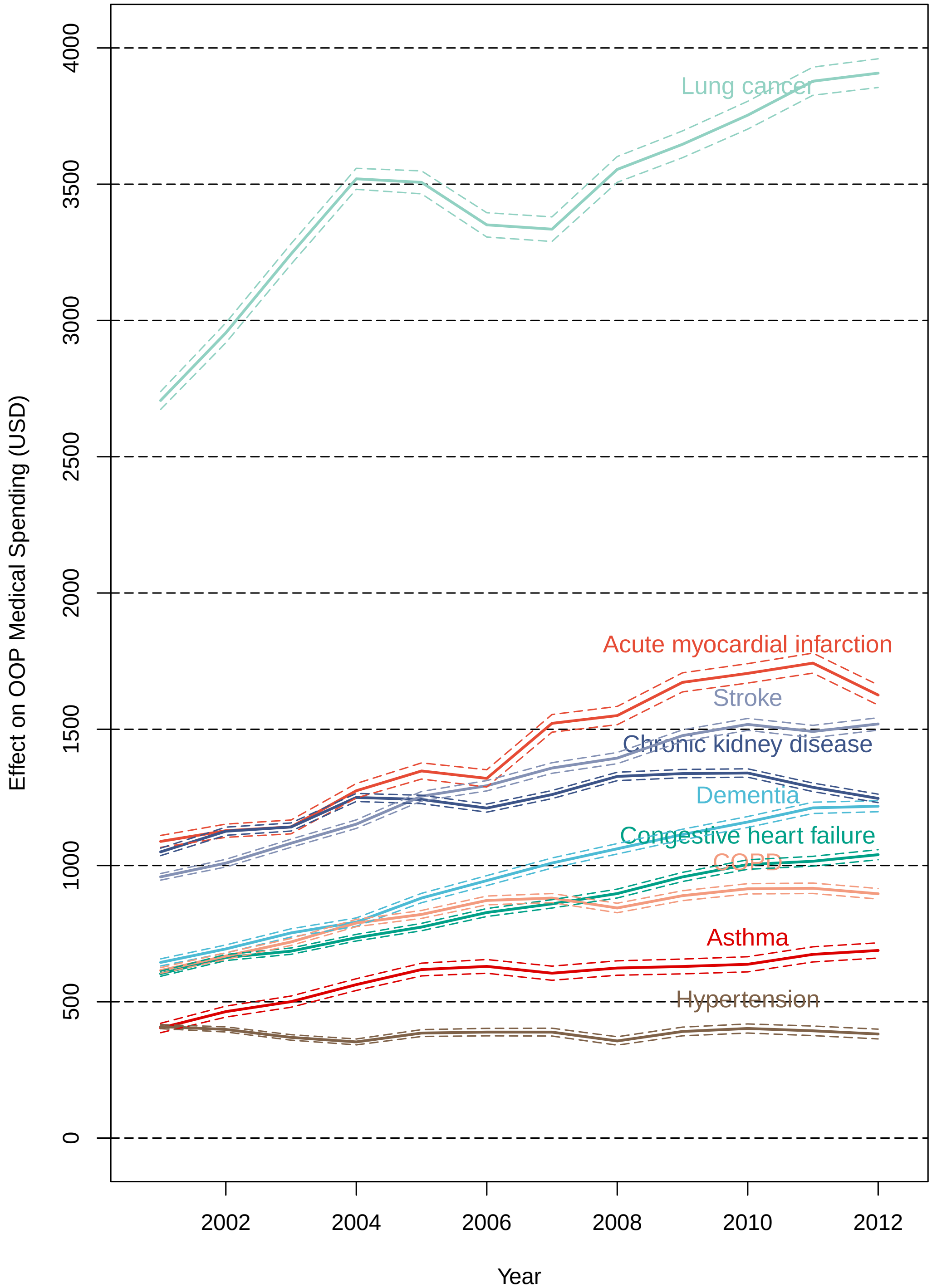
Notes: MCBS ($N = 9,931$) subsample. Low Income - less than \$15,000 per year, High Income - more than \$30,000 per year

sizable expenditure shock and affect other economic decisions.

2.4.3 Hypothesis 3: Lower Income Seniors Spend More on Health Care

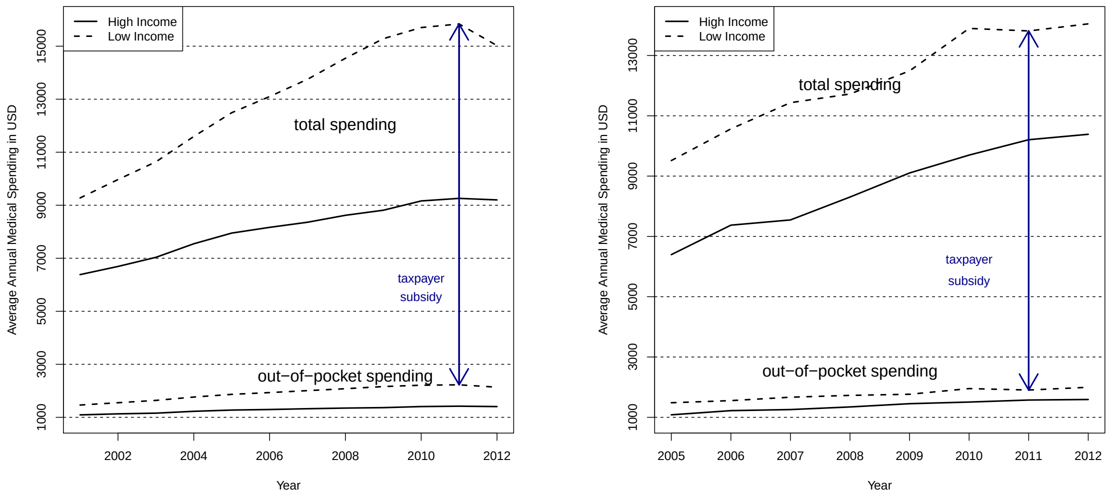
Figure 2.6 reports the differences in annual out of pocket medical spending between high and low income groups. The left panel measures high and low income status using Medicaid eligibility as a proxy. The right panel uses individual annual income for the small subset of individuals who are part of the MCBS. The dashed line shows the average out of pocket spending for the low-income group, again defined as individuals with an annual income of less than \$15,000. The solid line shows the average annual expenditures among the high-income group, again defined as individuals with an annual income higher than \$30,000. Consistent with the previous finding supporting Hypothesis (1) that lower income seniors are exposed to higher levels of pollution, potentially afflicting their health, lower income seniors also appear to incur higher

Figure 2.5: Impact of New Diagnoses on Out-of-Pocket Spending



Notes: Dashed lines mark 95 percent confidence intervals. Estimating Equation (2.6).

Figure 2.6: Medicare Spending by Income



Notes: Low Income - has been eligible for Medicaid at least once during the study period, High Income - never been eligible for Medicaid.

Notes: MCBS ($N = 9,931$) subsample. Low Income - less than \$15,000 per year, High Income - more than \$30,000 per year

out of pocket cost of medical care.

2.4.4 *Hypothesis 4: Health Shocks Increase Migration*

The vast majority of chronic illnesses that are observed increase the propensity to move significantly. While the annual propensity to move across all years averages at 3.27 percent, the event of a new COPD diagnosis in the past year increases the propensity to move by 0.53 percentage points, which amounts to an increase of 16 percent.[6] Figure 2.7 shows the impact of a new diagnosis on the propensity to move by condition and by year, for select conditions that have been linked to exposure to air pollution or are exacerbated by it. A recent dementia diagnosis increases the likelihood of moving by 130 percent on average. It is worth noting that dementia

[6] Averages are taken across years 2001 through 2012, significance is determined at the 5 percent level.

has been linked to prolonged exposure to air pollution in recent research (Bishop *et al.*, 2018). Appendix Table B.1 shows the average impact across all years for all conditions.

2.4.5 *Hypothesis 5: Migrants Who Suffered a Bad Health Shock Tend to Move to Low Amenity Places*

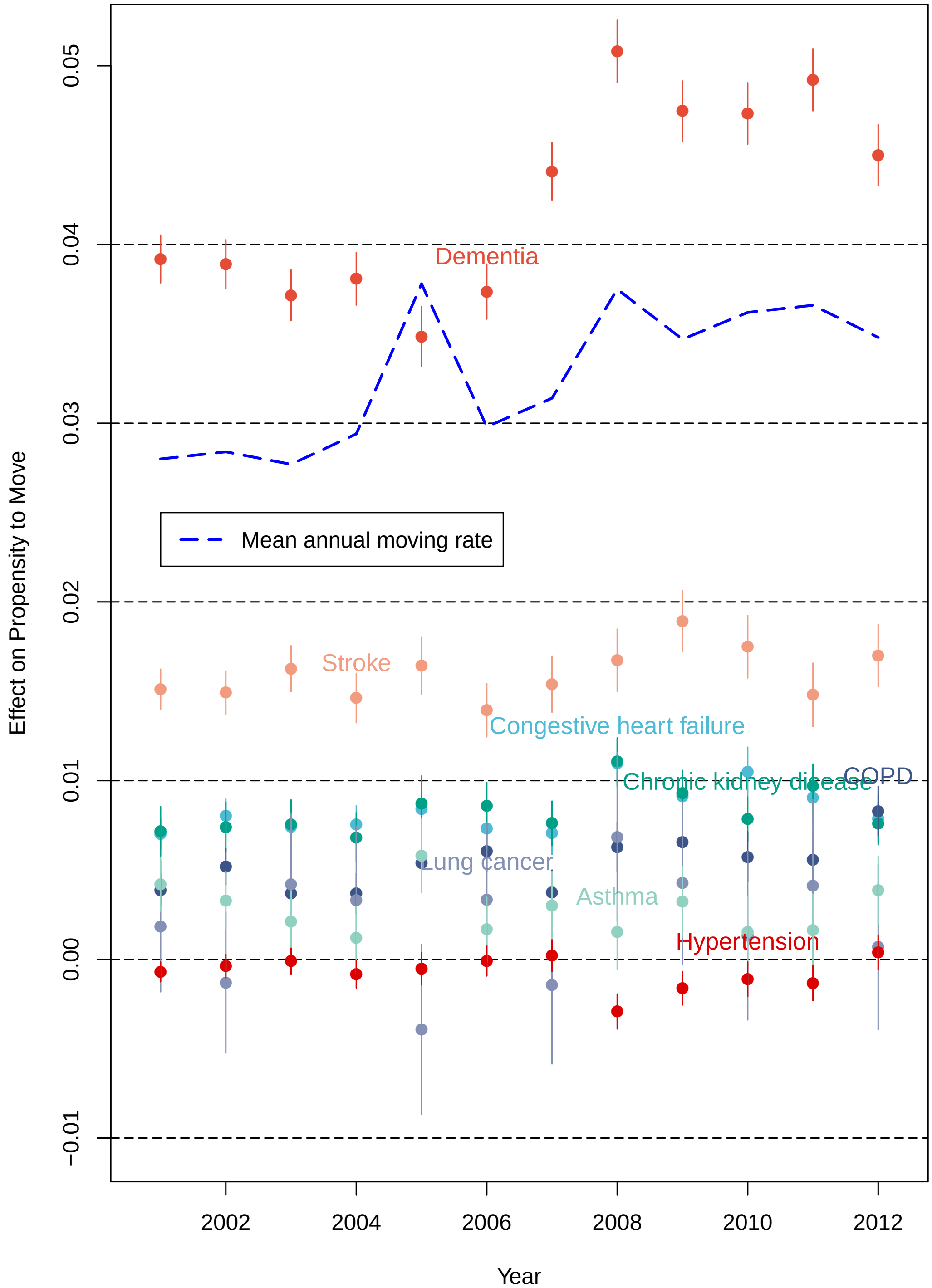
Figure 2.8 compares the average exposure to ambient air pollution in the form of fine particulate matter ($PM_{2.5}$) among movers with and without diagnosed respiratory conditions. Asthma, COPD, and lung cancer are considered specifically and summarized as "respiratory conditions". While it appears to be true that movers move to relatively less polluted areas, this is surprisingly less true for movers who have been diagnosed with respiratory conditions.

2.5 Conclusion

With rich administrative data on health and locations of seniors, I have been able to shed light on the economic interactions between health, income, and the environment among seniors in the US. A repeated static model framework rationalizes the puzzling fact that seniors who have been diagnosed with respiratory illnesses might in fact not move to systematically less polluted locations.

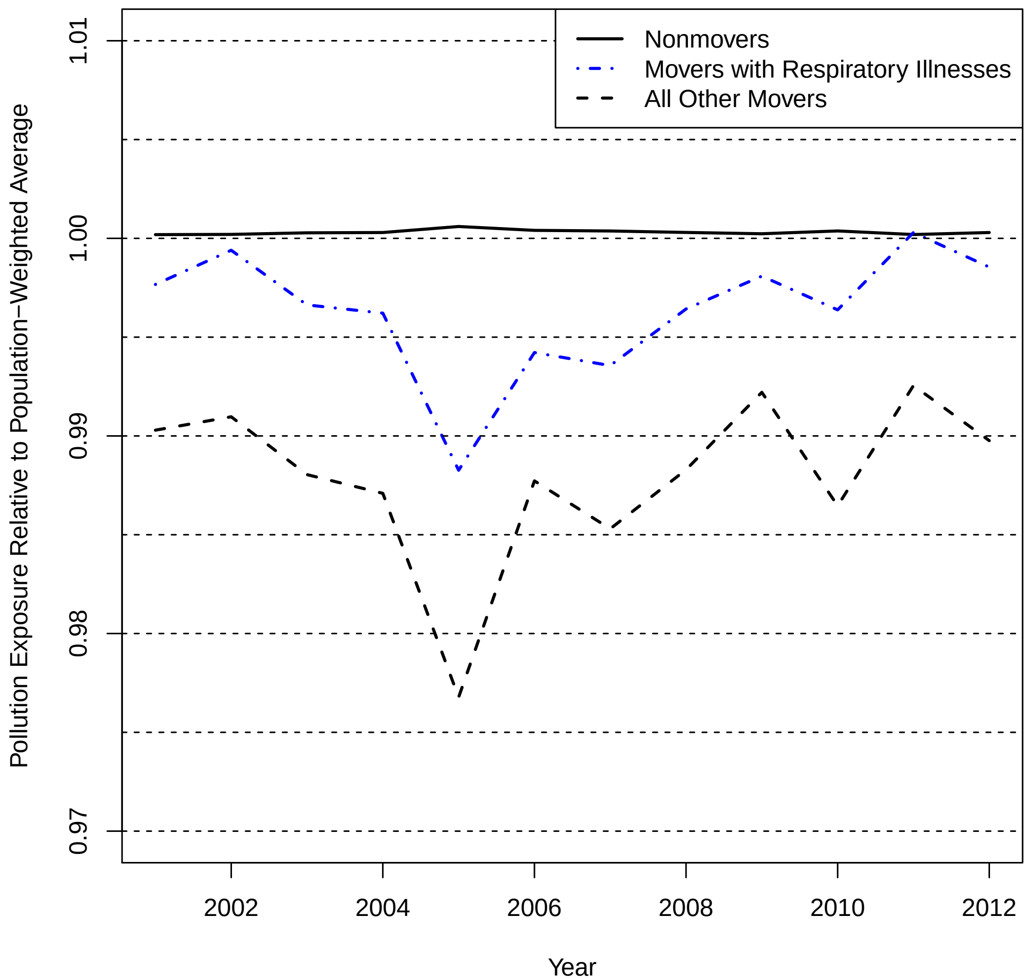
Negative health shocks increase out of pocket medical spending considerably, and also trigger spatial re-sorting. Constrained by less disposable income due to the expenditure shock, low income seniors might choose to move to even more inexpensive areas. Inexpensive locations offer less amenities and tend to be more polluted (Chay and Greenstone, 2005), leaving them more vulnerable to future negative health shocks. Together with the fact that lower income seniors already tend to live in more polluted areas, this suggests that initial differences in health and income might be reinforced

Figure 2.7: Impact of New Diagnoses on Annual Propensity to Move



Notes: Lines mark 95 percent confidence intervals. Estimating Equation (2.7).

Figure 2.8: Pollution Exposure for Movers With and Without Respiratory Illnesses



and exacerbated by the differential exposure to pollution and its adverse effects on health.

Chapter 3

SORTING FOR LIFE: HOUSING PRICES AND MORTALITY

Recent research has shown that there is considerable spatial heterogeneity in expected longevity in the US (Chetty *et al.*, 2016) and that locations in fact have a causal impact on the expected longevity of their residents (Finkelstein *et al.*, 2018). This implies that in principle, people can extend their expected lifespan by moving to high-longevity places. Assuming that these differences are known to people, and that a longer life is desirable, locations with more favorable effects on mortality can be expected to have higher equilibrium cost of housing. This study exploits the joint variation of causal local mortality effects and housing prices as a novel lever to estimate the value of a statistical life (VSL) for Americans over age 65.[1]

The VSL for seniors is perhaps the single most important and least understood statistic for evaluating public policies targeting human mortality. Seniors are the main beneficiaries of Medicare programs and environmental policies. For example, according to the EPA seniors account for approximately 78 percent of the deaths avoided by air pollution regulations (IEc, 2011). However, the academic literature and federal benefit-cost analyses routinely monetize the benefits of these mortality reductions by multiplying the number of avoided deaths by VSL estimates in the $5 to $10 million range derived from the behavior of workers who are much younger and healthier. Indeed, the average age in wage-hedonic VSL studies is typically close to 40 (Kniesner *et al.*, 2014; Lee and Taylor, 2019). Economic theory using life cycle models suggests that the VSL will evolve with age as health, wealth, and life years remaining change.

[1]This has been joint work with Kelly Bishop, Alvin Murphy, and Nicolai Kuminoff.

I estimate the VSL for seniors by extending the canonical Rosen (1979) and Roback (1982) model of spatial compensating differentials to determine how much homebuyers implicitly pay for statistical life extension. Intuitively, seniors can choose to pay more to live in areas with amenities that enhance their health and longevity (e.g. mild climates, clean air, low crime, good health care). These observed tradeoffs can be used to derive a revealed preference measure of the VSL. I accomplish this task in two stages. First, I extend the methodology from Finkelstein *et al.* (2018) to estimate how residential locations affect mortality rates among seniors in 5-year age bins (65-69, 70-74,...90+). Then I estimate an interregional hedonic model to estimate the WTP for a marginal increase in statistical life extension that can be scaled up to calculate the VSL for each age bin.

The main identification challenge is that the bundle of location-specific amenities that affect the quantity of life is also likely to affect the quality of life. For instance, elevated levels of air pollution simultaneously reduce utility from outdoor recreation and increase the risk of having a fatal heart attack or stroke. As a result, failing to separately control for how amenities affect the quality of life is likely to impart an upward bias on VSL estimates. On the other hand, controlling for location-specific amenities that simultaneously affect the quantity and quality of life will impart a downward bias on VSL estimates. I address this by using the logic of Manski (1999) and Nevo and Rosen (2012) to sign the direction of bias on VSL estimates in models that do and do not control for distinct location-specific amenities. I use this approach to estimate upper and lower bounds on the VSL. My bounds are informative in the sense that the upper bounds for the oldest age groups lie below the $8 to $10 million range of wage hedonic estimates commonly used to monetize mortality among seniors.

In my preferred specification, I find lower and upper bounds of $6.0 million and $41.5 million for 65-69 year olds in constant year 2000 dollars. This range includes the estimate of $8 million in year 2006 dollars used in the EPA's Second Prospective Analysis of the Clean Air Act IEc (2011). The ranges systematically decline for older age groups. For example, the estimated range for over 90 year olds ($0.6 to $4.4 million) is less than half of the EPA estimate. Thus, these revealed preference estimates suggest that the oldest seniors' willingness-to-pay for mortality risk reductions may be considerably smaller than commonly assumed when evaluating environmental regulations.

This is the first study to estimate the VSL for seniors using revealed preference evidence from housing markets. It is also one of very few studies to develop revealed preference estimates of VSL for seniors, or to estimate a VSL from the housing market. Prior evidence on the VSL for seniors has primarily come from stated preference studies. Perhaps the most closely related prior study is Ketcham *et al.* (2020) who estimate seniors' VSL from national evidence on medical expenditures and find estimates close to my lower bounds. While there is a large hedonic property value literature on how health risks are capitalized into housing values, Davis (2004) is perhaps the only study to use this information to calculate a statistic similar to the VSL. Using evidence from a cancer cluster in Churchill County, Nevada, Davis estimates the value of avoiding a statistical case of pediatric leukemia is approximately $5.6 million dollars. This estimate, while within my range of estimates for younger seniors, is not directly comparable to my estimates because it applies to children only, leukemia is not necessarily fatal, and the estimates are based on residents of two Nevada counties.

3.1 Related Literature

3.1.1 *Spatial Differences in Mortality*

Spatial differences in mortality have been first documented by Chetty *et al.* (2016), and soon after been found to be explained to a considerable degree by causal location-specific mortality effects (Deryugina and Molitor, 2018; Finkelstein *et al.*, 2018). Exposure to different levels of enironmental quality rationalizes some of the spatial differences in health (Pope III *et al.*, 2002; Schlenker and Walker, 2015; Bishop *et al.*, 2018; Deryugina *et al.*, 2019).

3.1.2 *Spatial Equilibria*

Early seminal literature has formalized spatial equilibria that rationalize housing price differences across space. Housing prices are part of general equilibria that include the market for public goods and labor markets (Rosen, 1979; Roback, 1982). Spatial differences in housing prices have been used to estimate valuation for public goods (Bayer *et al.*, 2009). Graves and Waldman (1991) show that when public goods are compensated for in both the housing markets and the labor markets through rents and wages, seniors who are retired from the labor force seek out locations that compensate for public goods through lower wages rather than higher rents, because retirees do not need to care about the wage levels and only care about rent levels.

3.1.3 *Classical Approaches to Estimating the VSL*

Willingness to pay to extend life or improve life quality has been estimated with a variety of methods. Alberini and Ščasnỳ (2018) provides a recent summary comparing different revealed preference methods and stated preference methods to estimate the VSL. The most popular revealed preference method in the past and present thus far has been compensating wage studies (Viscusi and Aldy, 2003; Kniesner *et al.*, 2014; Lee and Taylor, 2019). Stated preference studies have elicited the value of a statistical case of morbidity (Hammitt and Haninger, 2011; Alberini *et al.*, 2009).

Studies have pointed out that VSL estimates are very heterogeneous, and aimed at reconciling estimates. Among the reasons why they could differ are sensitivity to reference points (Kniesner *et al.*, 2014), different possibility sets across populations (Hersch and Viscusi, 2010), different risk preferences (Viscusi and Hersch, 2001), different demographics (Alberini *et al.*, 2004), and differences in age, health, and gender (Ketcham *et al.*, 2020).

3.1.4 Estimating Value of Health Through the Housing Market

Capitalization of local (dis)amenities into housing prices has been used plentifully to estimate willingness to pay for (dis)amenities, among them estimates of the value of a statistical case of morbidity, which is conceptually equivalent to the VSL. Gayer *et al.* (2000) estimate the value of a statistical case of cancer at USD 4.6 million, leveraging variation in the timing of the EPA's reassessment releases after Superfund cleanups. Davis (2004) estimates the value of a statistical case of pediatric leukemia (VPL), using information about a sudden cancer cluster within a county. This natural experiment mitigates the two main concerns that are omitted variable bias and sorting on unobservables. The resulting estimates of the VPL range between 3 and 9 million dollars (2000). Besley and Mueller (2012) estimate the WTP to live in peace, using variation in killings through the peace process in Northern Ireland. This study calculates hedonic estimates for WTP to avoid violent civil conflict, hence in principle the numbers could be used to estimate a VSL, assuming that killings could affect people randomly. Billings and Schnepel (2017) estimate impact of lead exposure risk on neighborhoods, finding that returns on investment in lead remediation exceed costs more than twofold. To my knowledge, the present study is the first to use capitalization effects to estimate the VSL for seniors.

3.2 Conceptual Framework

A location j is characterized by the amenities a_j that it offers, its housing prices r_j, and by its menu of causal annual mortality effects m_j for different age groups. Assume there are two types of individuals - adults and seniors. Assume furthermore that mortality differences across locations for adults are negligible. Then adults' utility from location j is a function of amenities and housing.

$$u^a(a_j, r_j) \tag{3.1}$$

Seniors' utility is a function of amenities, housing prices, and mortality

$$u^s(a_j, r_j, m_j) \tag{3.2}$$

Assume that seniors like to live. Then, ceteris paribus, locations that offer lower mortality should be in higher demand and thus be in equilibrium more expensive in terms of housing. If individuals are free to move across locations, Roback's (1982) framework suggests that housing prices should be a function of both mortality and amenities.

$$r = r(m_j, a_j) \tag{3.3}$$

Mortality however, is not only determined by location, but is also a function of seniors' own age. Naturally, mortality is an increasing function of age, and has been modelled as log-linear in age since Gompertz (1825), and recently in Finkelstein *et al.* (2018). Assume therefore that mortality is a function of age and a location-specific place effect γ_j.

$$m(age, j) = \exp\left(\beta \cdot age + \gamma_j\right) \tag{3.4}$$

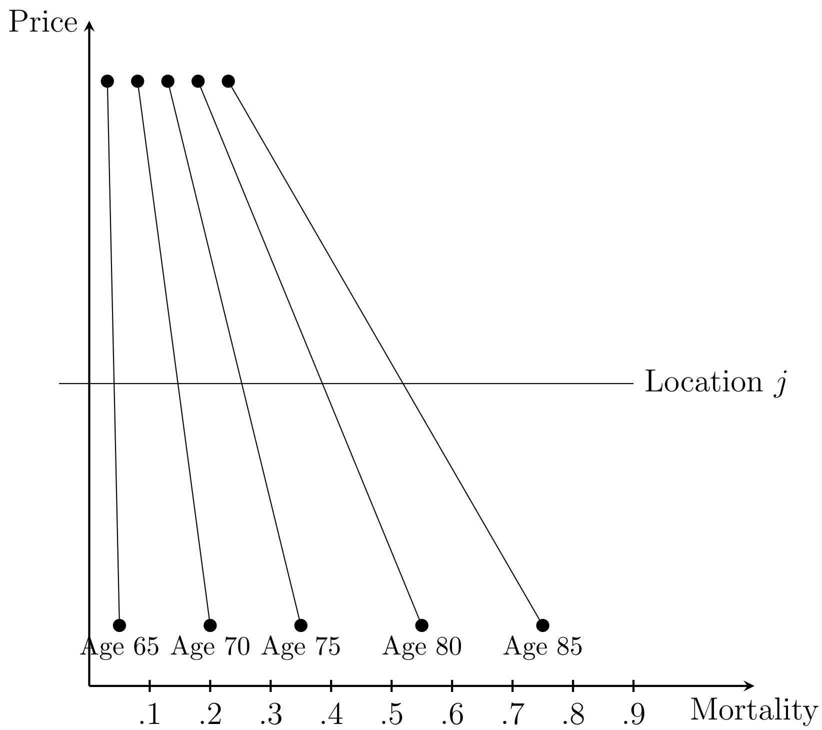
Assuming that γ_j is location-specific, this relationship implies that at age 65, differences in causal mortality effects across locations are somewhat small, but they become more pronounced as age progresses. At the same time, the price that an individual pays for housing can be reasonably expected to be independent of their own age. For an illustration of a spatial equilibrium, see Figure 3.1. The "Age 85" locus is the set of all available (price, mortality) location options for individuals aged 85. If prices are perfectly inversely correlated with mortality across locations at any given age, as they are in this theoretical exercise, and given that mortality increases monotonically in age, the age-mortality menus across locations will form a pattern similar to the one illustrated. A location will be characterized by one price level, and for different ages the location will be characterized by different levels of annual mortality. Renters (home buyers) will pay the same rent (price) for a given house, regardless of their own age. The location they choose however will provide different rates of mortality, depending on the individuals' own age.

An important point to note is that when mortality differences across locations increase in age, as they do in an age-mortality relationship like (3.4), individuals of older ages have to move to locations of much lower mortality rates and pay much higher price differences than individuals of younger ages to achieve the same absolute mortality reduction by moving. At the same time, the aggregate demand across all ages will determine the equilibrium price of a location.

3.3 Data

Data on individual health and mortality comes from administrative panels from the Centers for Medicare and Medicaid Services (CMS). The panel is a random 10 percent sample of all Medicare enrollees from 2000 to 2013. It contains annual information on residential location (ZIP+4), individual health, and individual demographics

Figure 3.1: Illustration of Mortality Menus - The Age-Mortality Curtain



age, gender, and race.

Data on housing cost and housing characteristics comes from the 2000 Census. The Census provides a rich representative national sample of the population of interest at a fine spatial resolution. The Census contains individual data on housing expenditures and housing characteristics together with comprehensive demographic information. To estimate the relationship between mortality and housing prices, the sample is restricted to individuals aged 20 years and older with information about either rent, for renters, or the value of the home, for home owners. The finest geographic unit that can be observed are Census PUMAs. Census PUMAs are spatially contiguous areas comprised of 100,000 individuals. There are 2,071 PUMAs observed in the data. Local causal mortality effects are estimated by PUMA, and identified off of

Table 3.1: Summary of Unconditional Annual Mortality by Age Group

	PUMA		SUPERPUMA	
Age	Mortality	SD	Mortality	SD
65	0.032	0.043	0.030	0.019
70	0.041	0.031	0.039	0.016
75	0.061	0.037	0.057	0.019
80	0.092	0.051	0.087	0.026
85	0.141	0.080	0.136	0.036
90	0.231	0.125	0.219	0.057

Notes: Data source: Center for Medicare and Medicaid services. Average annual mortality in each location in 2002. Standard deviations taken across locations.

cross-PUMA movers. [2]

3.4 Estimation

3.4.1 Causal Local Mortality Effects

To estimate the causal effect that each location has on the probability of survival, I use the estimation strategy of Finkelstein *et al.* (2018). The survival probabilities $\hat{s}_j^{\tau}$ are age and place specific and are assumed to be known to individuals. Empirical place-specific survival rates might differ from causal survival rates due to spatial sorting on underlying health. Since death can only be observed once, panel estimation is precluded. Finkelstein *et al.* (2018) use a selection correction procedure to esti-

[2] The ZIP+4 codes are mapped into 2010 Census block groups, and then mapped into 2000 Census PUMAs based on a crosswalk from the University of Missouri Data Center.

Table 3.2: Summary of Causal Annual Mortality Estimates by Age Group

	PUMA		SUPERPUMA	
Age	Mortality	SD	Mortality	SD
65	0.020	0.004	0.019	0.002
70	0.030	0.005	0.029	0.003
75	0.047	0.011	0.046	0.005
80	0.072	0.011	0.071	0.007
85	0.111	0.017	0.110	0.011
90	0.172	0.026	0.171	0.018

Notes: Data source: Center for Medicare and Medicaid Services. Causal mortality estimates based on the strategy by Finkelstein *et al.* (2018), calculated for each geographic unit using the national average health stock. Standard deviations taken across locations.

mate place specific survival effects δ_j^{surv} in a way that leverages variation in survival among movers. The identifying variation comes from movers who move to different destinations from the same origin location.

Equation 3.5 shows the estimating equation. Individual mortality m_i is is regressed on age, demographics x_i, health h_i, and place fixed effects for movers and nonmovers.

$$\log(m_i) = \varphi_1\, age_i + \varphi_2\, x_i + \varphi_3\, h_i + \delta_j^o\, \mathbb{I}_{j,orig} + \delta_j^d\, \mathbb{I}_{j,orig} + \delta_j^n\, \mathbb{I}_{j,dest} + \eta_i \tag{3.5}$$

Demographic variables contain gender, race, and an interaction term. The location fixed effects δ_j^o, δ_j^d, δ_j^n capture the location specific mortality effects of each location δ_j^n for non-movers, and δ_j^o and δ_j^n for the origin and destination locations of movers.

The location specific effects on mortality δ_j^d could be biased if movers sort into locations based on unobserved health. To address this concern, Equation 3.6 shows how $\hat{\delta}_j^d$ is corrected for spatial sorting on health, under the assumption that selection on unobserved health can be approximated by selection on observed health.

$$\hat{h}_i = \varphi_1^h \, age_i + \varphi_2^h \, x_i + \zeta_j^o \, \mathbb{I}_{j,orig} + \zeta_j^d \, \mathbb{I}_{j,dest} + \eta_i^h \tag{3.6}$$

The fitted health stock from Equation 3.5, $\hat{h}_i := \hat{\varphi}_3 h_i$, is then regressed on age, demographics, and location specific fixed effects. $\hat{\delta}_j^d$ is then corrected by the estimated health-sorting effect $\hat{\zeta}_j^d$. The causal place-specific mortality effect $\hat{\gamma}_j$ is then estimated as

$$\hat{\gamma}_j = \hat{\delta}_j^d - \frac{\hat{sd}(\hat{\delta}_j^o)}{\hat{sd}(\hat{\zeta}_j^o)}\hat{\zeta}_j^d \tag{3.7}$$

$\hat{sd}(\hat{\delta}_j^o)$ and $\hat{sd}(\hat{\zeta}_j^o)$ are estimated as the standard deviations of δ_j^o and ζ_j^o in a split-sample bootstrap.

3.4.2 Modelling the Spatial Unit of Choice

Residential sorting theory does not suggest a particular way to partition the country into residential locations. Empirical studies often use metropolitan statistical areas (e.g. Bayer *et al.* (2009)), counties (e.g. Blomquist *et al.* (1988)) or public use microdata areas (e.g. Albouy *et al.* (2016)). In my case, the spatial unit of observation should ideally be chosen to reflect spatial heterogeneity in mortality risk. Defining locations to be too small (e.g. Census blocks) will introduce measurement error because people routinely travel outside their immediate residential locations are are thereby subject to mortality effects at a larger spatial scale (e.g. local hospital quality). Likewise, the smaller the residential location, the greater the scope for measurement error in mortality rates. On the other hand, defining residential locations to be too large (e.g. states) will ignore meaningful identifying variation in mortality risk. I address these tradeoffs by considering differently sized areas that approximately match the range of areas used in prior national hedonic models. Specifically, I consider Public Use Microdata Areas (PUMAs), Super PUMAs, and hospital referral regions (HRR).

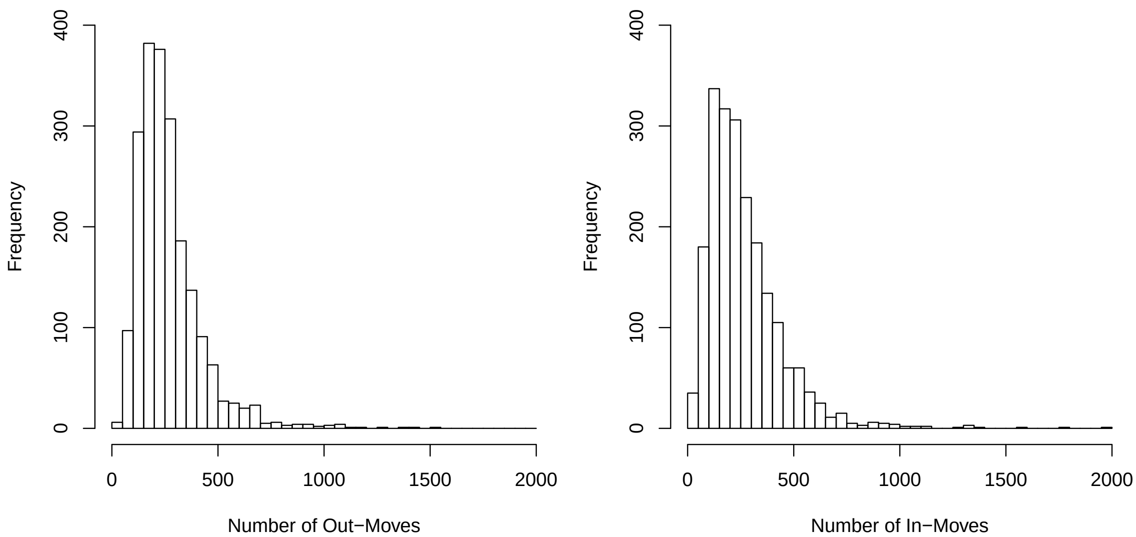
A Census PUMA is geographically contiguous area of approximately 100,000 residents, and could be thought of as a neighborhood. Census SUPERPUMAs are supersets of PUMAs and typically contain four to five PUMAs. Defining a location to be a PUMA requires the estimation of 2,071 distinct local mortality effects, compared to 532 in the case of SUPERPUMAs.

Since the mortality effects are estimated based on location-to-location movers, a few summary statistics are in order. On the PUMA-to-PUMA level, I observe a total of 552,003 moves between the years 2001 and 2012. Every PUMA has positive numbers of in-moves and out-moves. The median number of emigrants by PUMA is 233, the median number of immigrants is 224. The 10th percentile of emigrants is 122, the 10th percentile of immigrants is 146. The 90th percentile of emigrants is 440 and hence a bit lower than the 90th percentile of immigrants, which is 475, indicating that the distribution of immigrants across PUMAs has a larger right tail than the distribution across emigrants. Some PUMAs appear to be very popular destinations. Figure 3.2 shows the distributions of emigrants versus immigrants by PUMA.

Across SUPERPUMAs, I observe a total of 452,198 moves. This implies that almost exactly 100,000 moves across PUMAs have occurred within SUPERPUMA. Every SUPERPUMA has positive numbers of immigrants and emigrants, in fact a minimum of 146 immigrate into every SUPERPUMA and a minimum of 205 people emigrate from each SUPERPUMA. Again the distribution of immigrants across SUPERPUMAs has a larger right tail than the distribution of emigrants, which implies that some SUPERPUMAs are very popular destinations.

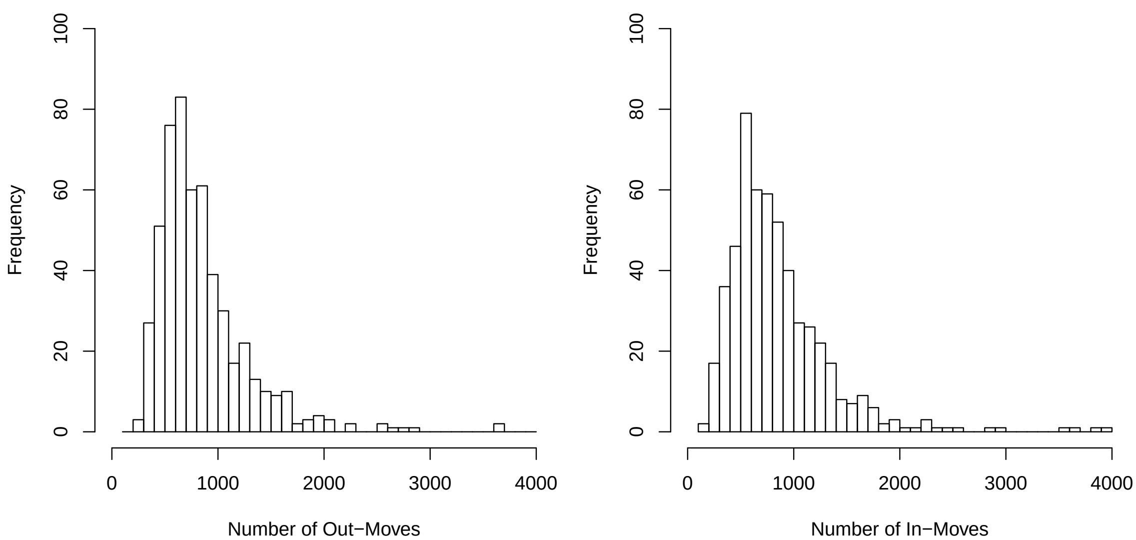
The central estimation equation is Equation (3.9), in which the log of housing cost r_{ijh} is regressed on the location specific mortality m_j, controlling for the characteristics

Figure 3.2: Histograms of Emigrants vs Immigrants by PUMA



Notes: Total number of in-moves and out-moves by PUMAs occurring in the sample among individuals who have moved exactly once across PUMAs during the sample period 2001-2012.
Data: Center for Medicare and Medicaid Services.

Figure 3.3: Histograms of Emigrants vs Immigrants by SUPERPUMA



Notes: Total number of in-moves and out-moves by SUPERPUMAs occurring in the sample among individuals who have moved exactly once across SUPERPUMAs during the sample period 2001-2012.
Data: Center for Medicare and Medicaid Services.

Table 3.3: Distribution of Moves Across PUMAs and SUPERPUMAs

	PUMA		SUPERPUMA		HRR	
	Out	In	Out	In	Out	In
Min	7	2	205	146	182	166
10th perc.	122	100	442	396	434	398
Median	233	224	748	740	1,122	1,094
90th perc.	440	475	13,80	1,359	3,222	3,442
Max	1,506	1,979	3,685	3,934	10,673	10,633
No. of Moves	552,003	552,003	452,198	452,198	485,659	485,659

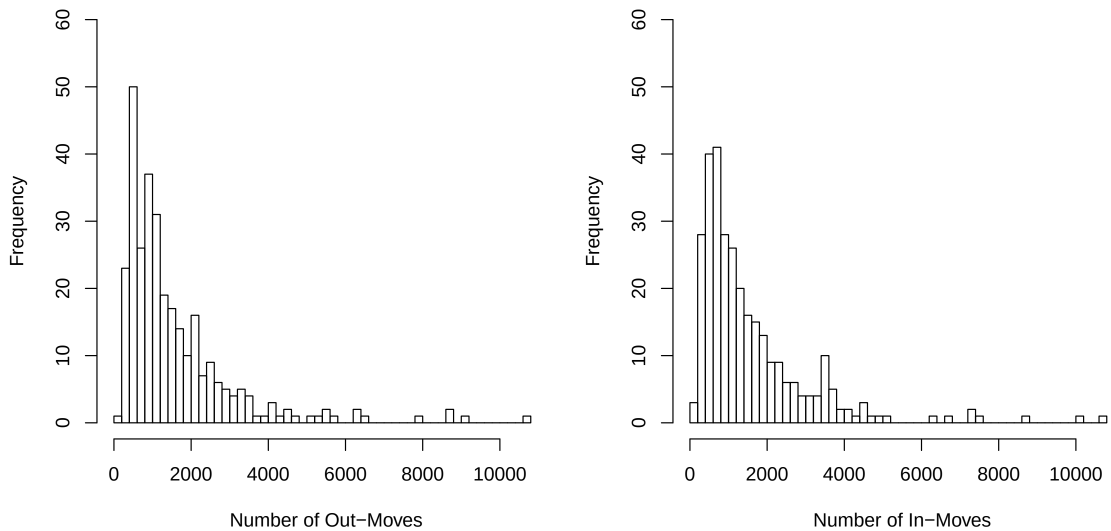
Notes: Sum of all moves occurring in the sample among individuals who have moved exactly once across geographies during the sample period 2001-2012. A move is defined as changing the residential address from one PUMA (SUPERPUMA, HRR) to another PUMA (SUPERPUMA, HRR).
Data: Center for Medicare and Medicaid Services.

of the house x_h such as the number of bedrooms and the decade in which it was built, and an indicator for ownership status own_h. The housing cost r is defined as the monthly gross rent for renters and the self-reported home value for home-owners, following the strategy of Bayer *et al.* (2009).

$$\log r_{ijh} = \beta_m m_j + \beta_h x_h + \beta_o own_h + \varepsilon_{ijh} \tag{3.8}$$

A natural concern in estimating β_m in this way is omitted variable bias. For example, great hospitals might decrease the causal mortality effect of a location, but also be valued for the utility they provide apart from extending expected longevity, and thereby increase rents. The bias however appears to be clearly signed. Amenities like great environmental quality, mild climates, low levels of crime, high quality of medical care, can all be reasonably expected to lower mortality and increase equilibrium

Figure 3.4: Histograms of Emigrants vs Immigrants by HRR



Notes: Total number of in-moves and out-moves by HRRs occurring in the sample among individuals who have moved exactly once across HRRs during the sample period 2001-2012.
Data: Center for Medicare and Medicaid Services.

rents. If local unobserved amenities that decrease the causal mortality effects are also independently valued by individuals, the estimate $\hat{\beta}_m$ provides an upper bound for the effect of mortality on prices. The same logic can be applied to the effect of local amenities on morbidity. Amenities that reduce mortality also tend to improve morbidity, increasing individuals' quality of life while they are alive. Assuming that the morbidity effect is non-negligible, controlling for amenities that also have an effect on morbidity will over-correct $\hat{\beta}_m$.

In order to also provide an estimate for the lower bound of the true β_m, Equation (3.9) is re-estimated including local amenities in Equation (3.8). Part of what people value in amenities is precisely that they reduce mortality. For example, controlling for the local quality of health care eliminates the upward bias from the effect of health care on mortality, but it leads to an over-correction since high quality health care is valuable to people beyond its effect on mortality. Therefore, the $\hat{\beta}_m$ from Equation (3.8) will provide an estimate for a lower bound on the true β_m, assuming that all relevant amenities are included in the model. To allow for the possibility that my set of observed amenities may exclude some that are important for mortality, I also repeat the estimation after including dummy variables for metropolitan areas.

$$\log r_{ijh} = \beta_m m_j + \beta_a a_j + \beta_h x_h + \beta_o own_h + \varepsilon_{ijh} \tag{3.9}$$

The second concern is sorting on unobservable amenities that correlate with mortality. For example, if the high-income individuals that inhabit the low mortality neighborhoods vote to tax themselves to build other nice amenities, the estimated relationship β_m will be overstated.

To investigate whether my estimates are sensitive to assumptions about the extent to which households are informed about mortality, I estimate Equation (3.9) with different measures of mortality. First, I use causal location-specific mortality estimates. I estimate these for each Census PUMA, by adapting the strategy of Finkelstein *et al.* (2018). The identifying variation comes from movers who are similar at baseline and move from the same origin to different destinations. Under the assumption that sorting on unobservable health is equally important as sorting on observable health, the selection correction strategy yields causal location-specific mortality effects. Using these measures in the hedonic model presumes that seniors have relatively accurate beliefs about the causal effects of place on mortality.

Then, I re-estimate Equation (3.9) using empirical unconditional mortality rates for different age groups. To rule out that sampling issues threaten comparability, I use the same sample assembled for the estimation of location specific mortality effects and record the empirical mortality rates per age group in the year 2002. Using these mortality measures in the hedonic model presumes that seniors have biased beliefs about the causal effects of place on mortality because they fail to adjust for the extent to which empirical survival probabilities are driven by spatial sorting on health, income, and other factors that contribute to longevity. I estimate each equation separately for the mortality estimates of the different age groups, e.g. 65-69 year olds, 70-74 year olds, 75-79 year olds, etc.

3.4.3 Interpretation: Willingness to Pay for Statistical Life Extension

To estimate the VSL, I use the calculation (3.10). Multiplying the estimated coefficient of mortality on housing prices $\hat{\beta}_m$ with the average level of monthly gross rents r, the number of months per year, and the denominator of the annual mortality rate yields the estimate.

$$\widehat{VSL} = -\left(\frac{\partial \hat{r}}{\partial m} = \hat{\beta}_m \cdot r\right) \cdot 12 \cdot 100 \tag{3.10}$$

3.5 Results

Table 3.4 shows the resulting VSL estimates where mortality effects are estimated at the PUMA level. Based on casual mortality effects, the VSL estimates for 65 to 69 year old seniors is 41.5 million dollars. I interpret this estimate as an upper bound for the VSL for 65 to 69 year olds, since the bias from omitted variables that correlate with mortality appears to be uniformly signed. The estimates based on causal mortality effects appear to be intuitively monotonic in age. The corresponding VSL estimate for 75 to 79 year old seniors is 16.1 million dollars, and 6.5 million dollars for 85 to 89 year olds. The estimates that are based on empirical mortality effects are much smaller, somewhat less intuitive in terms of there monotonicity in age, and when controlling for amenities are wrongly signed for the oldest age group. The differences between causal mortality and empirical mortality reflect spatial differences in the stock of health of the population.

Table 3.5 shows the same VSL estimates when local amenities, measured at the PUMA level, are controlled for. The amenities included here are summer temperature, winter temperature, precipitation, health care, $PM_{2.5}$, golf courses, and log population density. Additionally, I estimate all specifications using metro area fixed effects. Including these absorbs all between-metro variation in longevity. When I include both metro area fixed effects and observable amenities, I remove the between-metro variation as well as the within-metro variation in longevity that is caused by these amenities. Controlling for amenities and fixed effects results in a VSL estimate of 6.0 million dollars for 65 to 69 year old seniors. I interpret this as a lower bound on the VSL, since including amenities that affect mortality but also affect utility apart from their effect on mortality will over-correct the estimates. The lower bounds are informatively high relative to revealed preference evidence from medical expenditures based on Ketcham *et al.* (2020) and Hall and Jones (2007), especially for the youngest age groups. Meanwhile, the upper bounds for older cohorts (85 to 89 year olds and over 90 year olds) are informatively low relative to conventional revealed preference estimates from the wage hedonic literature. Kniesner *et al.* (2012) estimate a range of \$4 to \$10 million for the working age population, using wage hedonic estimation with occupational fatality risk and study period of 1993 through, slighly overlapping with the sample period of this study. Lee and Taylor (2019) estimate a range of \$8 to \$10 million dollars. Aldy and Viscusi (2008), also employing wage-fatality hedonic estimation and data from 1993 to 2000, estimate the VSL explicitly for different age groups. They do in fact find a hump-shaped relationship between age and the VSL that peaks around the age of 40 and estaimte a VSL of \$5.08 million dollars for their oldest cohort of 62 year old workers.

The estimated upper and lower bounds on the VSL when mortality estimates and amenities are measured at the geographic level of SUPERPUMAs or HRRs can be found in the Appendix Tables B.2, B.3, B.4, B.5.

Table 3.4: Implicit Price of Preventing One Fatality Per Age Group, Equation 3.8, by PUMA

	Age					
	65-69	70-74	75-79	80-84	85-89	90+
VSL, causal mortality	41.5	25.7	16.1	10.2	6.5	4.4
SE	(0.14)	(0.09)	(0.05)	(0.03)	(0.02)	(0.01)
CI, 95 percent	(41.2,41.7)	(25.6,25.9)	(16.0,16.2)	(10.1,10.3)	(6.5,6.6)	(4.4,4.5)
...with Metro Area FE	10.7	6.7	4.2	2.7	1.7	1.2
SE	(0.14)	(0.09)	(0.06)	(0.04)	(0.02)	(0.02)
CI, 95 percent	(10.5,11.0)	(6.5,6.8)	(4.1,4.3)	(2.6,2.7)	(1.7,1.8)	(1.1,1.2)
VSL, empirical mortality	1.9	3.1	2.5	0.9	0.1	0.0
SE	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)
CI, 95 percent	(1.9,2.0)	(3.0,3.1)	(2.5,2.5)	(0.9,0.9)	(0.1,0.1)	(0.0,0.0)
...with Metro Area FE	1.4	2.0	1.4	0.7	0.1	0.0
SE	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)
CI, 95 percent	(1.4,1.4)	(2.0,2.0)	(1.3,1.4)	(0.6,0.7)	(0.1,0.1)	(0.0,0.0)

Notes: VSL in million (USD 2000). Data source: Census 2000 5 percent sample. N with causal mortality estimates 6,605,617, N with empirical mortality estimates 6,682,714. Mortality estimates of one age group included as control.

Table 3.5: Implicit Price of Preventing One Fatality Per Age Group, Equation 3.9, by PUMA

	Age					
	65-69	70-74	75-79	80-84	85-89	90+
VSL, causal mortality	19.1	11.9	7.4	4.7	3.0	2.1
SE	(0.13)	(0.08)	(0.05)	(0.03)	(0.02)	(0.01)
CI, 95 percent	(18.9,19.4)	(11.7,12.0)	(7.3,7.5)	(4.7,4.8)	(3.0,3.1)	(2.0,2.1)
...with Metro Area FE	6.0	3.7	2.3	1.5	1.0	0.6
SE	(0.14)	(0.09)	(0.05)	(0.03)	(0.02)	(0.02)
CI, 95 percent	(5.7,6.3)	(3.6,3.9)	(2.2,2.4)	(1.4,1.6)	(0.9,1.0)	(0.6,0.7)
VSL, empirical mortality	1.9	2.4	2.0	0.6	0.0	-0.0
SE	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)
CI, 95 percent	(1.8,1.9)	(2.4,2.4)	(2.0,2.0)	(0.6,0.6)	(0.0,0.0)	(-0.0,-0.0)
...with Metro Area FE	1.0	1.5	1.0	0.4	-0.1	-0.0
SE	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)
CI, 95 percent	(1.0,1.0)	(1.5,1.5)	(1.0,1.0)	(0.3,0.4)	(-0.1,-0.0)	(-0.0,-0.0)

Notes: VSL in million (USD 2000). Data source: Census 2000 5 percent sample. N with causal mortality estimates 6,605,617, N with empirical mortality estimates 6,682,714. Mortality estimates of one age group included as control.

Amenities: Summer temperature, winter temperature, precipitation, health care, $PM_{2.5}$, golf courses, log population density.

3.6 Conclusion

Combining information on housing prices with estimated causal location-specific mortality effects, I have estimated lower and upper bounds for the Value of a Statistical Life. The estimated upper bounds for seniors over age 85 lie below the $8 to $10 million estimates that are commonly used to value mortality reductions in academic studies and that the EPA uses to evaluate the benefits of policies like the Clean Air Act (IEc, 2011). The estimated ranges for older individuals do cover this number. These coincide with the groups that often benefit most from environmental policies in terms of mortality and morbidity. The methodology used in this study advances on the previous literature by estimating the VSL for the under-studied subpopulation of seniors, leveraging local causal mortality effects across neighborhoods together with information on housing prices. Scope for future research will be to usefully aim to refine the econometric specification to tighten the bounds, possibly by finding a suitable instrument to pin down VSL values more narrowly within the value corridor found in this study.

Chapter 4

A DYNAMIC MODEL OF HEALTH AND RESIDENTIAL SORTING: IMPLICATIONS OF CLIMATE CHANGE FOR SENIORS IN THE US

Many policies that target environmental quality or issues of public health have spatially heterogeneous effects on urban populations. For example, federally subsidized health insurance plans are often sold in distinct state or regional markets, the EPA's Cross-State Air Pollution Rule obligates some states to reduce the pollution they export to other states, and national ambient air quality standards are only enforced in counties where pollution exceeds a given threshold.[1] Thus, federal policies affect people's health and pollution exposures differently depending on where they choose to live. The costs and benefits of these policies depend on how they change local environments, on how those changes affect people's health, and on how people react to these changes. People may react by moving, due to their preferences for local amenities or due to the effects of local amenities on their health, or both. Indeed, "Health Reasons" is among the top responses that seniors provide in the Health and Retirement Survey as a reason for their most recent move, and deciding where to live can be highly consequential for their health. The quality of local health care, environmental amenities such as climate and air pollution, and opportunities for social interaction, can all affect seniors' health and longevity.

This paper integrates the seminal ideas of Tiebout (1956) and Grossman (1972)

[1]Similarly, subsidizing the electric vehicle fleet may reduce air pollution and improve human health in areas where the energy used to power cars is predominantly generated from renewable sources, but increase pollution in areas where the electricity is generated by fossil fuel plants (Holland *et al.*, 2016).

into a new residential sorting model that allows individuals' preferences for residential location amenities may depend, in part, on their health, and that they recognize that the locations they choose may affect their health in the future. Thus, residential location decisions can serve as a costly and conscious form of investment in future health. Recent work has shown that life expectancy varies substantially across space in the US (Chetty *et al.*, 2016), and that the location of residence has a causal impact on life expectancy (Deryugina and Molitor, 2018; Finkelstein *et al.*, 2018). I incorporate these insights by making longevity and health endogeneous to location and by considering how changes in environmental quality affect welfare through amenity flows, the health stock, and longevity. I use the model to investigate the distributional welfare consequences of climate change projections for the United States, taking into account the effects on both residential amenity values and human health, while recognizing that migration can serve as a mitigation strategy.

My application focuses on senior citizens (people over age 65). Seniors are an especially important demographic group when it comes to health and environmental quality because they are known to be more vulnerable to extreme climates and pollution than younger adults in terms of morbidity and mortality, making them the primary beneficiaries of public policies targeting pollution, in addition to being the primary beneficiaries of Medicare programs. Furthermore, seniors are the wealthiest and fastest growing age group in the United States and many other countries, projected to account for one in five US residents by 2030. I study the co-evolution of seniors' health and residential location choices by leveraging rich panel data from the U.S. Centers for Medicare and Medicaid Services (CMS). These data allow me to precisely track the residential location decisions of 5.5 million seniors, their diagnoses of chronic medical conditions, and their deaths from 2001 through 2011.

I model their behavior by developing a dynamic discrete choice model in the spirit of Bayer *et al.* (2016). It incorporates health and age as sources of individual preference heterogeneity and introduces uncertainty about future health status. When individuals choose where to live, they are assumed to know how their location choices will affect their mortality risk and their probabilities of transitioning to various future health states. More precisely, an individual is characterized by age, health, and an individual random utility shock, and chooses a residential location in order to maximize total lifetime utility. Total lifetime utility is the sum of discounted per-period utilities over the remaining years of life. The choice of a residential location determines the levels of amenities that the resident gets to enjoy. Per-period utility from each place is a function of local amenities and prices and differs by health and age type. Future health is a function of both current health and current location. Thus, the model incorporates both static and dynamic tradeoffs between the quantity and quality of life. For example, places that are characterized by pleasant climate and high levels of cultural amenities, but also high levels of air pollution, might yield a high per-period utility, but affect future health negatively and hence shorten the remaining life span.

The estimation proceeds in three stages. First, I estimate the causal place-specific mortality risk following the selection correction regression procedure developed by Finkelstein *et al.* (2018). The estimation includes a highly flexible moving cost function that allows the utility cost of moving t o vary in distance. Next, I estimate the causal place-specific effects on the probabilities of transitioning to worse states of health using an ordered logit approach that leverages the panel data to mitigate potential biases from sorting on latent health. Finally, I estimate preference parameters using a version of Bayer et al.'s (2016) dynamic discrete choice estimator. To instrument the effect of rents on utility, I follow Bayer and Timmins (2007) and use amenities of distant, but similar locations. I innovate on this instrument by finding the most similar distant location through a Principle Component Analysis in the attribute space. The estimated structural parameters permit a novel, highly flexible approach to prospective policy analysis. Policies that change the provision of local amenities heterogeneously across space can be evaluated in terms of their effect on health, longevity, and welfare, while accounting for migration and health dynamics.

I first use the model to estimate seniors' preferences for local amenities, for avoiding migration, and for reducing their morbidity and mortality risk, allowing preferences to vary flexibilty across several age-health types. I find that seniors' preferences vary substantially across age and states of health. For example, I find that the willingness to pay (WTP) for warmer winters as a local amenity is uniformly positive, (ranging from \$104 to \$203 per year for a 1C increase across types) whereas the WTP to pay for cooler summers varies substantially by age and health and is largest among the oldest, sickest individuals (\$160 per year for a 1C decrease). Precipitation appears to be a significant disamenity, with an especially high WTP to avoid wetter climates among sicker and older individuals (\$1,333 per year for a 1 mm decrease in daily precipitation.[2]). I also find that seniors are willing to pay more for access to high-quality local health care, better air quality, and more social amenities, measured by the count of golf courses and country clubs.

I combine these estimates with the estimated effects of climate change on morbidity and mortality to evaluate the distributional welfare implications of the changes in average summer and winter temperatures and precipitation that are projected to occur under the World Climate Research Program's "business as usual" scenario for global carbon emissions through 2100. These changes affect utility flows from climate amenities as well as the present discounted value of changes in longevity and health caused by the way that additional warming is predicted to negatively affect

[2] 1 mm per day adds up to 14.4 inches per year

both mortality and morbidity. Ex ante, the net welfare effects are ambiguous because individuals value warmer winters and can pay to migrate to areas with relatively less warming, both of which can help to offset welfare losses from shortened lifespans. Indeed, I find that the welfare implications of climate change are very heterogeneous in age and health. Younger and healthier types are in fact made better off because they value warmer winters and even warmer summers, to an extent that offsets the adverse health effects of climate change (-$1,770 for the youngest and healthiest type). Older and sicker types suffer from warmer summers and also from increases in precipitation levels ($624 for the oldest and sickest type). Locations that are predicted to have warmer winters but only moderately warmer summers stand to gain the most from the climate change scenario considered here.

My study builds on prior literatures on Tiebout sorting and spatial variation in morbidity and mortality. The Tiebout sorting literature has previously analyzed the equilibrium implications of sorting on heterogeneous preferences and income (e.g. Epple and Platt (1998)) and developed static random utility representations of individual choice to estimate preferences for local amenities such as air pollution and school quality (e.g. Bayer *et al.* (2007) and Bayer *et al.* (2009)). Albouy *et al.* (2016) and Sinha *et al.* (2018b) used sorting models to analyze the welfare effects of climate change, but did so in a static environment that abstracted from the health impacts of climate change. Bayer *et al.* (2016) developed a dynamic discrete choice framework for modeling residential location decisions made by forward-looking agents. I extend their approach to treat health as an endogenous state variable that simultaneously reflects the amenity exposures determined by past location decisions and affects future amenity exposures via current location decisions. This two-way interaction allows me to connect the Tiebout sorting literature to a separate literature that has sought to explain how residential amenity exposures affect health without modeling the past location decisions that led to those exposures or the effects of those exposures on future location decisions. For example, Barreca *et al.* (2015) estimated the mortality effects of heat; Chetty *et al.* (2016) documented dramatic spatial variation in longevity across the U.S.; and Finkelstein *et al.* (2018) and Deryugina and Molitor (2018) used quasi-experimental research designs to establish that some of the spatial variation in mortality is in fact caused by the locations where individuals chose to live.

The rest of this chapter is organized as follows. Section 4.1 summarizes related literature, Section 4.2 outlines the model, Section 4.3 describes the data, Section 4.4 explains the estimation strategy, Section 4.5 reports results, Section 4.6 quantifies welfare effects under climate change, and Section 4.7 concludes.

4.1 Related Literature

This paper integrates the seminal ideas of Tiebout (1956) and Grossman (1972) by building a conceptual framework that recognizes that individuals may sort themselves across residential neighborhoods based on their heterogeneous preferences for local public goods, while recognizing that their choice of a residential location also constitutes an investment into their future health, because the quality of local health care and the natural environment may affect the evolution of their health stock. My framework builds on prior literature on residential sorting and prior literature on how variation in the local health care and local environmental quality affect health capital.

4.1.1 Residential Sorting

Residential sorting models aim to understand how heterogeneity in individual preferences and incomes induces people to sort themselves across differentiated neighborhoods; what those individual location decisions reveal about households' preferences for neighborhood amenities; and how those decisions translate into aggregate differences across communities.[3]. Examples of non-market amenities that have been studied with the help of sorting models include school quality (Bayer *et al.*, 2007), air quality (Bayer *et al.*, 2009), climate (Sinha *et al.*, 2018b). The dimensions of individual heterogeneity that are typically used to explain differences in location decisions are income, wealth, presence of children, and an all-encompassing "taste" parameter. I extend this literature to consider age and health as potential sources of individual heterogeneity that may be important for explaining how people make tradeoffs between consumption of public and private goods when they choose residential locations late in life.

Seniors tend to move less frequently than younger adults. With this in mind, an important feature of empirical sorting models is the ability to incorporate the disutility of moving associated with the physical, financial, and psychic costs of changing residential locations.[4]. Moving cost are typically modelled as a function of previous location of residence and can be interacted with individual characteristics (Hamilton and Phaneuf, 2015; Sinha *et al.*, 2018b).

Another important feature of residential sorting models is the ability to predict how changes in amenities, such as the local climate, will change residential sorting patterns, and how these changes will feed back into welfare measures used to evaluate public policies (e.g. Sieg *et al.* (2004); Galiani *et al.* (2015); Sinha *et al.* (2018b). However, most empirical studies have used static models. Recently, Bayer *et al.* (2016) advanced the sorting literature by developing a tractable framework for

[3]A comprehensive review can be found in Kuminoff *et al.* (2013)

[4]Abstracting from the cost of moving leads to considerably lower estimates for the valuation of amenities (Bayer *et al.*, 2009; Sinha *et al.*, 2018a)

modeling dynamic decision-making by forward-looking agents who have beliefs about how neighborhoods will evolve in the future. Individuals in their model form expectations about future changes in amenities and factor these into their current location decisions. Allowing for this behavior can substantially change estimates for the willingness to pay for amenities relative to a traditional static model. Bayer *et al.* (2016) abstract from the potential role of health, but they model wealth as a dynamic state variable that is affected by individuals' moving decisions. In contrast, I abstract from wealth in order to model health as a dynamic state variable that may simultaneously affect location decisions and be affected by location decisions.[5]

A few recent studies have used sorting models to estimate the welfare effects of climate change. Albouy *et al.* (2016) use a hedonic equilibrium framework to estimate the value of changes in climate amenities, Sinha *et al.* (2018b) use a discrete choice model, and Sinha *et al.* (2018a) compare both approaches. All three studies calculate the willingness to pay to avoid sudden climate change that would match the changes predicted to occur in the United States by the middle or end of the century. The predicted welfare changes are found to be equivalent to an annual loss of 1 to 4 percent of income. However, these studies abstract from the effects of climate change on mortality and morbidity, and instead focus exclusively on the consumption amenity value of climate, (i.e. utility flows from living in areas with particular climates). All three studies also use static models that abstract from forward looking behavior. Relative to these studies, my framework adds the health effects of climate change on morbidity and mortality and adds dynamic decision-making based on forward looking behavior with respect to the effects of climate change on health and amenity value.

[5]It would be interesting to combine the two ideas in future research, due to data constraints this has not been feasible as of now.

4.1.2 Health Effects of Residential Choice

There is a large literature showing how local environmental quality affects morbidity and mortality. Exposure to ambient air pollution has been found to increase infant mortality (Chay and Greenstone, 2003; Currie *et al.*, 2015; Currie and Walker, 2015), adult mortality (Pope et al. JAMA 2002, Deryugina et al. AER forthcoming), morbidity (Schlenker and Walker, 2015; Bishop *et al.*, 2018) and labor productivity during early adulthood (Isen *et al.*, 2017). Heat has also been shown to increase mortality (Barreca *et al.*, 2015; Burgess *et al.*, 2014; McMichael *et al.*, 2008).

My research is most closely related to a set of recent studies that estimate how residential location choices affect human mortality without focusing on any particular amenity (Chetty *et al.*, 2016; Deryugina and Molitor, 2018). Finkelstein *et al.* (2018) compare individuals who moved into the same place from different origins, accounting for aggregate spatial differences in health, and find that the choice of a residential location can increase or decrease life expectancy by more than a year. While there is revealed preference evidence on how locally determined environmental factors affect mortality and morbidity, and there is evidence that these factors are of concern to individuals since changes in amenities are often found to be capitalized into housing prices (Chay and Greenstone, 2005), this study is the first to investigate how individual location decisions are influenced by concerns about how those decisions feed back into health.

4.1.3 Connecting the Residential Sorting and Health Effects Literatures

I connect the residential sorting and health effects literatures by focusing on two distinct channels through which local amenities may affect individual utility apart from their effects on housing prices. First, like the residential sorting literature, I recognize that individuals may value the current and expected future consumption flows derived from local amenities. Second, like the health effects literature, I recognize that local amenities may affect future mortality and morbidity. Thus, forward looking individuals face a multi-dimensional intertemporal tradeoff between the quantity and quality of life. They can reduce their consumption of private goods by paying to move to more expensive neighborhoods that provide higher consumption value of amenities (i.e. Tiebout sorting). They can also reduce their consumption of private goods by paying to move to neighborhoods that increase their chances of survival and of remaining healthy in old age (Grossman sorting). The choices that households make when faced with these dual takeoffs will reveal features of their preferences that are relevant for evaluating the welfare effects of future climate change, and for evaluating a wide range of prospective polices targeting human health and environmental quality.

4.2 Model

I develop a dynamic discrete choice model of residential sorting after retirement that extends Bayer *et al.* (2016). Health and age are treated as sources of individual heterogeneity that affect decision-making. Age evolves deterministically conditional on survival, but survival and the health stock evolve as stochastic functions of location-specific amenities. More precisely, the probability of survival and the probability distribution over future states of health are each modelled as location-specific functions of observed amenities such as climate, local health care quality, crime, and air pollution.

The spatial landscape is divided into a finite number of residential locations. Locations differ in amenities, prices, and their effects on individuals' survival probabilities and probabilities of transitioning to different health states. Individuals are assumed to have knowledge about all of these attributes and to have perfect foresight over the future evolution of attribute levels. This allows individuals to decide on a residential location based on both quality and quantity of the expected remaining life span, and to trade off one for the other. Individuals are assumed to purchase continuous quantities of housing in their preferred locations at constant location-specific prices that reflect the implicit cost of consuming the bundle of location-specific amenities. Income is assumed to be derived from fixed sources such as social security and pensions since individuals are retired. Hence, income is invariant to location.

Individuals are characterized by type τ = (age, health) and the set of types is assumed to be discrete and finite in each dimension.[6] Locations are characterized by levels of prices and amenities. The current flow utility u_j from living in place j is a weighted sum of amenities X_j, the price level p_j that needs to be paid to live in j, and place-and-type-specific utility ξ_j^τ that captures all between-type heterogeneity in utility from location-specific amenities that are observed by individuals but not by the analyst.

$$u_{j,t}^\tau = X_{j,t}\beta^\tau + p_{j,t}\alpha^\tau + \xi_j^\tau \tag{4.1}$$

The marginal utility parameters β^τ and α^τ vary with type τ. Thus, individuals of different age and health types may have systematically different preferences over amenities and consumption. Further, flow utility may vary over time, with changes in amenity levels and prices.

Individuals survive to the next period with probability s_j^τ. This probability depends on type τ and location j. Specifically, survival at each location is modeled as a Gompertz function of age, a type-specific fixed effect, and a location-specific fixed

[6] If income were observed in the data, it could be added as another dimension of type, and could also be modelled to vary stochastically as a function of location.

effect.[7]

One model period spans five years, therefore the annual probability of survival has to be multiplied across five years.

$$s_j^\tau = \prod_{t=1}^{5}(1 - \exp(\varphi\ age_t + \gamma_j + h^\tau)) \tag{4.2}$$

γ_j is the place effect on survival. A higher γ_j decreases the probability of survival. h^τ summarizes the health capital of type τ which is assumed to be observed in the data and will be defined in detail in Section 4.4.

Conditional on survival, individuals transition deterministically to the next age type, and stochastically to a different health type. The probability of transitioning to a different type of health τ' is assumed to be a function of current age and health type τ, and current location effect $\gamma_j^{tr,\tau}$. Therefore, the health transition probabilities depend on both current type and location. The function f is an ordered probit specification and has been chosen to provide a mapping from age and location effects to health transition probabilities.

$$P_j(\tau, \tau') = f(\varphi^{tr,\tau}\ age^\tau + \gamma_j^{tr,\tau}) \tag{4.3}$$

If an individual reoptimizes location, they will have to pay moving cost $MC^{\tau'}$. Moving costs vary by origin-destination pair and, conditional on origin-destination, are allowed to vary across types. Moving costs capture the full utility cost of moving, and therefore may contain physical cost of moving, financial cost of moving (e.g. realtor fees, closing costs, housing search costs, cost of finding new doctors), and the psychological cost of moving away from family and friends.

[7]The Gompertz model (Gompertz, 1825) has been used for 200 years to describe human mortality as a function of age. Recently, it has also been used to model spatial variation in human mortality (Chetty *et al.*, 2016; Finkelstein *et al.*, 2018)

The lifetime utility V provided by place j to an individual of type τ is the discounted expected sum of flow utilities. The individual random utility shock is assumed to be an i.i.d. draw from a Type I EV distribution. Moving cost will be modelled with a flexible function of distance in miles.

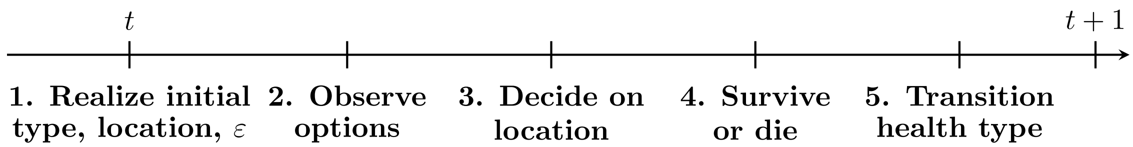
$$V_{j,t}^{\tau} = \underbrace{u_{j,t}^{\tau}}_{\text{flow utility}} + \underbrace{\beta\, s_j^{\tau} \sum_{\tau'} P_j(\tau, \tau')\, E(\max_k V_{k,t+1}^{\tau'} - MC^{\tau'}(k,j)) + \varepsilon_{i,k,t+1}}_{\text{discounted future utility, conditional on survival } s_j^{\tau}} + \underbrace{\beta\,(1 - s_j^{\tau})\,\theta}_{\text{value of death}} \tag{4.4}$$

The decision problem of a individual of type τ, initially located in l, is to maximize individual lifetime utility $V_{i,j,t}^{\tau}$ – which is the sum of type-place specific lifetime utility $V_{j,t}^{\tau}$, less moving cost MC if the optimal place is not equal to the initial location and an individual random utility shock ε_{ijt}.

$$\max_j V_{i,j,t}^{\tau}(l) = V_{j,t}^{\tau} - \underbrace{MC_t^{\tau}(j,l)}_{\text{moving cost}} + \underbrace{\varepsilon_{ijt}}_{\text{individual random utility}} \tag{4.5}$$

Figure 4.1 depicts the events that occur within each model period as a sequence for heuristic purposes. The individual state variables are current type $\tau =$ (age, health) and initial location l. Period t starts with the realization of random utility ε_{ijt}, and the initial type τ and location j. Each individual observes their options in terms of available locations, net of moving cost relative to the initial location. They decide on the optimal location j based on the maximization problem in Equation 4.5 and, if they relocate, pay the moving cost that depends on the distance of the move and the current type. Then, based on the chosen location and initial type, survival or death is realized. Conditional on survival, the individual transitions to a different health type, where the distribution over new health types also depends on chosen location and current type. Then the next period starts. In period $t+1$, the individual will start in the currently optimal location j. Future utility is uncertain (1) due to uncertainty about survival, (2) due to uncertainty about the future health type, and (3) due to

Figure 4.1: Sequence of Events Within One Model Period



uncertainty about future random utility shock $\varepsilon_{ij,t+1}$.

In summary, the model combines the ideas of Tiebout and Grossman by (1) modelling that individuals choose the locations that provides the highest utility to them, and (2) letting their residential location choices constitute health investment decisions, captured by the way that type-specific survival probabilities and type-specific probabilites of transitioning to different states of health vary across locations. If the dynamic channel were eliminated, there would be no concerns about future health and mortality, and the model would solely capture the current consumption value of amenities, similar to Bayer *et al.* (2007, 2009); Sinha *et al.* (2018b).

4.3 Data

Information on individual location, age, and health comes from administrative records from the U.S. Centers for Medicare and Medicaid services (CMS). The data are a 10 percent random sample of seniors who were enrolled in traditional Medicare in 2001 (i.e. Medicare Parts A and B)[8]. Traditional Medicare is universal health care coverage for all U.S. citizens over the age of 65. For each individual, I observe annual data on residential location, health, and demographics from 2001 to 2013, or until they die. Individuals exit the data when they die. Residential location is observed as a ZIP+4 code, which is a mail delivery point such as a unique address, one floor

[8]Individuals who are enrolled in Medicare Advantage during the years 2001 or 2006 are dropped because complete data on their chronic medical conditions are not available.

of an apartment building, or one side of a street on a city block. The average ZIP+4 code contains fewer than five households. Additionally, I observe annual data on the presence or absence of over forty common chronic medical conditions from CMS's chronic condition warehouse file. I focus on the twenty-seven conditions used in Finkelstein *et al.* (2018). Table 4.1 lists these conditions ranked by incidence in 2001. The most common condition by far is hypertension, which afflicts over 50 percent of individuals. Over 40 percent have had a cataract.

4.3.1 Health Capital

I quantify individual health capital using a version of the frailty index. The frailty index measures health capital as the accumulated sum of adverse health events. I define an adverse health event as the diagnosis of a chronic condition. Individuals are then grouped into quintiles, based on their number of chronic conditions. The resulting mapping from the number of diagnosed conditions to health type quintile is reported in Table 4.2.

The frailty index has been shown to predict mortality and institutionalization better than age (Mitnitski *et al.*, 2005; Goggins *et al.*, 2005). Hosseini *et al.* (2019) show that the frailty index outperforms self-reported health status in predicting mortality, nursing home entry and Social Security Disability Insurance recipiency. Obviously there is heterogeneity in the severity of different conditions, but one severe condition rarely comes alone. If the immune system has been compromised by a serious condition, other conditions tend to follow. For example, the average number of chronic conditions, conditional on having at least one chronic condition, is 4.7. Conditional on having cancer, individuals have on average 5.9 to 6.8 chronic conditions, depending on the type of cancer.

Table 4.3 shows the fraction of individuals per type that are observed in 2001

Table 4.1: Incidence of Chronic Conditions Ranked by Frequency

Condition	Percent
Hypertension	56.8
Cataract	43.8
Hyperlipidemia	36.9
Ischemic heart disease	34.4
Anemia	29.0
Rheumatoid arthritis, osteoarthritis	27.4
Diabetes	20.0
Congestive heart failure	19.6
COPD	16.2
Hypothyroidism	13.1
Glaucoma	12.6
Depression	12.5
Osteoporosis	10.1
Hyperplasia	10.1
Atrial fibrillation	9.7
Dementia	9.5
Stroke, transient ischemic attack	9.3
Chronic kidney disease	6.5
Asthma	5.2
Alzheimer's disease	4.2
Prostate cancer	4.1
Breast cancer	3.6
Acute myocardial infarction	2.5
Colorectal cancer	2.3
Hip fracture	2.2
Lung cancer	1.3
Endometrial cancer	0.4

Notes: This table reports the fraction of people over age 65 who had been diagnosed with each chronic condition before the end of 2001. It is based on data from CMS's chronic conditions warehouse file for the sample of 5.5 million people.

Table 4.2: Mapping From Count of Chronic Conditions to Health Quintiles

	Health Quintile				
	1	2	3	4	5
Number of conditions	0-1	2-3	4-5	6-7	8+
Interpretation	Excellent	Very Good	Good	Fair	Poor

and survive until 2006. For example, out of all 65-69 year olds that had one or zero diagnosed chronic condition in 2001, 94.0 percent lived to see the year 2006. At the opposite extreme, out of all those older than 90 who were diagnosed with 8 or more chronic conditions in 2001, only 16 percent lived to see the year 2006. The rest of the table shows considerable heterogeneity in survival rates by age and by health, with monotonicity in age conditional on health and health conditional on age.

Table 4.4 shows the unconditional health transition rates from 2001 to 2006. Out of all individuals with one or zero diagnosed chronic conditions in 2001, 30.4 percent still have only one or zero diagnosed chronic conditions in 2006. Since the frailty index is defined as the accumulated sum of adverse health events, transitions can only move upwards. This is why all elements below the diagonal are zero.

4.3.2 Residential Locations: Hospital Referral Regions

The geographic units that individuals can choose in the model are Hospital Referral Regions (HRR)[9]. An HRR is a collection of ZIP codes, in which primary care providers refer to the same hospitals and specialized care providers. This makes HRRs a natural unit of choice to study residential sorting on health and health care. HRRs

[9]Hospital referral regions were defined by The Dartmouth Atlas.

Table 4.3: Survival Rates by Type, From 2001 Until 2006

	Health Quintile				
Age	1	2	3	4	5
65-69	94.0	92.3	88.2	79.4	61.3
70-74	90.1	90.1	86.4	78.5	60.1
75-79	84.4	85.1	81.1	72.4	53.4
80-84	75.9	76.6	71.0	61.0	42.5
85-89	63.7	62.4	55.2	44.2	29.2
90+	48.4	40.8	33.5	24.9	16.0

are contiguous geographic units with populations of at least 120,000 individuals, and each HRR contains at least one hospital that performs major cardiovascular procedures and neurosurgery. There are 304 HRRs in the US, and roughly they can be thought of roughly as cities. Large metropolitan areas may contain multiple HRRs. To help visualize the geographic scale, Figure 4.2 provides a map of projected climate change by HRR. The largest HRR in the sample contains 1.8 percent of the total sample population and the median HRR contains 0.2 percent. Individuals in the CMS dataset are assigned to HRRs based on their ZIP code. Table 4.5 summarizes variation in amenity levels across HRRs.

4.3.3 Data on Climate Amenities

Data on climate are constructed from daily readings of temperature and precipitation by NOAA Weather Stations, provided by the Global Historical Climatology Network and retrieved using the R package "rnoaa" (Menne *et al.*, 2012b,a; Cham-

Table 4.4: Transition Rates Between Different States of Health

	Health Quintile 2006					
Health 2001	1	2	3	4	5	Total
1	30.4	25.7	22.5	12.7	8.7	100.0
2	0.0	16.0	34.7	27.2	22.1	100.0
3	0.0	0.0	17.2	35.4	47.4	100.0
4	0.0	0.0	0.0	17.4	82.6	100.0
5	0.0	0.0	0.0	0.0	100.0	100.0

Table 4.5: Amenity Levels Across Hospital Referral Regions

Amenity	Mean	Median	SD
Rentindex (USD 2000)	489.1	450.2	160.7
Summer temperature (Celsius)	30.8	30.4	3.3
Winter temperature (Celsius)	6.5	5.6	7.0
Precipitation daily (mm)	2.6	2.5	1.1
Ambulatory care-sensitive hospital stays			
(per 1,000 Medicare enrollees)	80.0	77.7	19.5
PM 2.5 (microgram per m^2)	12.8	13.0	2.5
No of golf courses and country clubs	38.6	28.0	34.5

berlain, 2019). All active weather stations during the year of interest are selected conditional on having information on both temperature and precipitation. There are 7,089 such stations in the US.

The daily maximum temperature is first averaged by station by month. Then the average maximum daily temperature of the hottest month is determined to be the summer temperature, the average daily maximum temperature of the coldest month to be the winter temperature. Precipitation is measured as an daily average per station per year. To measure climate amenities in the year 2001, summer temperature, winter temperature, and precipitation are averaged across the years 2000, 2001, and 2002, to reduce sensitivity of climate measures to annual variation in weather. This process is repeated for 2006, by averaging the climate amenity variables over 2005, 2006, and 2007. Including both winter and summer temperature in the model provides a more nuanced measure of climate compared to annual average temperature since prior research has found people, and especially seniors, to be sensitive to temperature extremes, and asymmetrically more sensitive to extreme heat compared to extreme cold (Albouy *et al.*, 2016; Sinha *et al.*, 2018b). Each ZIP code is assigned the temperature and precipitation levels of the weather station closest to its population weighted geographical centroid. The average daily maximum temperatures in summer and winter are then averaged across all ZIP codes within each HRR, weighted by the number of ZIP+4 codes per ZIP code.

Data on projected changes in climate come from the Climate Model Intercomparison Project (CMIP6) of the World Climate Research Programme that will be used in the 6th Assessment Report of the IPCC.[10] The projection data is available in a

[10]Publicly available at `https://esgf-node.llnl.gov/search/cmip6/`. Its main innovation over CMIP5 is the incorporation of changes in land use and other societal responses to changing climate into the future path of climate (Eyring *et al.*, 2016; O'Neill *et al.*, 2016).

global geoprahic grid of 100 km resolution, where over 1,000 points fall in the area of the continental United States. Following the approach of Albouy *et al.* (2016), the inverse square distance weighted temperature (and precipitation) of the four nearest gridpoints is taken to be the projected temperature (and precipitation) at a given geographic location. Figure 4.2 provides maps of expected temperature changes by 2100 for the "business as usual" scenario, where no large reductions in carbon emissions are assumed.[11] Average daily maximum temperatures in summer are projected to increase between 5 and 18 degrees (F) depending on location, while average daily maximum temperatures in winter would increase between 4 and 26 degrees (F). Appendix Figure C.2 provides a map of projected changes to annual average temperature under this scenario for reference. Note that the median projected change to average annual temperatures across HRRs is 9.7 degrees F (5.4 degrees Celsius). However, there is considerable spatial heterogeneity in the distribution of changes, and the right tail is wider than the left tail, especially for changes to winter temperature.

4.3.4 Housing Prices, and Other Location-Specific Amenities

The cost of housing in each HRR is estimated from a set of HRR-specific fixed effects that are estimated using data from the 2000 Census 5 percent sample and 2006 American Consumer Survey, following the regression procedure from Bayer *et al.* (2009), which I describe in more detail in Section 4.4.3. Gross rental prices are used to measure the per-period cost of living in an area, without reflecting future expectations about asset value that are contained in real estate prices. Gross rents are regressed on housing characteristics and a public use microdata area (PUMA) specific intercept. The PUMA specific intercepts are taken to be the price premiums that have to be paid to live in a certain PUMA. PUMA specific rental prices are then aggregated into

[11] The maps were created with help from code by Nancy Organ.

Figure 4.2: Expected Changes in Daily Maximum Summer Temperature (F) by the Year 2100 Under the "Business as Usual" Scenario CMIP6 SSP 585.

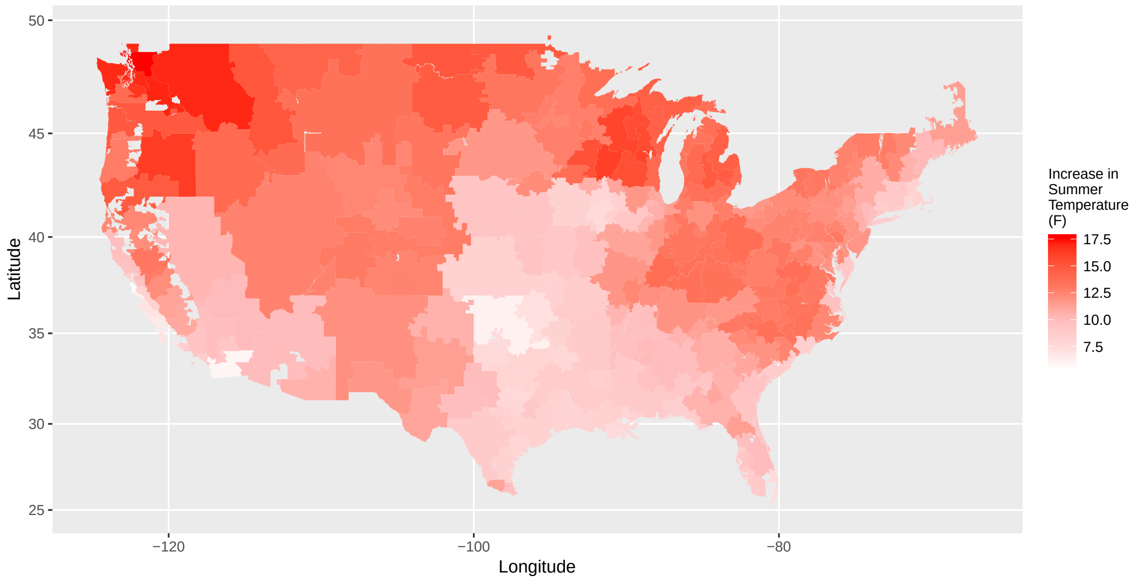
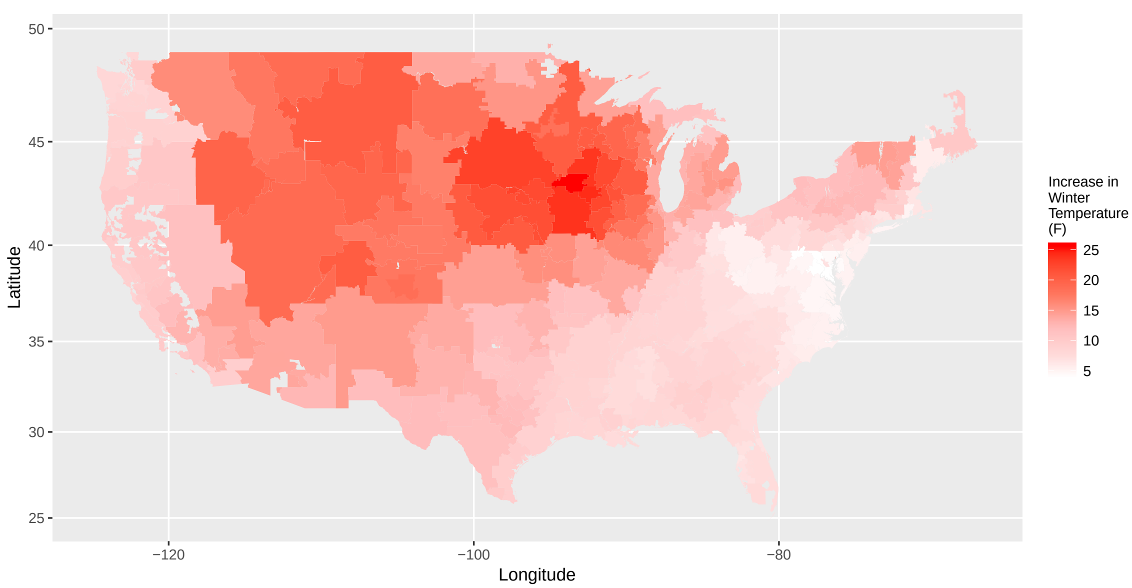


Figure 4.3: Expected Changes in Daily Maximum Winter Temperature (F) by the Year 2100 Under the "Business as Usual" Scenario CMIP6 SSP 585.



HRR units based on the Census crosswalks from PUMAs to block groups and from block group geocoordinates to ZIP codes. Local rental prices, adjusted for housing characteristics, reflect the current cost of living in a certain place more clearly than housing values, which contain expectations about future price developments, and have been found to correlate most accurately with observable amenity levels (Banzhaf and Farooque, 2013).

Data on fine particulate matter pollution (PM2.5) comes from air quality monitors that the Environmental Protection Agency (EPA) operates. There are over 3,000 air quality monitors in the US. Each ZIP+4 code is assigned the average annual daily pollution values of all surrounding air quality monitors, weighted by inverse squared distance.[12]. The values are then averaged across all ZIP+4 codes within an HRR.

Data on the amenity levels that characterize each HRR come from multiple sources and are all publicly available. Quality of health care is measured as the incidence per 1,000 Medicare enrollees of ambulatory care sensitive hospital stays (ACS). These are hospital stays that could have been prevented through adequate provision of ambulatory care. These data are available on an annual basis at the HRR level from the Dartmouth Atlas of Health Care.[13]

The Census Business Patterns 2001 and 2006 provides data on the number of establishments by ZIP code and NAICS codes. All establishments classified as golf courses and country clubs are summed up per HRR. The number of golf courses is intended to capture a proxy for the cultural and social appeal of a location and is consistently measurable at different points in time.

[12]These imputed data have been generously shared by the authors of Bishop *et al.* (2018)

[13]`http://archive.dartmouthatlas.org/tools/downloads.aspx?tab=41`

4.3.5 *Summary Statistics*

Table 4.6 summarizes key features of the estimation sample. The mean age in the sample is 75.4 years in 2001 and the average person is diagnosed with 4 chronic conditions. The table also shows the incidence of moving within the five year period from 2001 to 2005. Over 6 percent of individuals move across HRRs throughout this period. 4 percent of individuals move across state lines and 2 percent move across the four Census regions: Northeast, Midwest, South, and West. Individuals who move more than once across HRRs within one model period are dropped to ensure a clear definition of origin and destination.[14]

Finally, Table 4.7 summarizes unconditional moving patterns across Census regions. The large numbers on the diagonal foreshadow the importance of moving costs. Most individuals stay within their Census region. Conditional on moving across regions, the South is the most important destination region.

4.4 Estimation

There are three key sets of model parameters to estimate. The parameters describing health transitions are identified by differences in health transition rates among movers and stayers conditional on health. They will be estimated by extending the econometric logic of Finkelstein *et al.* (2018) procedure to a ordered choice framework. Second, the causal effects of place on survival γ_j^{surv} are identified by differences in survival rates among movers and stayers and can be estimated independently using a procedure developed by Finkelstein *et al.* (2018). The causal place effects of survival γ_j and health transition $\gamma_j^{h,\tau}$ are also of direct interest. Finally, conditional on the parametric assumption for flow utility, the marginal utility coefficients of amenities

[14] Less than one percent of the sample moves more than once within five years.

Table 4.6: Summary Statistics in 2001

Mean age in years	75.4
Mean number of diagnosed chronic conditions	4.0
Mobility from 2001 to 2005 (percent)	
... across HRR	6.1
... across state	3.9
... across Census regions	2.1
Mortality (percent)	
... within 2001	5.2
... until 2005	24.5
Number of observations (million)	5.5

Notes: Unconditional summary statistics of the full sample in 2001.

Table 4.7: Origin-Destination Combinations in 2001-2005 by Census Region

	Destination				
Origin	Northeast	Midwest	South	West	Total
Northeast	97.2	0.2	2.2	0.4	100.0
Midwest	0.1	98.0	1.4	0.5	100.0
South	0.7	0.7	98.2	0.4	100.0
West	0.2	0.6	1.0	98.1	100.0
Total	20.4	25.1	40.0	14.6	100.0

Notes: Contains non-movers and one-time movers who have been observed in 2001.

β^τ and consumption α^τ and parameters describing heterogeneity in moving costs are identified by how households choose residential locations each period. They will be estimated by adapting the dynamic sorting model from Bayer *et al.* (2016).

4.4.1 Location-Specific Health Transition Probabilities

As noted earlier, I assume that people make residential location decisions based, in part, on their knowledge of how living in different areas will affect their chances of transitioning to worse health states. These causal transition probabilities may differ from unconditional health state transition probabilities due to spatial sorting on health. I use panel data on individual health transitions to estimate a set of casual location-specific transition probabilities for each person type, τ.

For each health type τ in 2001, the probability of transitioning to health type τ' in 2006 is expressed as a function of age, demographics, and location fixed effects $\delta_j^{tr,\tau}$, using an ordered logit model. Equation 4.6 shows the estimation equation. The estimation is run on a 20 percent random sample due to computational constraints. To calculate the implied location-specific transition probabilities for each type, I use the average demographics $\bar{demog}^\tau$ and the midpoint age for each type.

$$P_{i,j}(\tau, \tau') = f(\varphi_1^{tr,\tau}\ age_i + \varphi_2^{tr,\tau}\ demog_i + \delta^{tr,\tau}\ \mathbb{I}_j) + \eta_i^{tr} \quad \forall\tau \tag{4.6}$$

The demographic variables included in the model are gender, race, and an interaction between gender and race. The identifying variation of the effect of location on health transitions comes from spatial variation in the average health type-specific transition probabilities, netting out the effects of age and local demographic composition. Estimating the change for each baseline type of health addresses individual time-fixed confounders, reducing concern about sorting on unobserved health. [15]

[15] Sorting on unobservable, time-varying health remains a concern. Finkelstein *et al.* (2018) suggest

4.4.2 Location-Specific Survival Probabilities

To estimate the causal effect that each location has on the probability of survival, I adapt the estimation strategy of Finkelstein *et al.* (2018). Like the health transition probabilities, the survival probabilities $\hat{s}_j^{\tau}$ are type and place specific and are assumed to be known by individuals when they make location decisions. Unconditional place-specific survival rates might differ from causal survival rates due to spatial sorting on underlying health. Since death can only be observed once, panel estimation is precluded. Finkelstein *et al.* (2018) use a selection correction procedure to estimate place specific survival effects δ_j^{surv} in a way that leverages variation in survival among movers. The identifying variation comes from movers who move to different destinations from the same origin location.

Equation 4.7 shows the estimating equation. Individual mortality m_i is is regressed on age, demographics $demog_i$, health h_i, and place fixed effects for movers and nonmovers.

$$\log(m_i) = \varphi_1\, age_i + \varphi_2\, demog_i + \varphi_3\, h_i + \delta_j^o\, \mathbb{I}_{j,orig} + \delta_j^d\, \mathbb{I}_{j,orig} + \delta_j^n\, \mathbb{I}_{j,dest} + \eta_i \quad (4.7)$$

Demographic variables contain gender, race, and an interaction term. The location fixed effects δ_j^o, δ_j^d, δ_j^n capture the location specific mortality effects of each location δ_j^n for non-movers, and δ_j^o and δ_j^n for the origin and destination locations of movers.

The location specific effects on mortality δ_j^d could be biased if movers sort into locations based on unobserved health. To address this concern, Equation 4.8 shows how $\hat{\delta}_j^d$ is corrected for spatial sorting on health, under the assumption that selection

that panel estimates with individual fixed effects would be the "gold standard" to address spatial sorting. Since health outcomes can be observed more than once while mortality cannot be observed after the event of death, spatial sorting is more difficult to address when estimating location-specific effects on mortality.

on unobserved health can be approximated by selection on observed health.

$$\hat{h}_i = \varphi_1^h \, age_i + \varphi_2^h \, X_i + \zeta_j^o \, \mathbb{I}_{j,orig} + \zeta_j^d \, \mathbb{I}_{j,dest} + \eta_i^h \tag{4.8}$$

The fitted health stock from Equation 4.7, $\hat{h}_i := \hat{\varphi}_3 h_i$, is then regressed on age, demographics, and location specific fixed effects. $\hat{\delta}_j^d$ is then corrected by the estimated health-sorting effect $\hat{\zeta}_j^d$. The causal place-specific mortality effect $\hat{\gamma}_j$ is then estimated as

$$\hat{\gamma}_j = \hat{\delta}_j^d - \frac{\hat{sd}(\hat{\delta}_j^o)}{\hat{sd}(\hat{\zeta}_j^o)} \hat{\zeta}_j^d \tag{4.9}$$

$\hat{sd}(\hat{\delta}_j^o)$ and $\hat{sd}(\hat{\zeta}_j^o)$ are estimated as the standard deviations of δ_j^o and ζ_j^o in a splitsample bootstrap. Finally, to translate the location specific mortality effects, $\hat{\gamma}_j$, into survival rates for a model period of five years, the resulting estimates are converted to five-year periods using Equation 4.10.

$$\hat{s}_j^\tau = \prod_{t=1}^{5} \Big(1 - \exp(\hat{\varphi}_1 \, age_t^\tau + \hat{\gamma}_j + \hat{h}^\tau)\Big) \tag{4.10}$$

To survive one model period of five years, the death hazard has to be avoided five consecutive times. Type specific health capital $\hat{h}^\tau$ is averaged across all non-movers of type τ. Type specific age is fitted starting from the midpoint age per type.

4.4.3 Dynamic Discrete Choice Model of Residential Sorting

The discrete choice model takes the estimated health transition probabilities and the estimated survival probabilities as given and uses them to infer the preference parameters that rationalize individuals' observed choices. The estimation framework builds on Bayer *et al.* (2016). The standard assumption of an additive Type 1 Extreme Value random utility term ε_{ijt}, implies that the probability of individual i of type τ choosing location j can be expressed as

$$P_{j,t}^\tau(l) = \frac{\exp(V_{j,t}^\tau - MC_t^\tau(j,l))}{\sum_k \exp(V_{k,t}^\tau - MC_t^\tau(k,l))} \tag{4.11}$$

The lifetime utility values V and moving cost MC are estimated separately for each type, and for the periods 2001-2005 and 2006-2011, with a maximum likelihood estimation (Equation 4.13). Maximizing over 304 location-specific parameters for V_t^τ would be computationally prohibitive, so the values of V_t^τ are estimated by applying a Berry contraction mapping (Equation 4.14) (Berry, 1994). $\pi(V)$ are the fitted population shares that arise if lifetime utility values are V, π_{true} are the true population shares. x denotes the number of iterations.

$$L_{i,t}^\tau = \sum_j \log P_{j,t}^\tau(l)\ \mathbb{I}(choice_{i,t} = j) \tag{4.12}$$

$$LLF_t^\tau = \max_{V,\gamma} \sum_i L_{i,t}^\tau \tag{4.13}$$

$$\text{s.t.} \quad V_t^\tau = \lim_{x\to\infty} V_{x+1}^\tau = \lim_{x\to\infty} V_x^\tau + \log(\pi_{true}) - \log(\pi(V_x^\tau)) \tag{4.14}$$

Moving cost are modelled as a utility cost. This addresses the fact that moving is costly not only financially, but also psychologically, in ways that cannot be directly observed (e.g. finding new doctors, moving away from family, friends, and familiar neighborhoods). Moving cost are parametrized with a flexible function of distance in miles (Equation 4.15). This allows moves of longer distances to be more costly, but does not restrict ex ante whether moving cost are convex or concave in distance.

$$\begin{aligned} MC_t^\tau(k,l) = {} & \mu_1^\tau\ \mathbb{I}_{state}(k,l) + \mu_2^\tau\ \mathbb{I}_{>50mi}(k,l) + \mu_3^\tau\ \mathbb{I}_{>100mi}(k,l) + \mu_4^\tau\ \mathbb{I}_{>500mi}(k,l) \\ & + \mu_5^\tau\ \mathbb{I}_{>1000mi}(k,l) + \mu_6^\tau\ \mathbb{I}_{>1500mi}(k,l) + \mu_7^\tau\ \mathbb{I}_{\text{Midwest-Northeast}}(k,l) \\ & + \mu_8^\tau\ \mathbb{I}_{\text{Midwest-South}}(k,l) + \mu_9^\tau \mathbb{I}_{\text{Midwest-West}}(k,l) + \mu_{10}^\tau\ \mathbb{I}_{\text{Northeast-South}}(k,l) \\ & + \mu_{11}^\tau\ \mathbb{I}_{\text{Northeast-West}}(k,l) + \mu_{12}^\tau \mathbb{I}_{\text{West-South}}(k,l) \end{aligned} \tag{4.15}$$

This estimation proess is performed separately for each of the 30 age-health types, and can therefore capture substantial heterogeneity in relative preferences and in the cost of moving. An indicator for moves that cross state lines is included to capture additional costs that may arise from adjustment to a new state (e.g. getting a new driver's license and learning state tax laws). In addition, there are fixed effects included for all pairwise origin-destination combinations of the four Census regions, to allow for systematic variation in moving costs that might be associated with particular migration paths, such as the degree of differences in cultural and urban amenities that are shaped by aggregate migration flows.

Identification of Moving Cost and Lifetime Utility

As in Bayer *et al.* (2016), implementing the dynamic discrete choice estimator requires normalizing some parameters. The individual random utility parameter ε^{τ}_{ijt} is i.i.d. according to a Type I Extreme Value distribution with location parameter $\mu = 0$ and a shape parameter β, that is assumed to be common to individuals of all types. Conditional on this assumption, it is well known that the shape parameter can be normalized. Given this normalization, the parameters describing variation in moving costs are identified by the rates at which people make moving versus staying decisions and the variation in distance conditional on moving. The identifying variation for mean lifetime utility values comes from the cross-section of location decisions, conditional on moving cost.

The assumption that the individual random utility component is distributed with a Type 1 Extreme Value distribution also allows me to reformulate the expected future utility as an expectation over the standard log-sum formula taken with respect to the future health state.[16]

$$E(\max_k V^{\tau'}_{k,t+1} - MC^{\tau'}(k,j) + \varepsilon_{ik,t+1}|j,\tau) = \tag{4.16}$$
$$E\left[\log \sum_k \exp\left(V^{\tau'}_{k,t+1} - MC^{\tau'}(k,j)|k,\tau'\right) + c_{EM}\middle| j,\tau\right]$$

[16] c_{EM} is the Euler-Mascheroni constant. If X is a random variable, distributed along a Type 1 EV distribution with location μ and scale β, the expected value of X is $\mu + \beta \cdot c_{EM}$.

The current flow utility u is computed as the difference between the mean lifetime utility values at two different points in time. In order to do this, Equations 4.4 and 4.16 are combined as follows

$$u_{j,t}^{\tau} = V_{j,t}^{\tau} - \beta\ s_{j,t}^{\tau}\ E_{j,t}^{\tau}\left[c_{EM} + \log\sum_{k}\exp(V_{k,t+1}^{\tau'} - MC^{\tau'}(k,j))\right] - \beta\ (1 - s_{j,t}^{\tau})\ \theta_{j,t}^{\tau} \tag{4.17}$$

Estimates for current flow utility values $\tilde{u}$ are obtained by plugging in lifetime utility value estimates $\tilde{V}$, moving cost estimates $\widehat{MC}$, estimated survival rates $\hat{s}_j^{\tau}$ and health transition probabilities $\hat{P}_j(\tau, \tau')$.

$$\tilde{u}_{j,t}^{\tau} = \tilde{V}_{j,t}^{\tau} - \beta\ s_{j,t}^{\tau}\ E_{j,t}^{\tau}\left[c_{EM}\ + \log\sum_{k}\exp(\tilde{V}_{k,t+1}^{\tau'} - \widehat{MC}_{t+1}^{\tau'}(k,j))\right] \tag{4.18}$$

Two numerical challenges arise at this point. First, the estimation of V by type requires a normalization by type that precludes adding up $\tilde{V}$ estimates across types. I address this by normalizing the utility from one place for each type to zero, and address this normalization in the next stage of the estimation. Appendix Section A.1 provides the technical details. Second, the utility flow from death $\theta_{j,t}^{\tau}$ (e.g. from leaving bequests) must be normalized, to ensure that life is always preferrable to death. I address this by normalizing $\theta_{j,t}^{\tau}$ to equal the utility of being in the worst state of health in the least desirable location. Doing this yields an implicit estimate of the VSL, that varies by age, health type, and location. The population-weighted average VSL for a 65 year old individiual in excellent health is \$119,367, for a 65 year old in poor health it is \$59,035. This range is lower than the VSL estimates in Ketcham *et al.* (2020), who find a VSL of around \$402,000 for 67 year olds. This most likely reflects the fact that even living in the worst state of health in the least desirable location is preferrable to death. Finally, the discount factor β is set to 0.85, extrapolating the 3 percent annual discounting from Aldy and Viscusi (2008) to a period of five years.

Identification of Marginal Rates of Substitution

To obtain measures for HRR-specific housing prices paid by seniors, rent price indices are estimated for each HRR. Specifically, gross rents $p_{i,j,t}$ are regressed on physical housing characteristics $H_{i,t}$ and location-fixed effects to obtain location-specific rent price intercepts. Data on gross rental prices and housing characteristics comes from the 2000 Decennial Census, restricted to individual observations over the age of 65.[17] This captures how much extra a given individual will pay if they move from one HRR to another. These intercept differences are estimates of the true difference in housing costs across locations only with the additional assumption that the choice of housing quantity does not vary across locations.

$$p_{i,j,t} = \beta^p \; H_{i,t} + \delta^p \; \mathbb{I}_j + \varepsilon^p_{i,t} \tag{4.19}$$

Estimates for current flow utility $\hat{u}$ are then regressed on local amenities $X_{j,t}$ and the HRR-specific house prices $p_{j,t}$ to obtain marginal utility of amenities, β^τ, and prices, α^τ, for each age type and health type. These parameters are then used to compute the willingness to pay (WTP) for amenities by type as $\frac{\beta^\tau}{\alpha^\tau}$. Estimating marginal utilities raises a standard concern about endogeneity. Unobserved amenities can increase both the estimated utility levels $\hat{u}_{j,t}$ and be capitalized into local housing prices $p_{j,t}$. Therefore, housing prices need to be instrumented in order to estimate α^τ consistently.

I develop instruments for price by adapting the procedure from Bayer and Timmins (2007). To define the most similar HRR in type space, a principal component analysis (PCA) is run on all observed amenities. The intuition for this approach is that in a

[17]The place fixed effects $\hat{\delta}^p_j$ are estimated for 2000 PUMAs. To reassemble these PUMA-specific estimates to the HRR level, a crosswalk provided by the Missouri Data Center assigns 2000 PUMA to 2010 Census blockgroups. The 2010 Census block groups are then mapped on ZIP+4 codes and finally averaged across all ZIP+4 codes per HRR.

spatial housing market equilibrium, the price of housing in location j will be a function of the attributes of locations that are close substitutes. Focusing on physically distant locations mitigates potential spatial correlation in unobserved attributes. The PCA reveals the most important dimensions of joint variation in amenities. The Euclidean distance between all principal components determines the most similar location, a.k.a. the nearest neighbor in type space. To exclude geographically adjacent locations, admissible nearest neighbors need to be at least 100 miles away and belong to a different state.[18]

$$p_{j,t} = X_{j',t}\,\tilde{\beta} + \tilde{\xi}_{j'} \tag{4.20}$$

$$\hat{u}^{\tau}_{j,t} = X_{j,t}\,\beta^{\tau} + p_{j,t}\,\alpha^{\tau} + \xi^{\tau}_{j} \tag{4.21}$$

Equation 4.20 shows the first stage of the IV. It regresses housing prices in location j on amenity levels of location j', where location j' is the nearest neighbor of location j in the amenity space. Equation 4.21 shows the decomposition of mean flow utility values $\hat{u}$ on local prices and amenity levels.[19]

4.5 Results

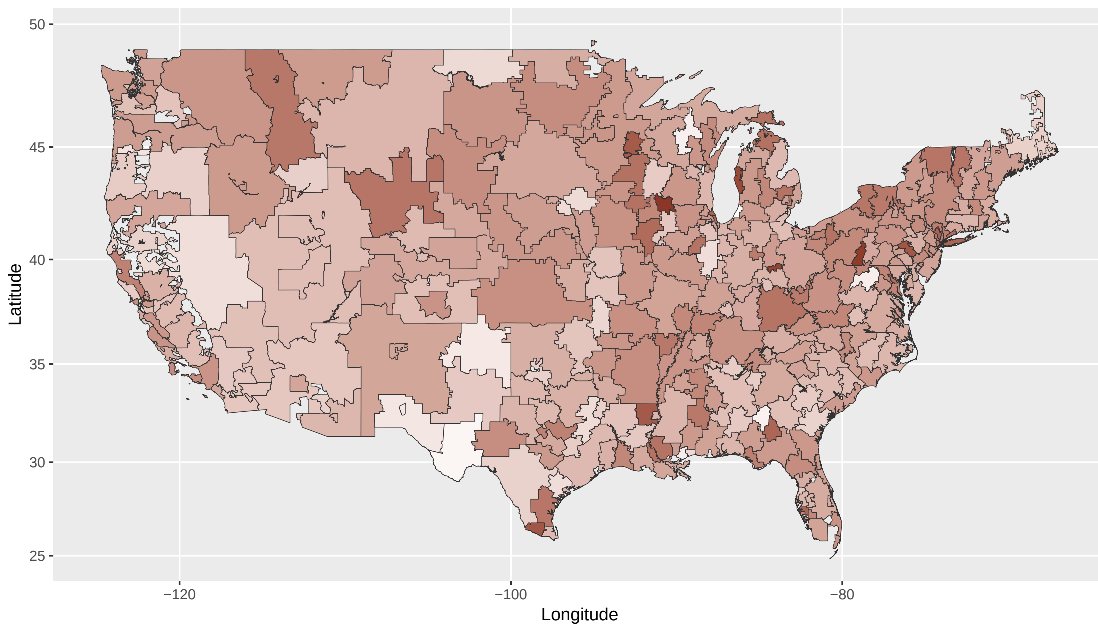
4.5.1 Survival and Health Fixed Effects

Figure 4.4 provides a map of the estimated place-specific survival effects. Darker shades represent higher probabilities of survival. Notice that these place-specific effects operate conditional on age and most importantly, conditional on current health type.

[18] A plot of the first and second principal component can be found in Appendix Figure C.1. Places that are plotted close to each other are similar in amenities.

[19] The full decomposition estimation equation, accounting for previous normalization of $\tilde{V}$, is detailed in Appendix Section A.1.

Figure 4.4: Estimated Causal Place-Fixed Effects on Survival



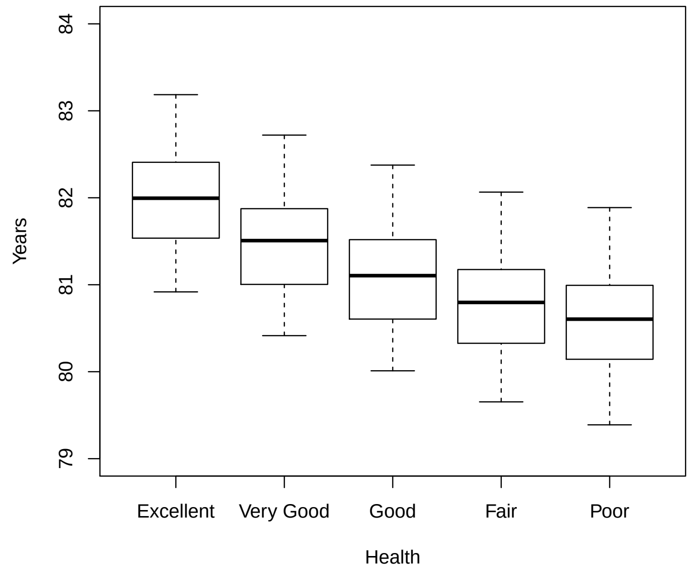
Notes: Darker shades indicate higher probability of survival, conditional on health status.

With the estimated survival rates and health transition rates, life expectancy for a given individual at age 65 in a given state of health can be calculated for each of the 304 available locations. Figure 4.5 shows a whisker plot of life expectancy at age 65 across locations, for each initial type of health. What stands out is that the variation across space conditional on health is larger than the variation in median life expectancy across health bins at age 65.

4.5.2 Moving Cost Parameter Estimates

Moving costs and mean lifetime utility values are estimated separately for each age and health type. To develop intuition, Table 4.8 reports the moving cost parameters from a pooled estimation over all types. A complete set of heterogeneous moving cost parameters by type is reported in the Appendix Table B.9.

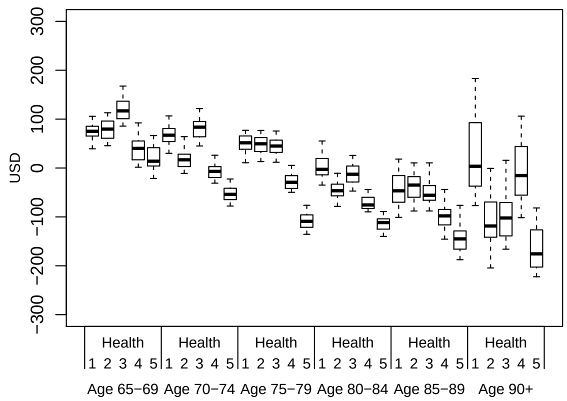
Figure 4.5: Spatial Variation in Life Expectancy at Age 65



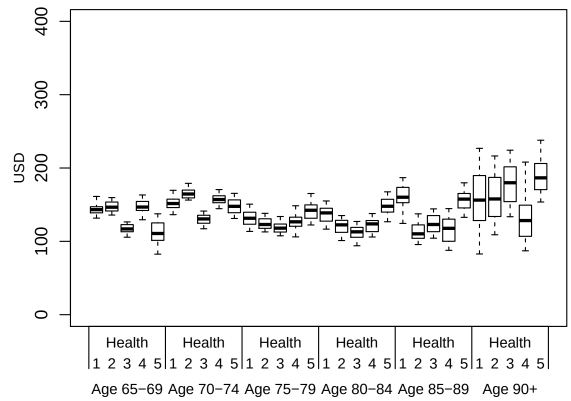
Notes: Boxes plot the range of life expectancy across all available locations, plotted by initial state of health.

Table 4.8 shows that moves of relatively short distances are relatively expensive, indicating a high fixed utility cost of moving. An in-state move between 50 and 100 miles is estimated to cost 4.6 utils, which is larger than the range of mean lifetime utils across space (-3.7,0.7). The distance parameters add up sequentially. For example, an in-state move of 200 miles is estimated to cost 5.6 utils. Moving across state lines increases costs further. Moving costs increase in distance at a decreasing rate and decrease between 500 and 1,500 miles, suggestive of concave moving costs up until 1,500 miles. Indicators for cross-region moves are included to capture unobserved factors that drive popular migration patterns. For example, the high estimated cost for moves between the Midwest and Northeast reflect the fact that very few moves occur between these two adjacent regions. The relatively low moving cost to the South reflects the popularity of the South as a destination (Table 4.7).

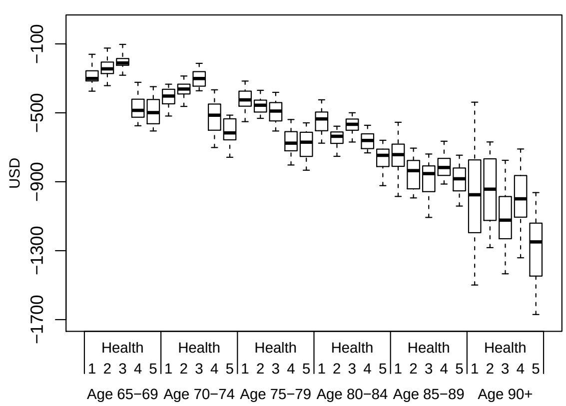
Figure 4.6: Annual MWTP for Amenities by Age and Health Type



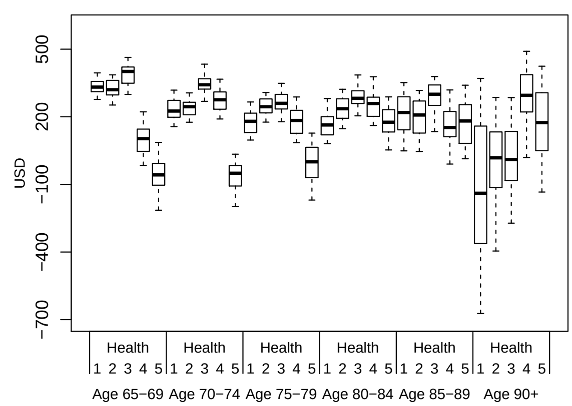
(a) Summer temperature (C)



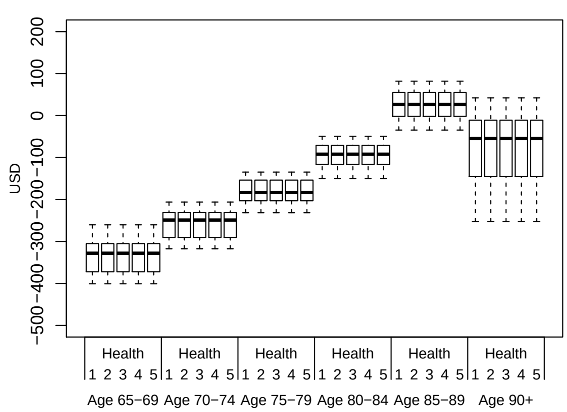
(b) Winter temperature (C)



(c) Precipitation (mm)



(d) ACS hospital stays (1 SD)



(e) PM 2.5 (microgram per m^2)

Notes: Whisker plots with 90 percent Confidence Intervals from 50 bootstrap resamples.

Table 4.8: Moving Cost Parameter Estimates

Cross state	2.9
Distance indicator	
>50 miles	4.6
>100 miles	0.8
>500 miles	-0.3
>1,000 miles	-0.6
>1,500 miles	0.7
Origin-destination combinations	
Midwest-Northeast	2.3
Midwest-South	0.8
Midwest-West	1.2
Northeast-South	0.5
Northeast-West	1.5
West-South	1.1

Notes: Estimated moving cost parameters of Equation 4.15 for full sample, 2001-2006

4.5.3 Willingness to Pay for Local Amenities

Observed amenities are an important determinant of individual location decisions.[20] Figure 4.6 shows the estimates for annual marginal willingness to pay (WTP) for amenities in 2000 USD. More precisely, these are estimates for the WTP to change amenity levels in the current period, but not future periods.

The amenity with the most consistent magnitude across types appears to be av-

[20]The adjusted R^2 is higher than 40 percent for all second stage decompositions.

erage winter temperature. Contrary to the findings of Albouy *et al.* (2016) and Sinha *et al.* (2018b), individuals appear to value an increase in average winter temperature more highly than a decrease in average summer temperature. Across all types, the WTP for 1 C higher average temperature in winter is consistently positive between 100 and 200 dollars.

For summer temperatures, the younger types even have a slightly positive valuations. The WTP estimates for summer temperature have a distinct trend in age and in health: older and sicker types exhibit larger WTP to avoid summer heat than younger and healthier types. Further, humidity - defined as daily precipitation - is viewed as a strong disamenity, with a clear age trend. As individuals get older, they appear to increasingly dislike humidity. Willingness to pay to avoid 1mm of daily rainfall increases from around 200 dollars for 65-69 year olds up to almost $1,400 for those older than 90. Measures of WTP for non-climate amenities are also typically intuitive. For example, most types have a positive willingness to pay to live in locations with better health care, at an annual average of $207. For tractability, the WTP to avoid ambient air pollution is restricted to vary only by age type. Younger types exhibit the largest willingness to pay to avoid PM 2.5, but this fades with age.[21]

4.5.4 Model Fit

The estimated model does a reasonable job in predicting moves compared to Bayer *et al.* (2016) who focused on a single metrpolitan area. Using the same diagnostic measures of model fit as their study I find that, across the full sample, 97 percent of individuals choose a location from the top 5 percent of their respective choice set, ranking locations by their model predicted choice probabilities. Note that this

[21]A complete set of marginal utility estimates for all types and amenities with standard errors is reported in Appendix Table B.11.

number includes a large mass of individuals who do not move at all. Conditional on moving, 45 percent of individuals choose a location from the top 5 percent of their choice set, and 66 percent choose a location from the top 15 percent of their choice set. In comparison, Bayer *et al.* (2016) found that 31 percent of households choose a neighborhood that would have been ranked in the top 5 percent of their choices and 47 percent choose one from the top 10 percent of ranked choices.

4.6 Climate Change

As an illustrative example, I simulate climate change projections for 2100 as if they had occurred in 2001, the first model period, and remain unchanged thereafter. This acts as a discrete shock to amenity levels, and it also affects survival rates and health transition rates. Then I use my model estimates to gauge the extent to which people may choose to adapt by moving, along with the associated health implications and welfare implications. In addition to migration, the key channels affecting welfare include the consumption value of climate and the health investment value of climate. I quantify the relative magnitude of each channel.

Data on projected climate change in terms of average summer winter temperature, average winter temperature, and average daily precipitation levels comes from the World Climate Research Programme. I simulate these changes for a "business as usual" scenario[22], in which there are no significant reductions in carbon emissions (O'Neill *et al.*, 2016). Temperature and precipitation data are available on a global grid with a nominal resolution of 100 kilometers. There are over 1,000 grid points fall in the continental US. I project the gridded data onto HRRs by spatial interpolation, using inverse squared weighted distances of the closest four grid points similar to Albouy *et al.* (2016). Figure 4.2 shows a map of the implied changes to average

[22]World Climate Research Programme Database CMIP6 ScenarioMIP SSP585

daily maximum temperatures in the hottest month (summer) and the coldest month (winter) of the year.

4.6.1 Predicting Counterfactual Mortality and Health Transition Rates

To predict how climate change would affect mortality and morbidity in the climate change scenario, the estimated HRR fixed effects for mortality and morbidity from Equations 4.6 and 4.7 are regressed on all observed amenities. The regression coefficients are reported in Table 4.9. Higher temperatures are found to increase mortality and morbidity. Humidity, proxied by precipitation, has somewhat ambiguous effects. The estimated marginal effects of the climate variables are multiplied by the predicted changes in temperature and precipitation in order to predict counterfactual mortality and health transition rates.[23] Since both the survival rates (Equation 4.10) and the health transition rates (Equation 4.6) are non-linear functions of the place fixed effects, the marginal effects of climate change on health will be non-linear across types. Specifically, the estimated parameters imply that warmer temperatures will have larger negative effects on health for older and sicker types.

To simulate how climate change would affect individuals' choices and welfare, it is necessary to first calculate place-specific lifetime utility values under actual and counterfactual conditions. Equation 4.17, rearranged for V on the left hand side, provides the foundation for a bottom-up approach to constructing the values of V, described in Equation 4.22. The terminal period is defined to be the period after Age type 6. In the terminal period the individual only consumes their flow utility and dies in the next period with certainty. This restriction provides a reasonable approximation to the data in which only 0.3 percent of seniors are older than 100

[23] There are no estimated transition rates for Health type 5, since it is modelled as an absorbing state.

Table 4.9: Marginal Effects of Amenities on Place-Specific Health and Mortality

	Mortality	Health 1	Health 2	Health 3	Health 4
Summer (C)	0.0036	0.0152	-0.0015	0.0022	-0.0671
	(0.0032)	(0.0053)	(0.0051)	(0.0075)	(0.0467)
Winter (C)	0.0032	0.0002	0.0116	0.0038	0.0467
	(0.0014)	(0.0023)	(0.0028)	(0.0035)	(0.026)
Precipitation (mm)	-0.0184	0.0684	0.0039	0.0147	-0.3304
	(0.0088)	(0.0156)	(0.0167)	(0.0176)	(0.1389)
PM 2.5 (mg per m^2)	-0.0028	0.0036	0.0103	0.0035	-0.0106
	(0.0029)	(0.0055)	(0.0058)	(0.0073)	(0.065)
ACS (per 1,000 enrollees)	-0.0004	0.0016	0.0066	0.0067	0.0006
	(0.0006)	(0.0009)	(0.001)	(0.0011)	(0.0112)
Golf courses	0.0001	-0.0003	-0.0003	-0.0006	-0.0039
	(0.0001)	(0.0002)	(0.0003)	(0.0005)	(0.0032)
Rentindex (USD 2000)	-0.0001	0.0001	0.0008	0.0008	-0.0011
	(0)	(0.0001)	(0.0001)	(0.0002)	(0.001)
Constant	0.1574	-0.9845	-1.1413	-1.0984	3.448
	(0.1606)	(0.2129)	(0.2226)	(0.2703)	(1.6687)
N	304	304	304	304	304
R^2	0.12	0.12	0.34	0.25	0.04
Adjusted R^2	0.1	0.1	0.33	0.23	0.02

Notes: Dependent variables: Causal place fixed effects for mortality $\hat{\delta}_j$ and health transition $\hat{\delta}_j^{\tau}$. Higher values imply higher mortality and higher rates of transition to worse states of health. Standard errors in parentheses, obtained with 50 bootstrap repetitions.

years.

Lifetime utility of Age type 6 is constructed for each possible health type, as outlined in Equation 4.22. The future lifetime utility is simply the flow utility of the terminal period, less moving costs, depending on the current location. Next, the flow utility of Age type 5 is calculated for each possible health type, as the sum of the current flow utility plus the discounted lifetime utility of Age type 6, which is the lifetime utility in the next period, again less moving costs. This future lifetime utility, which is the lifetime utility of Age type 6, needs to be added as a weighted sum across all possible health types that the current health type might transition to. This recursive structure is applied back until Age type 1.

I make two assumptions in order to build flow utility measures for future periods. First, I assume that individuals are fully informed about future amenity levels in 2006 when making their decisions in 2001. Second, I assume that individuals expect these future amenity levels to remain constant further into the future. In other words, I assume perfect foresight for one period and constant expectations thereafter.

$$\hat{V}^{\tau}_{j,t} = \hat{u}^{\tau}_{j,t} + \beta\ \hat{s}^{\tau}_{j,t}\ E^{\tau}_{j,t}\left[c_{EM} + \log\sum_{k}\exp(\hat{V}^{\tau'}_{k,t+1} - \hat{MC}^{\tau'}_{t+1}(k,j))\right] + \beta\ (1-\hat{s}^{\tau}_{j,t})\ \theta \tag{4.22}$$

Following the strategy outlined earlier, the utility value of death is normalized to be equal to the certain value of living in the least desirable place in the poorest state of health.

4.6.2 Welfare implications

The annual willingness to pay (WTP) to avoid this scenario varies across health and ages types, ranging from \$962 to -\$1,894. Perhaps surprisingly, the population weighted average WTP is negative (-\$540); i.e. the average senior benefits from the combined health and amenity effects of climate change. This finding is driven by the large WTP for warmer winter temperatures discussed earlier. Figure 4.7 summarizes heterogeneity in welfare effects by reporting the WTP by (age, health) type. The youngest types benefit the most. The youngest and healthiest types have an average annual WTP of \$1,770. This stems from their relatively strong preferences for warmer winters, their weaker preferences for warmer summers, and their relative indifference to additional precipitation (Figure 4.6a and 4.6c). In contrast, older, sicker types are affected relatively negatively by hotter summers and higher precipitation.

Figure 4.8 decomposes the mechanisms underlying the WTP measures by contrasting the average WTP to avoid the climate change scenario (Figure 4.7) with an the average WTP from an alternative scenario that ignores climate change's effects on health and survival. If there were no effects on health and mortality, the WTP for the changes in climate would be as high as \$2,382 for the youngest and healthiest types, which is \$613 higher than when health effects are taken into account. The change in the population-weighted average is \$234, due to climate change's adverse health effects. Younger and healthier types are somewhat less vulnerable to the averse health effects of warming in the short run, but they have longer remaining life spans that are negatively affected, driving up the cost they incur from averse health effects. Still, their discounted values of the future negative health consequences are more then offset by the enormous positive effects of warmer temperatures on their current utility flows.

Taking away the opportunity to move comes with a large welfare cost. In a world without climate change, the annual welfare cost of being stuck in the initial location is estimated at a population weighted average of \$2,125. By fixing optimal migration choices from the scenario without climate change and then introducing climate change, I can quantify the role of migration for adaptation to climate change within one model period of five years. All individuals are strictly worse off if they are not able to reoptimize by changing their moving decision in response. The population-weighted average welfare cost of not being able to move in response to climate change adds only \$10 to the welfare cost of not being able to move at all. Therefore, adaptation to climate change through moving is found to play a quite small role. This result is due to the enormous utility cost of re-optimizing, i.e. moving, that leads most individuals to stay with their optimal choice before introducing climate change. Very few individuals would actually alter their location choices in response. Across types, the welfare cost of not being able to adjust is higher for younger and healthier types, because they would be the most likely to adjust through migration. Over a longer time horizon, migration responses will certainly play a larger role, but this would require introducing new cohorts, because the lion's share of the initial cohorts will have died within a few model periods.

After introducing climate change and altering the survival probabilities and health transition probabilities accordingly, life expectancy at age 65 reduces by 0.2 years on average. Due to the small migration responses, this change in life expectancy is not mitigated by migration.

Finally, Figure 4.9 shows a spatial map of population-weighted aggregate gains and losses. Darker shades indicate larger welfare gains. Notice that the regions that most stand to gain are those with large expected increases in winter temperature, but modest expected increases in summer temperature.

4.6.3 Comparison to Prior Literature

My findings on WTP for summer temperatures and winter temperatures differ from prior studies (Albouy *et al.*, 2016; Sinha *et al.*, 2018b). Individuals appear to value warmer winters more highly than cooler summers, and in the case of summer temperature, some younger and healthier types even appear to have a positive

Figure 4.7: WTP to Avoid Climate Change by Age and Health Type: Total Effect

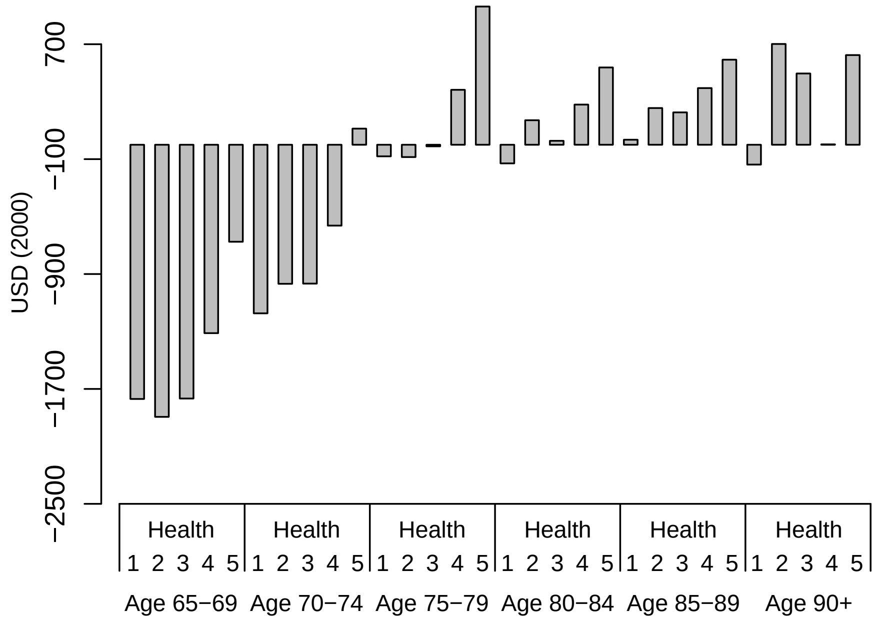


Figure 4.8: WTP to Avoid Climate Change by Age and Health Type: Amenity Effect Only

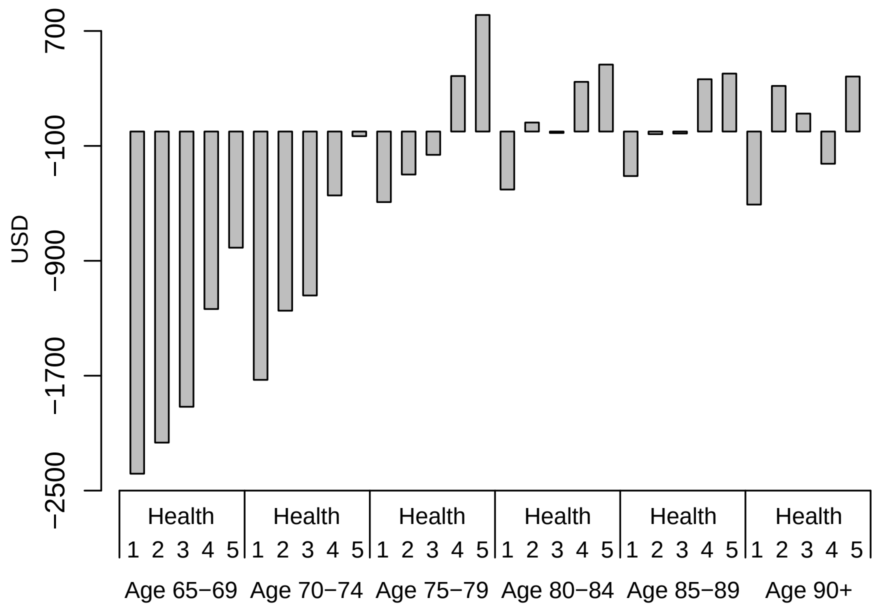
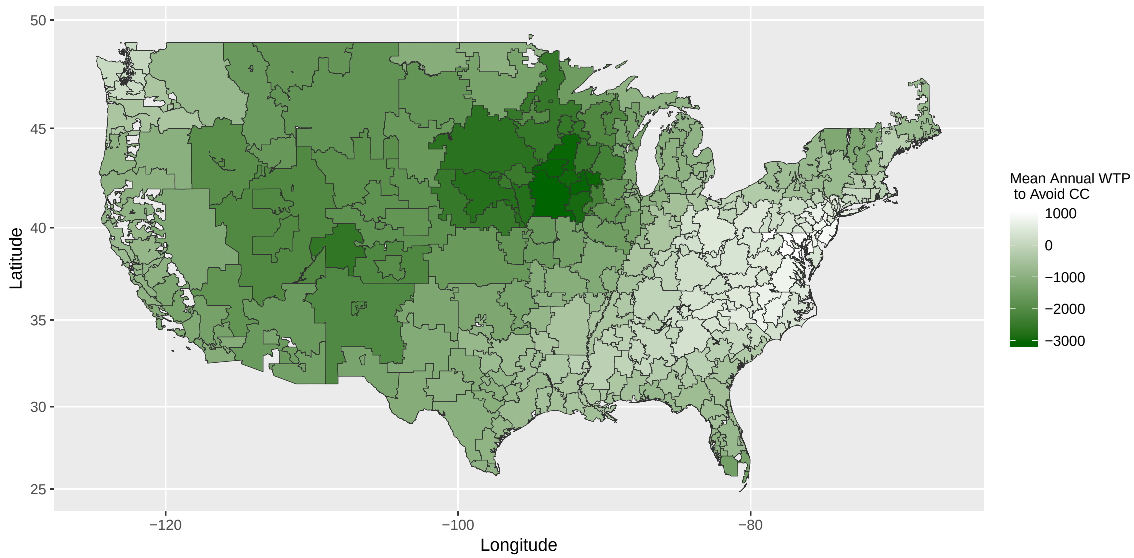


Figure 4.9: Spatial Distribution of Welfare Gains from Climate Change Under "Business as Usual"



valuation for warmer summer temperatures.

Both the model and the sample used in this study differ in several ways from the prior literature. The sample focuses exclusively on seniors over the age of 65 in contrast to the prior literature's primary focus on younger households. In addition, my moving cost specification is more flexible than in prior studies, and a move is defined as occurring within a relatively narrow window of five years. Perhaps most important, I depart from prior climate applications by modeling people as being forward looking, while simultaneously recognizing that climate affects health and survival. In contrast to prior studies, this allows me to disentangle the consumption value of climate amenities from the anticipated future health effects of climate, both of which are important for assessing welfare changes.

In constrast to Sinha *et al.* (2018b) and Albouy *et al.* (2016)'s results for younger households, I find that older adults value moderate winters more highly than moderate summers. I find the population-weighted mean annual MWTP for a 1C reduction in average summer temperature is 7 dollars per individual and 142 dollars for a 1C increase in average winter temperature, whereas Sinha *et al.* (2018b) find annual MWTP of 1,424 dollars per household for a 1F reduction in average summer temperature and 1,035 dollars per household for a 1F increase in winter temperature when they use their most directly comparable subsample of households older than 55 years.

4.6.4 Caveats and Possible Directions for Future Research

It is important to note that my estimates for the WTP to avoid climate change are limited to the extent to which changes in average temperatures and precipitation affect health and neighborhood amenity values. The effects of climate change on natural disasters, (e.g. floods, hurricanes, wildfires), agricultural yields, manufacturing, and other sectors of the economy are left to future research.

Another channel worth exploring in future research is the volatility in weather, including the risk of and damage from catastrophic weather events. The migration responses to the climate change scenario have been found to be relatively small due to the large utility cost of moving. It would be interesting to investigate how catastrophic events (e.g. Hurricane Katrina) affect welfare and migration responses over longer periods. More broadly, it would be interesting to extend this model to make the supply of housing endogenous to population flows, building on insights from Diamond (2016) and Murphy (2018).

4.7 Conclusion

Residential sorting models have been widely used to extract information about consumer preferences from housing market outcomes that can be used to evaluate distributional welfare effects of policies targeting urban and environmental amenities. I have extended the literature by developing and estimating a dynamic model of location choice that incorporates individual heterogeneity in health and age among forward-looking agents who anticipate the future health consequences of their current location choices. I estimated the model using administrative data containing detailed information about the evolution of individual health, mortality and location choice. My results suggest that seniors are forward looking in choosing locations based on their preferences for comfortable climates, for avoiding air pollution, and for access to high quality of health care, in part, because they anticipate how these amenities will contribute to their future health and wellbeing.

I used the model estimates to simulate how sorting patterns, health, and welfare would be affected by future climate change under a "business as usual" scenario for carbon emissions, I find that, on average, younger and healthier seniors benefit from the combined health and amenity effects of climate change, due to their preferences for warmer climates and their ability to move. Older and sicker seniors are made relatively worse off by the hotter summers and increased humidity. Ignoring climate change's adverse effects on health would cause me to understate climate change's welfare losses. The welfare consequences are also spatially heterogeneous. For example, the Midwest is projected to have warmer winters but only moderately warmer summers, leading to welfare gains for many current residents. In contrast, other regions with hotter summers and higher humidity incur welfare losses.

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APPENDIX A

OMITTED PROOFS

A.1 Normalization of Lifetime Utility

Estimated lifetime utility values $\tilde{V}$ have to be normalized for each type for technical reasons. In this estimation, the mean lifetime utility of location 1 - Birmingham AL - is set to zero for each type. This implies that each estimated utility value is a sum of the true utility value plus a type-specific normalization constant $\tilde{V}_j^\tau = V_j^\tau + m^\tau$. When calculating $\tilde{u}$ from $\tilde{V}$, a "normalization bias" arises since $\tilde{V}$ enters the equation several times. The following Equation A.1 rewrites Equation 4.18 with $\tilde{V}^\tau = V^\tau - m^\tau$ to illustrate the relationship between the estimated $\tilde{u}$ and the true u.

$$\begin{aligned}
\tilde{u}_{j,t}^\tau &= \underbrace{V_{j,t}^\tau - s_{j,t}^\tau \cdot \beta E_{j,t}^\tau \left[c_{EM} + \log \sum_k \exp(V_{k,t+1}^{\tau'} - MC_{t+1}^{\tau'}(k,j)) \right]}_{= u_{j,t}^\tau + \beta(1-s_{j,t}^\tau)\theta} - \underbrace{(m_t^\tau - s_{j,t}^\tau \cdot \beta E_{j,t}^\tau \left[m_{t+1}^{\tau'} \right])}_{\text{normalization bias}} \\
\tilde{u}_{j,t}^\tau &= X_{j,t}\beta^\tau + p_{j,t}^\tau \alpha^\tau + \beta(1-s_{j,t}^\tau)\theta - (m_t^\tau - s_{j,t}^\tau \cdot \beta E_{j,t}^\tau \left[m_{t+1}^{\tau'} \right]) \qquad \text{(A.1)}
\end{aligned}$$

The expectation in the last equation is with respect to the uncertainty about future health type τ'. Since there is a finite number of types that an individual can transition to, it can be rewritten as

$$\tilde{u}_{j,t}^\tau = X_{j,t}\beta^\tau + p_{j,t}^\tau \alpha^\tau + \beta(1-s_{j,t}^\tau)\theta - m_t^\tau + s_{j,t}^\tau \, \beta \sum_{\tau'} P_{j,t}^\tau(\tau,\tau') \, m_{t+1}^{\tau'}$$

The normalization bias has two components: (1) the type-specific constant m^τ, and (2) the sum of future type-specific constants, weighted by the product of place-specific survival and health transition probabilities. To estimate the coefficients β^τ and α^τ, the estimated $\tilde{u}$'s will be regressed on amenities X, prices p, and a set of correction variables to address the aforementioned normalization bias (Equation A.2). The regression is run separately for each age type. To address component (2), the product of survival probabilities $\hat{s}_{j,t}^\tau$ and health transition probabilities $\hat{P}_{j,t}(\tau,\tau')$ for all possible future health types τ' will be included as a separate set of variables. Under the assumption that for a given state of health, lifetime utility does not change in age (i.e. $m_t^\tau = m_{t+1}^\tau$), the type specific constant can be added to the respective product of survival and health transition probability. The probability of death $(1-s)$ cannot be added as a separate variable to obtain θ as a regression coefficient because the health transition probabilities P add up to 1. Therefore, the utility value of death will be absorbed into the regression constant, but cannot be identified separately. When simulating counterfactual outcomes, lifetime utility values need to be calculated based on counterfactual amenities, survival rates, and health transition probabilities. To account for the utility value of death, it will be assumed that an individual is indifferent between death and being *with certainty* in the worst state of health in the location with the lowest mean utility value. Equation A.2 specifies the estimation equation for decomposing $\tilde{u}$.

$$\tilde{u}_{j,t}^\tau = \beta^\tau X_{j,t} + \alpha^\tau p_{j,t} + \sum_{\tau' \neq \tau} m^{\tau'} \cdot (\beta \; \hat{s}_{j,t}^\tau \; \hat{P}_{j,t}(\tau,\tau')) + m^\tau \left(\beta \; \hat{s}_{j,t}^\tau \; \hat{P}_{j,t}(\tau,\tau) - \mathbb{1} \right) + \beta \; (1 - \hat{s}_{j,t}^\tau)\theta \qquad \text{(A.2)}$$

A.2 Estimated Normalization Correction

The following provides a consistency check for the estimated normalization constants $\hat{m}^{\tau}$: For each type, the lifetime utility of place 1 has been normalized to zero, i.e. $m = -V_1$. This implies that the normalization constant equals the total lifetime utility from living in place 1. So if it can be assumed that being in a better state of health (say $\tau > \tau'$) improves the utility of living in 1, $V_1^{\tau} > V_1^{\tau'}$, then it must be true that $m^{\tau} < m^{\tau'}$. The estimated $\hat{m}$'s are equal to $-m$, so in turn it must be true that $m^{\tau} > m^{\tau'}$. The estimated normalization constants $\hat{m}^{\tau}$ are monotonically decreasing across health types, which can be seen in Table B.11. Note that $\hat{m}^{\tau}$ equals $-V^{\tau}$.

APPENDIX B

SUPPLEMENTARY TABLES

Table B.1: Mean Impact of New Diagnosis on Propensity to Move

Dementia	4.25
Alzheimer's	3.50
Hip fracture	2.84
Depression	1.90
Stroke	1.60
Congestive heart failure	0.84
Chronic kidney disease	0.83
Acute myocardial infarction	0.64
Atrial fibrillation	0.53
COPD	0.53
Anemia	0.35
Osteoporosis	0.34
Asthma	0.28
Ischemic heart disease	0.22
Lung cancer	0.19
Hypothyroidism	0.19
Diabetes	0.18
Rheumatic arthritis, osteoarthritis	0.10
Colorectal cancer	0.09
Prostate cancer	0.00
Hyperplasia	-0.05
Hypertension	-0.07
Glaucoma	-0.11
Breast cancer	-0.12
Endometrial cancer	-0.23
Hyperlipidemia	-0.24
Cataract	-0.27
Mean annual moving rate	3.27

Notes: Dependent variable in linear probability model: Indicator for moving. Average coefficient across 2001-2012 in percentage points. Estimating Equation (2.7)

Table B.2: Implicit Price of Preventing One Fatality Per Age Group, Equation 3.8, by SUPERPUMA

	Age					
	65-69	70-74	75-79	80-84	85-89	90+
VSL, causal mortality	79.0	48.9	30.3	19.2	12.2	8.3
SE	(0.19)	(0.12)	(0.07)	(0.05)	(0.03)	(0.02)
CI, 95 percent	(78.6,79.4)	(48.6,49.1)	(30.2,30.5)	(19.1,19.3)	(12.2,12.3)	(8.2,8.3)
...with Metro Area FE	12.2	7.6	4.7	3.0	1.9	1.3
SE	(0.26)	(0.16)	(0.10)	(0.06)	(0.04)	(0.03)
CI, 95 percent	(11.7,12.7)	(7.2,7.9)	(4.5,4.9)	(2.9,3.1)	(1.8,2.0)	(1.2,1.3)
VSL, empirical mortality	5.1	5.2	4.1	2.1	0.6	-0.1
SE	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)
CI, 95 percent	(5.0,5.1)	(5.1,5.2)	(4.1,4.2)	(2.1,2.1)	(0.5,0.6)	(-0.1,-0.0)
...with Metro Area FE	3.7	4.6	2.8	2.1	0.9	0.2
SE	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)
CI, 95 percent	(3.7,3.8)	(4.6,4.7)	(2.7,2.8)	(2.1,2.1)	(0.9,0.9)	(0.2,0.2)

Notes: VSL in million (USD 2000). Data source: Census 2000 5 percent sample. N with causal mortality estimates 6,603,326, N with empirical mortality estimates 6,685,677. Mortality estimates of one age group included as control.

Table B.3: Implicit Price of Preventing One Fatality Per Age Group, Equation 3.9, by SUPERPUMA

	Age					
	65-69	70-74	75-79	80-84	85-89	90+
VSL, causal mortality	48.6	30.1	18.7	11.8	7.6	5.1
SE from rent-mort regression	(0.19)	(0.12)	(0.07)	(0.05)	(0.03)	(0.02)
CI, 95 percent	(48.2,49.0)	(29.8,30.3)	(18.5,18.8)	(11.8,11.9)	(7.5,7.6)	(5.1,5.2)
...with Metro Area FE	7.7	4.8	3.0	1.9	1.2	0.8
SE	(0.26)	(0.16)	(0.10)	(0.06)	(0.04)	(0.03)
CI, 95 percent	(7.2,8.2)	(4.5,5.1)	(2.8,3.2)	(1.8,2.0)	(1.1,1.3)	(0.8,0.9)
VSL, empirical mortality	4.5	4.6	3.1	1.9	0.5	-0.1
SE	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.00)
CI, 95 percent	(4.4,4.5)	(4.5,4.6)	(3.1,3.1)	(1.9,1.9)	(0.4,0.5)	(-0.1,-0.1)
...with Metro Area FE	2.2	3.3	1.6	0.9	0.0	0.1
SE	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)
CI, 95 percent	(2.2,2.2)	(3.2,3.3)	(1.5,1.6)	(0.9,1.0)	(0.0,0.0)	(0.1,0.1)

Notes: VSL in million (USD 2000). Data source: Census 2000 5 percent sample. N with causal mortality estimates 6,603,326, N with empirical mortality estimates 6,685,677. Mortality estimates of one age group included as control.

Amenities: Summer temperature, winter temperature, precipitation, health care, $PM_{2.5}$, golf courses, log population density.

Table B.4: Implicit Price of Preventing One Fatality Per Age Group, Equation 3.8, by HRR

	Age					
	65-69	70-74	75-79	80-84	85-89	90+
VSL, causal mortality	104.0	64.5	40.4	25.6	16.5	11.1
SE	(0.24)	(0.15)	(0.09)	(0.06)	(0.04)	(0.03)
CI, 95 percent	(103.6,104.5)	(64.2,64.8)	(40.2,40.6)	(25.5,25.8)	(16.4,16.5)	(11.1,11.2)
...with Metro Area FE	46.9	29.1	18.2	11.6	7.5	5.1
SE	(0.68)	(0.42)	(0.26)	(0.17)	(0.11)	(0.07)
CI, 95 percent	(45.6,48.2)	(28.3,29.9)	(17.7,18.7)	(11.3,11.9)	(7.3,7.7)	(4.9,5.2)
VSL, empirical mortality	7.8	13.2	10.7	11.9	0.9	2.4
SE	(0.05)	(0.04)	(0.03)	(0.03)	(0.02)	(0.01)
CI, 95 percent	(7.7,7.9)	(13.1,13.2)	(10.6,10.7)	(11.8,11.9)	(0.9,1.0)	(2.4,2.5)
...with Metro Area FE	7.1	8.6	5.4	4.0	1.2	-0.4
SE	(0.08)	(0.08)	(0.06)	(0.08)	(0.05)	(0.03)
CI, 95 percent	(7.0,7.3)	(8.4,8.7)	(5.2,5.5)	(3.8,4.1)	(1.1,1.3)	(-0.5,-0.3)

Notes: VSL in million (USD 2000). Data source: Census 2000 5 percent sample. N with causal mortality estimates 4,861,034, N with empirical mortality estimates 4,780,834 . Mortality estimates of one age group included as control.

Table B.5: Implicit Price of Preventing One Fatality Per Age Group, Equation 3.9, by HRR

	Age					
	65-69	70-74	75-79	80-84	85-89	90+
VSL, causal mortality	66.6	41.3	25.9	16.4	10.6	7.2
SE	(0.28)	(0.18)	(0.11)	(0.07)	(0.04)	(0.03)
CI, 95 percent	(66.1,67.2)	(41.0,41.7)	(25.6,26.1)	(16.3,16.6)	(10.5,10.7)	(7.1,7.2)
...with Metro Area FE	22.6	14.0	8.8	5.6	3.6	2.4
SE	(0.78)	(0.48)	(0.30)	(0.19)	(0.12)	(0.08)
CI, 95 percent	(21.0,24.1)	(13.1,14.9)	(8.2,9.4)	(5.2,5.9)	(3.3,3.8)	(2.3,2.6)
VSL, empirical mortality	6.4	4.4	4.1	3.1	0.1	0.3
SE	(0.05)	(0.04)	(0.03)	(0.03)	(0.02)	(0.01)
CI, 95 percent	(6.3,6.5)	(4.3,4.4)	(4.1,4.2)	(3.1,3.2)	(0.1,0.1)	(0.3,0.4)
...with Metro Area FE	4.2	5.1	1.9	3.5	-0.1	-0.5
SE	(0.12)	(0.11)	(0.08)	(0.09)	(0.06)	(0.04)
CI, 95 percent	(4.0,4.4)	(4.9,5.3)	(1.8,2.0)	(3.3,3.7)	(-0.2,0.0)	(-0.5,-0.4)

Notes: VSL in million (USD 2000). Data source: Census 2000 5 percent sample. N with causal mortality estimates 4,861,034, N with empirical mortality estimates 4,780,834. Mortality estimates of one age group included as control.

Amenities: Summer temperature, winter temperature, precipitation, health care, $PM_{2.5}$, golf courses, log population density.

Table B.6: Share of Individuals Per Health Type, Conditional on Age in 2001

	Health Quintile					
Age	1	2	3	4	5	Total
65-69	45.5	25.8	16.8	7.6	4.3	100.0
70-74	22.4	27.1	25.8	14.9	9.8	100.0
75-79	15.0	23.3	27.3	19.0	15.4	100.0
80-84	11.0	19.9	26.5	21.6	21.0	100.0
85-89	8.4	17.4	25.2	23.0	26.0	100.0
90+	7.8	16.2	24.4	24.1	27.5	100.0

Notes: Full sample observed in 2001, conditional on moving once between 2001 and 2005, by region of origin.

Table B.7: Number of Individuals Per Type in 2001

	Health Quintile				
Age	1	2	3	4	5
65-69	661,722	374,827	243,946	110,659	62,108
70-74	291,949	353,959	337,097	193,894	128,007
75-79	171,443	265,895	312,375	216,874	176,055
80-84	91,482	165,299	220,368	179,812	174,182
85-89	41,200	84,715	122,808	112,475	127,023
90+	19,788	41,134	61,769	60,956	69,556

Table B.8: Cross-Region Migration Flows 2001-2005

	Destination				
Origin	Northeast	Midwest	South	West	Total
Northeast	53.3	3.8	37.0	5.9	100.0
Midwest	2.6	59.2	27.3	10.9	100.0
South	10.5	11.7	71.0	6.8	100.0
West	2.7	8.1	13.2	76.1	100.0

Notes: Full sample observed in 2001, conditional on moving once between 2001 and 2005, by region of origin.

Table B.9: Moving Cost Parameter Estimates by Age and Health Type - Part 1

Age	Health	Cross state	Distances in miles					Origin-Destination Combinations of Census Regions					
			>50	>100	>500	>1,000	>1,500	Midwest -Northeast	Midwest -South	Midwest -West	Northeast -South	Northeast -West	West -South
65-69	Excellent	2.93	4.69	0.76	-0.19	-0.31	0.56	2.14	0.74	0.89	0.48	1.19	0.67
65-69	Very Good	2.9	4.74	0.71	0.13	-0.23	0.83	3.86	0.48	0.28	0.19	0.48	0.3
65-69	Good	2.97	4.79	0.72	-0.11	-0.23	0.79	2.21	0.37	0.3	0.14	0.55	0.31
65-69	Fair	2.98	4.65	0.9	-0.21	-0.4	0.96	1.96	0.56	0.66	0.27	0.59	0.5
65-69	Poor	3.14	4.66	0.79	0.13	-0.15	1.39	1.44	-0.05	-0.5	-0.24	-1.18	-0.25
70-74	Excellent	3.04	4.84	0.71	-0.01	-0.13	0.71	1.42	0.47	0.17	0.31	0.62	-0.05
70-74	Very Good	3.08	4.83	0.75	-0.05	-0.09	1.13	1.45	0.33	-0.2	-0.17	-0.58	-0.17
70-74	Good	3.07	4.81	0.73	-0.16	-0.2	0.69	1.98	0.29	0.22	0.06	0.37	0.33
70-74	Fair	3.09	4.6	0.89	-0.22	-0.16	1.16	2.39	0.37	-0.07	-0.22	1.62	0.18
70-74	Poor	3.1	4.58	0.96	-0.15	-0.26	0.73	1.38	0.23	0.14	-0.08	0.3	0.41
75-79	Excellent	3.1	4.81	0.69	-0.07	-0.28	0.29	1.49	0.34	0.57	0.14	0.86	0.52
75-79	Very Good	3.03	4.82	0.75	-0.1	-0.26	1.21	1.43	0.34	0.24	-0.16	-0.82	0.15
75-79	Good	2.98	4.65	0.9	-0.4	-1.03	0.99	2.63	1.05	2.05	1.08	3.14	2.04
75-79	Fair	3.08	4.63	0.81	0.09	-0.21	1.27	1.29	0.14	-0.46	-0.28	-1.01	-0.35
75-79	Poor	3.06	4.45	0.99	0.23	-0.62	1	1.73	0.28	-0.24	-0.25	1.05	-0.1

Notes: Estimates from Equation 4.15 for the time period 2001 to 2005, by health and age type. Magnitudes are comparable across types because the individual random utility is assumed to be drawn from identical Type I EV distributions.

Table B.10: Moving Cost Parameter Estimates by Age and Health Type - Part 2

								Origin-Destination Combinations of Census Regions					
Age	Health	Cross state	Distances in miles					Midwest	Midwest	Midwest	Northeast	Northeast	West
			>50	>100	>500	>1,000	>1,500	-Northeast	-South	-West	-South	-West	-South
80-84	Excellent	2.98	4.66	0.67	0.15	-0.08	0.65	0.76	0.44	-0.28	-0.08	-0.15	0.12
80-84	Very Good	2.84	4.66	0.69	0.13	-0.1	0.52	1.43	0.45	0.17	0.1	0.36	0.32
80-84	Good	2.89	4.58	0.71	0.21	-0.25	0.86	1.4	0.41	-0.14	0.04	-0.25	0.24
80-84	Fair	2.91	4.47	0.84	0.1	-0.47	1.01	1.49	0.49	0.52	-0.1	-0.24	0.66
80-84	Poor	3.08	4.51	0.86	-0.07	-0.3	0.58	1.2	0.28	0.21	-0.15	0.25	0.42
85-89	Excellent	2.91	4.52	0.93	-0.14	0.37	1.15	1.54	0.46	-0.38	0.28	-0.94	-0.59
85-89	Very Good	2.71	4.47	0.77	0.32	-0.56	0.02	1.5	0.66	1.12	0.39	1.8	1.62
85-89	Good	2.7	4.41	0.86	0.18	-0.57	-0.33	1.47	0.78	1.48	0.46	2.27	1.85
85-89	Fair	2.89	4.43	0.9	0.11	-0.46	-0.13	1.26	0.54	1.02	0.18	1.44	1.33
85-89	Poor	2.99	4.33	1.19	-0.04	-0.42	-0.01	1.57	0.26	0.99	-0.16	1.63	0.91
90+	Excellent	2.97	4.75	0.61	0.27	-0.24	0.51	1.04	0.5	0.28	-0.05	0.35	0.4
90+	Very Good	2.9	4.49	0.88	0.58	-0.31	-0.09	0.44	0.24	0.35	-0.21	0.78	0.63
90+	Good	3.03	4.51	0.9	0.38	-0.65	0.3	1.1	0.42	0.62	0.07	0.98	0.93
90+	Fair	3.05	4.63	0.99	-0.02	-0.41	0.09	0.99	0.47	0.68	0.17	1.15	1.01
90+	Poor	3.14	4.71	0.83	0.07	-0.58	0.66	1.48	0.55	1.13	0.05	0.59	0.97

Notes: Estimates from Equation 4.15 for the time period 2001 to 2005, by health and age type. Magnitudes are comparable across types because the individual random utility is assumed to be drawn from identical Type I EV distributions.

Table B.11: Marginal Utility Estimates and Bootstrapped Standard Errors - Part 1

	Age 65-69	Age 70-74	Age 75-79	Age 80-84	Age 85-89	Age 90+
Rentindex (USD 2000)	-0.0034	-0.0032	-0.0031	-0.0031	-0.0028	-0.0018
	(2e-04)	(2e-04)	(1e-04)	(2e-04)	(2e-04)	(3e-04)
ACS (per 1,000)	-0.0921	-0.0655	-0.0543	-0.0426	-0.0415	0.0316
	(0.0141)	(0.0155)	(0.0146)	(0.0185)	(0.0268)	(0.0727)
...2	3e-04	-0.0056	-0.0186	-0.0159	-0.0103	-0.0209
	(0.0123)	(0.0149)	(0.0138)	(0.0168)	(0.0289)	(0.071)
...3	-0.0151	-0.0306	-0.0544	-0.0236	-0.0377	-0.0355
	(0.0167)	(0.019)	(0.017)	(0.0206)	(0.0228)	(0.0684)
...4	0.0624	-0.0094	0.0152	-0.0233	-0.0075	-0.0696
	(0.0223)	(0.0176)	(0.0194)	(0.0202)	(0.0242)	(0.0689)
...5	0.1082	0.0841	0.0666	0.0035	-0.0027	-0.061
	(0.0253)	(0.0228)	(0.0234)	(0.0259)	(0.0312)	(0.0789)
PM 2.5 (mg per m^2)	-0.0869	-0.068	-0.0396	-0.025	-2e-04	-0.0198
	(0.0096)	(0.0082)	(0.0071)	(0.0076)	(0.0097)	(0.0147)
Summer (C)	0.0203	0.0178	0.0094	0.0014	-0.0086	0.0042
	(0.0048)	(0.0055)	(0.0051)	(0.0073)	(0.0099)	(0.0138)
...2	0.0012	-0.0147	-0.0012	-0.0112	0.0019	-0.0227
	(0.0048)	(0.0052)	(0.0054)	(0.0072)	(0.0104)	(0.0163)
...3	0.0115	0.0023	-0.0027	-0.0026	3e-04	-0.0185
	(0.0056)	(0.0057)	(0.0057)	(0.0066)	(0.0083)	(0.0123)
...4	-0.0116	-0.0217	-0.0187	-0.0194	-0.0118	-0.0033
	(0.0062)	(0.0055)	(0.0052)	(0.0058)	(0.0095)	(0.0145)
...5	-0.0188	-0.0335	-0.0409	-0.0315	-0.0218	-0.0286
	(0.0072)	(0.0065)	(0.0058)	(0.0064)	(0.0088)	(0.0144)
Winter (C)	0.0398	0.044	0.0344	0.0352	0.036	0.0237
	(0.0034)	(0.0034)	(0.003)	(0.0042)	(0.0063)	(0.0103)
...2	0.0021	0.001	-0.0019	-0.0045	-0.0099	0.0011
	(0.003)	(0.0028)	(0.0036)	(0.0042)	(0.0052)	(0.0103)
...3	-0.0063	-0.009	0.0055	-0.0078	-0.0068	0.0041
	(0.0029)	(0.0029)	(0.0039)	(0.0042)	(0.0053)	(0.0099)
...4	0.0021	-0.0021	-0.0035	-0.0033	-0.0092	-0.0047
	(0.0037)	(0.0029)	(0.0039)	(0.0034)	(0.0057)	(0.0113)
...5	-0.0077	-0.0047	5e-04	0.0036	0	0.0073
	(0.0059)	(0.0037)	(0.0045)	(0.0042)	(0.0053)	(0.0098)

Notes: Results from estimating Equation A.2. Decomposition of flow utility values on amenities, rent indices, and variables to correct normalization in the first stage of the estimation. Standard errors in parentheses, obtained with 50 bootstrap repetitions.

Table B.12: Marginal Utility Estimates and Bootstrapped Standard Errors - Part 2

	Age 65-69	Age 70-74	Age 75-79	Age 80-84	Age 85-89	Age 90+
Precipitation (mm)	-0.096	-0.116	-0.1143	-0.1365	-0.1584	-0.1677
	(0.02)	(0.0171)	(0.0184)	(0.0245)	(0.0388)	(0.0484)
...2	0.0146	0.0204	0.0071	-0.0272	-0.0583	0.0086
	(0.022)	(0.0183)	(0.0219)	(0.0297)	(0.0429)	(0.0587)
...3	0.0254	0.0351	-0.0992	-0.0038	-0.0649	-0.0246
	(0.0195)	(0.022)	(0.0271)	(0.0254)	(0.0471)	(0.0531)
...4	-0.0388	-0.026	-0.031	-0.0363	-0.039	0.014
	(0.0258)	(0.0301)	(0.0241)	(0.0265)	(0.0431)	(0.0509)
...5	-0.0237	-0.0428	-0.0571	-0.0599	-0.0513	-0.0358
	(0.034)	(0.0244)	(0.0237)	(0.031)	(0.0419)	(0.0584)
Golf courses	0.012	0.0122	0.0123	0.0129	0.0131	0.013
	(2e-04)	(1e-04)	(1e-04)	(2e-04)	(2e-04)	(3e-04)
Correction 1	1.9636	0.938	0.246	0.7936	0.4762	0.5951
	(0.8524)	(0.345)	(0.3188)	(0.2532)	(0.4125)	(0.6912)
Correction 2	2.1973	1.7442	0.774	1.3615	0.7133	0.9538
	(0.848)	(0.3782)	(0.3446)	(0.2743)	(0.4536)	(0.5448)
Correction 3	2.2562	1.5375	1.3373	1.1424	1.2318	0.9869
	(0.8528)	(0.4088)	(0.3077)	(0.245)	(0.3738)	(0.4233)
Correction 4	3.1234	2.6684	1.7657	1.6067	1.3649	0.306
	(0.8623)	(0.3509)	(0.3065)	(0.2099)	(0.301)	(0.4093)
Correction 5	3.4226	2.9359	2.3711	1.8114	1.6112	1.4771
	(0.8734)	(0.3309)	(0.295)	(0.2091)	(0.2302)	(0.2809)
Constant	-1.2089	-0.6217	-0.2393	-0.2145	-0.0756	-0.5006
	(0.3267)	(0.1931)	(0.2281)	(0.2552)	(0.4467)	(0.4654)
N	1520	1520	1520	1520	1520	1520
R^2	0.48	0.46	0.45	0.44	0.46	0.44
Adjusted R^2	0.47	0.45	0.44	0.43	0.45	0.43

Notes: Results from estimating Equation A.2. Decomposition of flow utility values on amenities, rent indices, and variables to correct normalization in the first stage of the estimation. Standard errors in parentheses, obtained with 50 bootstrap repetitions.

APPENDIX C

SUPPLEMENTARY FIGURES

Figure C.1: Similar Places in Amenity Space - Principal Component Analysis

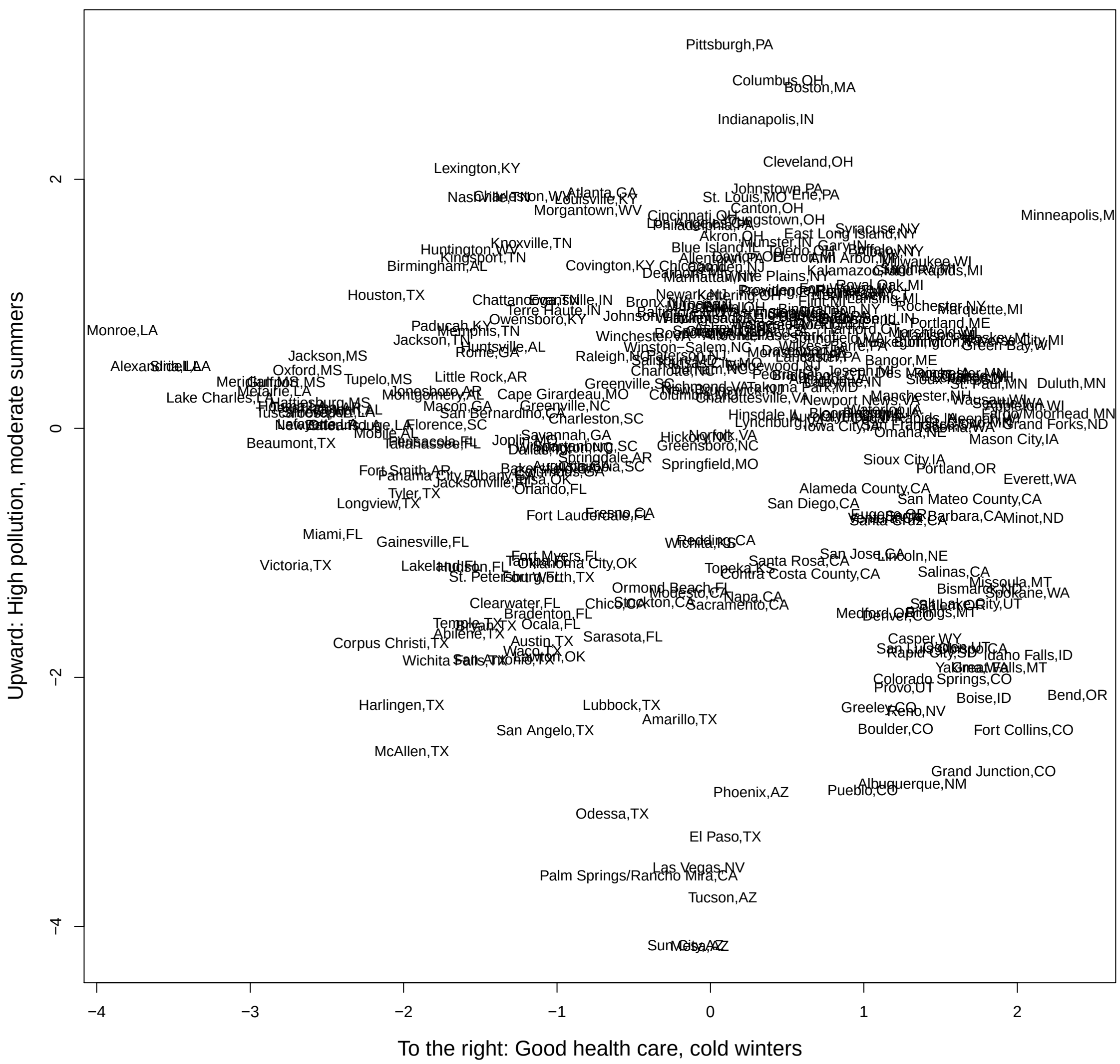

Figure C.2: Expected Changes in Average Annual Temperature (F) by the Year 2100 Under the "Business as Usual" Scenario CMIP6 SSP 585.