The Dynamics of Residential Sorting and Health: Implications of Climate Change in the U.S.

Sophie Mathes*

February 3, 2022

Abstract. This study combines the seminal ideas of Tiebout (1956) and Grossman (1972) to develop a new empirical framework for evaluating treatments that have spatially differentiated effects on health and environmental quality. Individuals are modeled as choosing a residential location based on their heterogeneous preferences for local public goods and their beliefs about how their location choices will affect the future evolution of their health. Thus, the choice of residential location constitutes a health investment, in addition to providing current and future consumption values of local public goods. To estimate the dynamic model of location choice, I employ a sample of 4.5 million seniors from 2001-2013. Seniors' preferences for public goods, private goods, and their rates of intertemporal substitution between health and consumption are allowed to vary flexibly with age and health. Results suggest that seniors' willingness-to-pay (WTP) for warmer winters is uniformly positive, while WTP to avoid warmer summers varies with age and health. Their average annual WTP to avoid future climate change in the U.S. predicted under a "business as usual" scenario for global carbon emissions ranges from \$1,431 for older, sicker groups who are more vulnerable to climate change's negative effects on health to -\$3,813 for younger, healthier groups, who value warmer winters and are relatively resilient and mobile.

JEL: *D1, I1, J1, Q5, R2*
Keywords: *Dynamic Discrete Choice, Climate Change, Non-Market Valuation, Seniors*

---

*FGV-EPGE

Acknowledgements: I thank my advisors Nick Kuminoff and Alvin Murphy for help and comments. I thank Kelly Bishop, Jonathan Ketcham, Alex Bick, Joe Hotz, Maureen Cropper, Derek Lemoine, Randy Walsh, Joe Aldy, Pat Kline, Tomas Sanguinetti, seminar participants at Arizona State University, Binghamton University, University of British Columbia, FGV-EPGE, Pontificia Universidad Javeriana, conference participants at the AERE summer meetings, ASHEcon 8th annual conference, WEAI annual meeting, ASU PhD reunion conference, EEE Sloan Summer School at UC Berkeley, EAERE post-conference workshop, RIDGE Environmental, for comments and suggestions. I acknowledge the World Climate Research Programme, which, through its Working Group on Coupled Modelling, coordinated and promoted CMIP6. I thank the climate modeling groups for producing and making available their model output, the Earth System Grid Federation (ESGF) for archiving the data and providing access, and the multiple funding agencies who support CMIP6 and ESGF. Financial support is gratefully acknowledged from Rede de Pesquisa Aplicada FGV and from Coordenação de Aperfeiçoamento de Pessoal de Nível Superior - Brasil (CAPES) - Grant # 001.

1. Introduction

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, one in four seniors report "Health Reasons" as one of the reasons for their most recent move, placing "Health Reasons" among the top responses in the Health and Retirement Survey 2008. Deciding where to live can be highly consequential for 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) 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

[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).

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, 2020; Finkelstein et al., 2021). 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 4.5 million seniors, their diagnoses of chronic medical conditions, and their deaths from 2001 through 2013.

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. The unit of choice modelled here is a Hospital Referral Region (HRR) of which there are 306 in the US. 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. Notice that the utility cost of moving is modelled as a flexible function of both distance and current health and age type, therefore the effect of age on the propensity to move is well captured.

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. (2021). 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. 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 flexibly 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 $62 to $170 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 ($151 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 (up to $438 per year for a 1mm decrease in daily precipitation.[2]). I also find that seniors are willing to pay more for better air quality, and for access to social amenities, as measured by variables containing the log number of apparel stores, dining places, golf courses, and movie theaters.

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 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.

[2] 1mm per day translates to 14.4in per year

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. The welfare gain in the above climate change scenario for the youngest and healthiest type amounts to $1,357 annually. Older and sicker types suffer from warmer summers and also from increases in precipitation levels. The oldest and sickest type would realize a welfare loss equivalent to $739 annually in the climate change scenario compared to the baseline of no climate change. Comparing different geographic locations, the 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. These results are relevant for policy-makers due to potential implications for the voting behavior of seniors and soon-to-be seniors.

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. (2021) and Deryugina and Molitor (2020) 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 the paper is organized as follows. Section 2 summarizes related literature, Section 3 outlines the model, Section 4 describes the data, Section 5 explains the estimation strategy, Section 6 reports results, Section 7 quantifies welfare effects under climate change, and Section 8 concludes.

2. 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.

2.1. 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), and 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.

[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)

(2004); Galiani et al. (2015); Sinha et al. (2018b). However, most empirical studies have used static models. Bayer et al. (2016) advanced the sorting literature by developing a tractable framework for 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. There are two main reasons for doing so. First, health and wealth are correlated (Chetty et al., 2016), so modelling different health types will partly capture differences in preferences that arise from differences in wealth. Secondly, the unit of choice in this paper is a relatively aggregated spatial unit, comparable to a city. Sorting on wealth plays an important role for sorting within a city (Epple and Sieg, 1999), but less so for large-scale spatial sorting across cities. Sorting on climate for example might be motivated by health concerns, and there is little climatic variation within a city.

A few more 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.

2.2. 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 III et al., 2002; Deryugina et al., 2019), 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, 2020). Finkelstein et al. (2021) 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.

2.3. 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 tradeoffs 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.

3. 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. Notice that this implies that individuals in the model period 2001-2006 anticipated perfectly both amenity levels and rent levels in the model period 2007-2013. 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 $\tau =$ (age, health) and the set of types is assumed to be discrete and finite in each dimension. The state space of each individual therefore is their type and their current location at the beginning of a model period. 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.

$$u_{j,t}^\tau = X_{j,t}\beta^\tau + p_{j,t}\alpha^\tau + \xi_j^\tau \tag{1}$$

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 Gompit function of age, a type-specific fixed effect, and a location-specific fixed effect.[5]

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

$$s_j^\tau = \prod_{t=1}^{6} \exp\left(-\exp(\varphi\ age_t + \gamma_j + h^\tau)\right) \tag{2}$$

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

[5]The Gompertz mortality function (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., 2021). Here I use a variation dubbed the Gompit mortality function $m_j(a) = 1 - \exp(-\exp(\varphi a + \gamma_j + h^\tau))$ which offers the benefit of being bounded by 0 and 1.

defined in detail in Section 5.

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.

$$P_j(\tau, \tau') = f(\varphi^{tr,\tau}\; age^{\tau} + \gamma_j^{tr,\tau}) \tag{3}$$

If an individual reoptimizes their location decision, they will have to pay moving cost MC. Moving costs vary by origin-destination pair and, conditional on origin-destination, are allowed to vary across types τ. 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.

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 kilometers.

$$V^{\tau}_{i,j,t} \;=\; \underbrace{u^{\tau}_{j,t}}_{\text{flow utility}} \;+\; \underbrace{\beta\, s^{\tau}_{j} \sum_{\tau'} P_j(\tau,\tau')\; E\left(\max_{k} V^{\tau'}_{k,t+1} - MC^{\tau'}(k,j) + \varepsilon_{i,k,t+1}\right)}_{\text{discounted future utility, conditional on survival } s^{\tau}_{j}} \;+\; \underbrace{\beta\,(1-s^{\tau}_{j})\,\theta}_{\text{value of death}} \tag{4}$$

The decision problem of a individual of type τ, initially located in l, is to maximize individual lifetime utility $V^{\tau}_{i,j,t}$. $V^{\tau}_{i,j,t}$ is the sum of type-place specific lifetime utility $V^{\tau}_{j,t}$ and an individual random utility shock ε_{ijt}, less moving cost MC that has to be paid in case the optimal location j is not equal to initial location l. Notice that $MC(j,j) = 0$ for all j.

$$\max_{j} V^{\tau}_{i,j,t}(l) = \; V^{\tau}_{j,t} \;-\; \underbrace{MC^{\tau}_{t}(j,l)}_{\text{moving cost}} \;+\; \underbrace{\varepsilon_{ijt}}_{\text{individual random utility}} \tag{5}$$

Figure 1 depicts the events that occur within each model period as a sequence. The individual state variables are current type $\tau = (\text{age}, \text{health})$ 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 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 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).

An important source of individual heterogeneity in the sorting literature has been income (Epple and Platt, 1998; Epple and Sieg, 1999; Bayer et al., 2004; Calabrese et al., 2006). While I do not observe income in the data, I observe eligibility for Medicaid. Medicaid eligibility is a noisy proxy for income, especially since it can causally covary with age, as people spend down their assets and become eligible for Medicaid over time. This implies that the composition of Medicaid-eligible individuals can look very different at age 65 compared to age 75 or 85. More importantly, studies that highlight the role of income for sorting typically focus on a city or a metro area, within which residents sort by income. In this study, the choice set is - roughly - a collection of cities, and across cities, sorting on income is arguably less important than within cities. In addition to that, this study uses health as a source of individual heterogeneity, and health has been shown to be systematically related to income (Chetty et al., 2016). Therefore, some of the variation captured by different types of health reflects differences in preferences by income.

A further issue to point out is that in the data, I am not able to observe neither the marital status of individuals nor the locations of family members, e.g. adult children. While locations

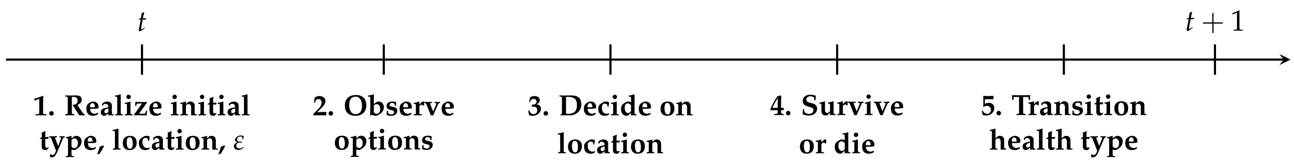


Figure 1: TIMELINE OF EVENTS WITHIN ONE MODEL PERIOD

of adult children certainly play an important role in location decisions of the elderly, the following considerations might alleviate the reader's concern. Firstly, some of the variation stemming from locations of adult children will be captured by the individual random utility. As long as not all seniors in one specific location have all of their children in one different specific location, the individual random utility will account for a large part of this. Second, whenever seniors have more than one adult child living in separate locations, they still have more than one option to choose from if they wish to live close to them and at this point, considerations about local amenities and price levels will enter the decision. Finally, the pairwise regional dummies in the moving cost function account for popular migration channels, for example seniors from the Northeast tend to move to the South and seniors from the Midwest tend to move to the West. This will further clean up some of the variation that is induced by adult children's location because it will make it cheaper to return to the region of origin, where adult children might potentially have stayed, in the subsequent model period.

4. Data

Information on individual location, age, and health comes from confidential 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 1999-2013 (i.e. Medicare Parts A and B)[6]. 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 1999 to 2013, or until they die. Individuals exit the data when they die. Their residential locations are observed as a ZIP+4 code, which is a mail delivery point such as a unique address, one floor of an apartment building, or one side of a street on a city block.[7] 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. (2021). Table 1 lists these conditions ranked by incidence in 2001, which is the start of the designated first model period 2001-2006. The most common condition by far is hypertension, which afflicts over 40 percent of individuals. Over 30 percent are diagnosed with ischemic heart disease.

4.1. 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 quartiles, based on their number of chronic conditions. The resulting mapping from the number of diagnosed conditions to health type quartile is reported in Table 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. (2021) show that the frailty

[6] Individuals who are enrolled in Medicare Advantage during the years 2001, 2007, or 2013 are dropped from the main estimation because the data on chronic medical conditions is not available for these individuals.
[7] The average ZIP+4 code contains fewer than five households.

Table 1: INCIDENCE OF CHRONIC CONDITIONS

Condition	Percent
Hypertension	45.1
Ischemic heart disease	30.9
Hyperlipidemia	26.7
Cataract	26.3
Rheumatoid arthritis, osteoarthritis	23.2
Diabetes	18.8
Anemia	18.3
Congestive heart failure	16.5
COPD	10.1
Glaucoma	9.6
Hypothyroidism	9.0
Dementia	8.8
Depression	7.5
Atrial fibrillation	6.9
Osteoporosis	5.7
Chronic kidney disease	5.0
Hyperplasia	4.8
Stroke, transient ischemic attack	4.8
Alzheimer's disease	3.9
Prostate cancer	3.3
Asthma	3.0
Breast cancer	2.7
Colorectal cancer	1.5
Acute myocardial infarction	0.9
Hip fracture	0.9
Lung cancer	0.7
Endometrial cancer	0.2

Notes: This table reports the fraction of people over age 65 who had been diagnosed with each chronic condition in 2001. It is based on data from CMS's chronic conditions warehouse file for the sample of 4.5 million people.

Table 2: MAPPING FROM COUNT OF CHRONIC CONDITIONS TO HEALTH QUARTILES

	Health Quartile			
	1	2	3	4
Number of conditions	0-1	2-3	4	5+
Interpretation	Excellent	Good	Fair	Poor

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 3.6. Conditional on having cancer, individuals have on average 4.7 chronic conditions.

Table 3 shows the fraction of individuals per type that are observed in 2001 and survive until January 1, 2007. For example, out of all 65-70 year olds that had one or zero diagnosed chronic condition in 2001, 90.0 percent lived to see the year 2007. At the opposite extreme, out of all those older than 83 who were diagnosed with 5 or more chronic conditions in 2001, only 69.3 percent lived to see the year 2007. The rest of the table shows considerable heterogeneity in survival rates by age and by health, with clear reassuring monotonicity in age conditional on health and health conditional on age.

Table 4 shows the health transition rates from 2001 to 2007, conditional on survival until 2007. Out of all individuals with one or zero diagnosed chronic conditions in 2001, 38.4 percent still have only one or zero diagnosed chronic conditions in 2007.

Table 3: SURVIVAL RATES BY TYPE, FROM 2001 UNTIL 2006

	Health Quartile			
Age	Excellent	Good	Fair	Poor
65-70	90.0	87.5	82.8	69.3
71-76	84.3	82.6	78.3	64.5
77-82	75.0	72.6	67.7	53.4
83+	54.4	49.3	43.1	31.0

Table 4: TRANSITION RATES BETWEEN DIFFERENT STATES OF HEALTH

	Health Quartile 2007				
Health 2001	1	2	3	4	Total
1	38.4	29.7	11.3	20.6	100.0
2	11.5	30.9	17.5	40.1	100.0
3	5.3	20.7	17.4	56.7	100.0
4	2.7	11.7	11.9	73.7	100.0

4.2. Residential Locations: Hospital Referral Regions

The geographic units that individuals can choose in the model are Hospital Referral Regions (HRR)[8]. 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 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 306 HRRs in the US, and they can be thought of roughly as cities. Large metropolitan areas may contain multiple HRRs. To help visualize the geographic scale, Figure 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

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

Table 5: AMENITY LEVELS ACROSS HOSPITAL REFERRAL REGIONS, 2001-2006

	Mean	Median	SD
Rentindex	336.0	283.7	174.9
Summer temperature (C)	30.9	30.5	2.9
Winter temperature (C)	6.7	6.0	6.9
Precipitation daily (mm)	2.7	2.9	1.0
Apparel stores	408.3	220.9	536.8
Dining places	1,342.8	821	1,537
Golf courses & country clubs	32.4	22.3	28.8
Movie theaters	13.1	8.2	14.3
PM 2.5 (microgram per m^3)	12.1	12.4	2.2
Ambulatory care-sensitive hospital stays (per 1,000 Medicare enrollees)	78.7	77.5	19.2

Notes: The mean, medians, and standard deviations presented in this table are taken across HRRs. For any given HRR, the respective amenity level is averaged across all years in the model period 2001-2006.

HRRs based on their ZIP code. Table 5 summarizes variation in amenity levels across HRRs.

4.3. 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; Chamberlain, 2019). All NOAA weather stations that continuously report temperature and precipitation from 1999 until 2012 are selected. There are 9,959 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 model period 2001-2006, summer temperature, winter temperature, and precipitation are averaged across the years 2001-2006, to reduce sensitivity of climate measures to annual variation in weather. This process is repeated for the model period 2007-2012, by averaging the climate amenity variables across all years in the model period. Including both winter and summer temperature in the model provides a more nuanced measure of climate compared to annual average temperature. 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). The climate at a given HRR is interpolated as the weighted average across all weather stations, weighted at the inverse squared distance in kilometers from each station to the population-weighted centroid of each HRR.

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.[9] The projection data is available in a global geopraphic grid of 100 km resolution, where over 1,000 points fall in the area of the United States. Following the approach of Albouy et al. (2016), the projected climate of an HRR is approximated as the weighted average of the projected climate at the four nearest grid points, weighted by the inverse square distance between the HRR population weighted centroid and the four grid points in kilometers. Figure 2 provides maps of expected temperature changes by 2100 for the "business as usual" scenario, where no large reductions in carbon emissions are assumed. Summer temperatures are projected to increase between 4 and 9 degrees (C), while winter temperatures would increase

[9] 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).

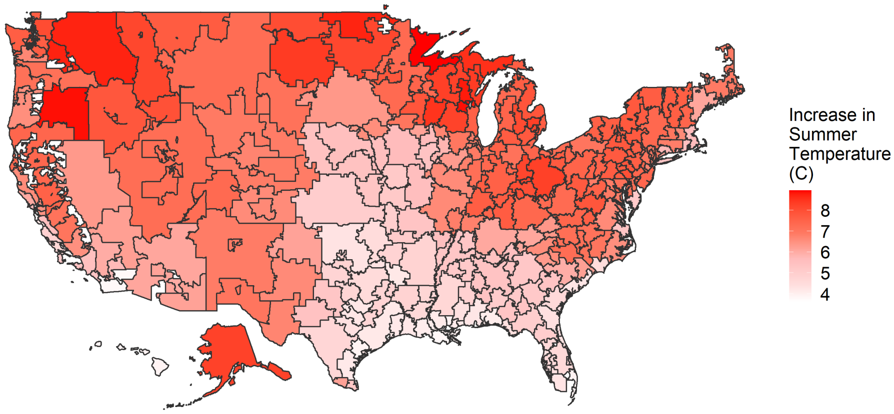
between 3 and 14 degrees (C). Total annual precipitation is projected to change between -0.5 and 0.9 mm per day depending on location, which corresponds to -7 and 12 inches in annual rainfall.

4.4. Housing Prices, and Other Location-Specific Amenities

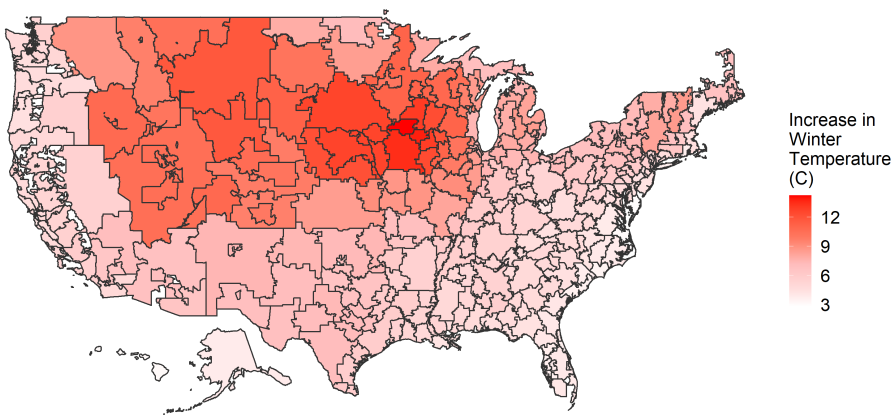
The differences in cost of housing across HRRs are estimated using data from the 2000 Census 5 percent sample and the 2005-2012 American Consumer Survey, following the regression procedure from Bayer et al. (2009), which I describe in more detail in Section 5.3.2. Gross rental prices are used to measure the per-period cost of living in an area, without reflecting future expectations about asset value that are contained in real estate prices. For each year in the model periods, gross rents are regressed on housing characteristics and public use microdata area (PUMA) specific intercepts. These PUMA specific rent indices are taken to be the price premiums that have to be paid to live in a certain PUMA. The PUMA specific rent indices are then aggregated into HRR specific rent indices based on crosswalks from PUMAs to zip code tabulation areas, which can be aggregated into HRRs.[10] The HRR-specific rent indices are finally averaged across the years 2000, 2005, and 2006, to form a measure of the location-specific rent premia throughout the model period 2001-2006.[11] 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. Rental prices have been found to correlate most accurately with observable amenity levels (Banzhaf and Farooque, 2013). All following amenities measures have been constructed on the HRR-level

[10] Crosswalks from PUMA (2000) to ZCTA were taken from the MCDC Geographic Correspondence Engine 2014.

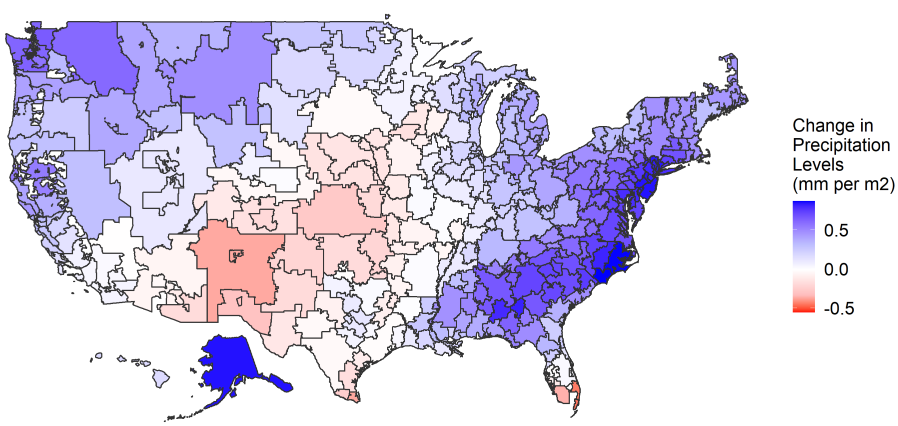
[11] The American Consumer Survey does not contain information on PUMAs for the years 2001-2004, therefore this geographic aggregation cannot be applied for these years.



(a) Projected Changes in Summer Temperature (C)



(b) Projected Changes in Winter Temperature (C)



(c) Projected Changes in Precipitation Levels (Daily mm per m2)

Figure 2: EXPECTED CHANGES BY THE YEAR 2100 UNDER THE "BUSINESS AS USUAL" SCENARIO CMIP6 SSP 585.

for each year from 2001 to 2006, and finally averaged across years to measure amenity levels throughout the model period. Amenity levels for the model period 2007-2012 were built analogously.

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 annual Census Business Patterns (CBP) provide data on the number of establishments by ZIP code and NAICS codes. All establishments classified as golf courses, country clubs, dining places, apparel stores, or movie theaters are added up per HRR. These variables are intended to capture a proxy for the cultural and social appeal of a location and are 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`

Table 6: SUMMARY STATISTICS IN 2001

Mean age (years)	75.5
Mean number of diagnosed chronic conditions	2.9
Mobility from 2001 to 2006 (percent)	
... across HRR	7.2
... across state	4.6
... across Census regions	2.4
Mortality (percent)	
... until 2006	28.8
Number of observations (million)	4.5

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

4.5. Summary Statistics

Table 6 summarizes key features of the estimation sample. The mean age in the sample is 75.5 years in 2001 and the average person is diagnosed with 2.9 chronic conditions. The table also shows the incidence of moving within the six year period from 2001 to 2006. Over 7 percent of individuals move across HRRs throughout this period. 4.6 percent of individuals move across state lines and 2.4 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 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.

[14]Only 1.3 percent of individuals in the raw sample move more than once within six years.

Table 7: CROSS-REGIONAL MIGRATION FLOWS IN MODEL PERIOD 2001-2006

	Destination				
Origin	Northeast	Midwest	South	West	Total
Northeast	96.8	0.3	2.5	0.4	100.0
Midwest	0.1	97.7	1.5	0.7	100.0
South	0.8	0.9	97.8	0.5	100.0
West	0.2	0.8	1.2	97.8	100.0
Total	20.1	25.6	39.1	15.2	100.0

Notes: Contains non-movers and one-time movers who have been observed in 2001. The definition of region corresponds to Census regions.

5. 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. (2021) 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. (2021). 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 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).

5.1. 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 states of health. 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. This strategy mirrors the estimation strategy of mortality fixed effects from Finkelstein et al. (2021), with the additional benefit that unlike mortality, health can be observed at multiple points in time for the same individual. Therefore, the location-specific causal effects on health transitions can be estimated even more credibly without the need to apply the more sophisticated selection-correction strategy detailed in Section 5.2.

For each health type τ in 2001, the probability of transitioning to health type τ' in 2007 is expressed as a function of age fixed effects $\varphi^{tr,\tau}_{1,age}$, demographics, and location fixed effects $\delta^{tr,\tau}_{j}$, using an ordered logit model. Equation 6 shows the estimation equation. To calculate the fitted location-specific transition probabilities for each type, I use the national average demographics to eliminate confounding effects from changes in demographic composition across types.

$$P_{i,j}(\tau,\tau') = f(\varphi^{tr,\tau}_{1,age}\mathbb{1}_{age} + \varphi^{tr,\tau}_{2}\ demog_i + \delta^{tr,\tau}_{j}\ \mathbb{1}_j) + \eta^{tr}_{i} \quad \forall \tau \tag{6}$$

The demographic variables included in the model are gender, race, and a proxy for low income. 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]

5.2. 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. (2021). 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. (2021) 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 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.

$$\log(m_i) = \varphi_1 \ age_i + \varphi_2 \ demog_i + \varphi_3 \ h_i + \delta_j^o \ \mathbb{1}_{j,orig} + \delta_j^d \ \mathbb{1}_{j,dest} + \delta_j^n \ \mathbb{1}_{j,nonmove} + \eta_i \tag{7}$$

Demographic variables contain gender, race, an interaction term, and a proxy for low income. Health variables contain annual utilitization and a set of indicators for the presence of chronic conditions. The location fixed effects δ_j^o, δ_j^d, δ_j^n capture the location specific mortality effects

[15] Sorting on unobservable, time-varying health remains a concern. Finkelstein et al. (2021) suggest 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.

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 8 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.

$$\hat{h}_i = \varphi_1^h \, age_i + \varphi_2^h \, demog_i + \zeta_j^o \, \mathbb{1}_{j,orig} + \zeta_j^d \, \mathbb{1}_{j,dest} + \eta_i^h \tag{8}$$

The fitted health stock from Equation 7, $\hat{h}_i := \hat{\varphi}_3 h_i$, is 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

$$\hat{\gamma}_j = \hat{\delta}_j^d - \frac{\hat{sd}(\hat{\delta}_j^o)}{\hat{sd}(\hat{\zeta}_j^o)} \hat{\zeta}_j^d \tag{9}$$

$\hat{sd}(\hat{\delta}_j^o)$ 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 six years, the resulting estimates are converted to six-year periods using Equation 10.

$$\hat{s}_j^\tau = \prod_{t=1}^{6} \Big(\exp(-\exp(\hat{\varphi}_1 \, age_t^\tau + \hat{\gamma}_j + \hat{h}^\tau) \Big) \tag{10}$$

To survive one model period of six years, annual survival has to succeed six consecutive times. Type specific health capital $\hat{h}^\tau$ is averaged across all non-movers of type τ.

5.3. 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

$$P^{\tau}_{j,t}(l) = \frac{\exp(V^{\tau}_{j,t} - MC^{\tau}_{t}(j,l))}{\sum_k \exp(V^{\tau}_{k,t} - MC^{\tau}_{t}(k,l))} \tag{11}$$

The lifetime utility values V and the utility cost of moving MC are estimated separately for each type, and for the periods 2001-2006 and 2007-2012, with a maximum likelihood estimation (Equation 13).[16] Notice that the lifetime utility values are identified from observed choice probabilities only up to a constant. Adding a constant to all estimated lifetime utility values V does not alter the conditional choice probabilities P, in line with standard microeconomic theory. To facilitate the estimation, the average V per type τ and time t is normalized to 0.

$$\begin{aligned} L^{\tau}_{i,t} &= \sum_j \log P^{\tau}_{j,t}(l)\, \mathbb{1}(choice_{i,t} = j) && (12) \\ LLF^{\tau}_{t} &= \max_{V,\gamma} \sum_i L^{\tau}_{i,t} && (13) \\ \text{s.t.} \quad V^{\tau}_{t} &= \lim_{x\to\infty} V^{\tau}_{x+1} = \lim_{x\to\infty} V^{\tau}_{x} + \log(\pi_{true}) - \log(\pi(V^{\tau}_{x})) && (14) \end{aligned}$$

$\pi(V)$ 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. Moving cost are modelled as a utility

[16] Maximizing over 306 location-specific parameters for V^{τ}_{t} would be computationally prohibitive, so the values of V^{τ}_{t} are estimated by applying a Berry contraction mapping (Equation 14) (Berry, 1994).

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 kilometers (Equation 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.

$$\begin{aligned} MC_t^{\tau}(k,l) \;=\;& \mu_1^{\tau}\,\mathbb{1}_{state}(k,l) + \mu_2^{\tau}\,\mathbb{1}_{>100km}(k,l) + \mu_3^{\tau}\,\mathbb{1}_{>500km}(k,l) + \mu_4^{\tau}\,\mathbb{1}_{>1{,}000km}(k,l) \\ &+ \mu_5^{\tau}\,\mathbb{1}_{>1{,}500km}(k,l) + \mu_6^{\tau}\,\mathbb{1}_{>2{,}000km}(k,l) + \mu_7^{\tau}\,\mathbb{1}_{\text{Northeast-Midwest}}(k,l) \\ &+ \mu_8^{\tau}\,\mathbb{1}_{\text{Northeast-South}}(k,l) + \mu_9^{\tau}\,\mathbb{1}_{\text{Northeast-West}}(k,l) + \mu_{10}^{\tau}\,\mathbb{1}_{\text{Midwest-South}}(k,l) \\ &+ \mu_{11}^{\tau}\,\mathbb{1}_{\text{Midwest-West}}(k,l) + \mu_{12}^{\tau}\,\mathbb{1}_{\text{South-West}}(k,l) \end{aligned} \tag{15}$$

This estimation process is performed separately for each of the 16 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.[17]

[17]Table 12 illustrates migration flows across regions.

5.3.1. Identification of Moving Cost and Utility Values

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, the shape parameter is normalized for each type, analogous to Bayer et al. (2016). 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 V comes from the cross-section of location decisions, conditional on moving cost. Mean lifetime utility values V^{τ}_{t} per type τ and period t are only identified up to an additive constant. I estimate $\tilde{V}^{\tau}_{t}$, where $\tilde{V}^{\tau}_{t} = V^{\tau}_{t} + a^{\tau}_{t}$ with some unknown constant a^{τ}_{t}. Normalizing the average mean utility value to zero in the estimation implies that the unidentified constant equals the average mean utility values per type per period in absolute terms.

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.[18]

$$E(\max_k V^{\tau'}_{k,t+1} - MC^{\tau'}(k,j) + \varepsilon_{ik,t+1}|j,\tau) = \\ E\left[\log \sum_k \exp\left(V^{\tau'}_{k,t+1} - MC^{\tau'}(k,j)|k,\tau' \right) + c_{EM} \middle| j,\tau \right] \tag{16}$$

[18] 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 $\mu + \beta \cdot c_{EM}$.

To infer flow utility values u_t^τ, Equations 4 and 16 are combined as follows

$$u_{j,t}^{\tau} = V_{j,t}^{\tau} - \beta\, s_{j,t}^{\tau}\, E_{j,t}^{\tau}\left[c_{EM} + \log\sum_{k}\exp(V_{k,t+1}^{\tau'} - MC^{\tau'}(k,j))\right] - \beta\,(1 - s_{j,t}^{\tau})\,\theta \tag{17}$$

In overly simple terms, the current flow utility u_t^τ is computed as the difference between the mean lifetime utility values at two different points in time. If there were no type transitions, no uncertainty, and no time discounting, inferring u would amount to taking simple differences $u_1 = V_1 - V_2$. To see how the current flow utility is identified, consider this simplified example: The lifetime utility values V are identified up to a constant, per type τ and per time t. If $V_{1,1}$ is the utility value of location 1 in period 1, and $V_{1,2}$ is the utility value of location 1 in period 2, their difference identifies the flow utility $u_{1,1}$ in location 1, period 1. Call the true unidentified utility constant at time 1 a, and the true unidentified utility constant at time 2 b, so the estimation yields $\tilde{V}_{1,1} = V_{1,1} + a$ and $\tilde{V}_{1,2} = V_{1,2} + b$. Then the flow utility will be computed as $\tilde{u}_{1,1} = \tilde{V}_{1,1} - \tilde{V}_{1,2} = V_{1,1} - V_{1,2} + a - b$. When the estimated flow utilities $\tilde{u}$ are decomposed to recover the model parameters α^τ and β^τ, the unidentified constant $a - b$ will be absorbed into the regression constant. The differences in flow utility values u would be identified off of the differences in lifetime utility values V.

In a dynamic setting with type transitions, more restrictions need to be placed to identify variation in u in order to ultimately identify the model parameters α^τ and β^τ. In a simple extension to the example above, consider the possibility of two different health types i and ii, where the transition to type i in period 2 occurs with probability p. Estimating lifetime utility values for each period and each type yields $\tilde{V}_1^i = V_1^i + a^i$, $\tilde{V}_1^{ii} = V_1^{ii} + a^{ii}$, $\tilde{V}_2^i = V_2^i + b^i$,

$\tilde{V}_2^{ii} = V_2^{ii} + b^{ii}$. Now

$$\begin{aligned}
\tilde{u}_1^i &= \tilde{V}_1^i - p\tilde{V}_2^i - (1-p)\tilde{V}_2^{ii} = V_1^i + a^i - p(V_2^i + b^i) - (1-p)(V_2^{ii} + b^{ii}) \\
&= u_1^i + a^i - pb^i - (1-p)b^{ii} \\
\tilde{u}_1^{ii} &= \tilde{V}_1^{ii} - p\tilde{V}_2^i - (1-p)\tilde{V}_2^{ii} = V_1^{ii} + a^{ii} - p(V_2^i + b^i) - (1-p)(V_2^{ii} + b^{ii}) \\
&= u_1^{ii} + a^{ii} - pb^i - (1-p)b^{ii}
\end{aligned}$$

To be able to estimate the model parameters α^τ and β^τ via a decomposition of $\tilde{u}$, I assume that $a^i = b^i$ and $a^{ii} = b^{ii}$. Intuitively, this assumption requires that conditional on maintaining the same health status, individuals are indifferent to aging. More precisely in the context of this study, the assumption requires that a perfectly healthy 65 year old in the period 2001-2006 is just as happy as a perfectly healthy 71 year old in the period 2007-2013. Finally, notice that the type transition probabilities p depend on the current type i versus ii and vary across locations. Therefore, when I estimate the model parameters α^τ and β^τ through a decomposition of $\tilde{u}$, I pool the estimated $\tilde{u}$ values across health types for each given age type, and include interactions between transition probabilities and health type dummies. The previously unidentified constants are thus identified after imposing this assumption, and the estimated correction constants are included in Table 14. The fact that the estimated type-specific correction constants are monotonically decreasing in absolute terms from health type 1 to health type 4 is intuitively appealing because it is consistent with the idea that better health is more desirable.

In short, 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 $\hat{P}_j(\tau, \tau')$.

$$\tilde{u}^{\tau}_{j,t} = \tilde{V}^{\tau}_{j,t} - \beta\, s^{\tau}_{j,t}\, E^{\tau}_{j,t} \left[c_{EM} + \log \sum_k \exp(\tilde{V}^{\tau'}_{k,t+1} - \widehat{MC}^{\tau'}_{t+1}(k,j)) \right] \tag{18}$$

Appendix Section A.1 provides more technical details. Finally, the discount factor β is set to 0.833, extrapolating the 3 percent annual discounting from Aldy and Viscusi (2008) to a period of 6 years.

5.3.2. 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.[19] This captures how much in additional rent 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. Rents capture the cost of housing for renters, and the opportunity cost of using the house instead of renting it out for home owners. Notice that even when concerns about future house prices affect house sales decisions due to bequest motives, home-owning seniors still have the option to rent out the house and locate elsewhere in the mean time.

[19] 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.

$$p_{i,j,t} = \beta^p \; H_{i,t} + \delta^p \; \mathbb{1}_j + \varepsilon^p_{i,t} \tag{19}$$

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 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 150 kilometers (approximately 93 miles) away and belong to a different state.[20]

$$p_{j,t} = X_{j',t}\,\tilde{\beta} + \tilde{\xi}_{j'} \tag{20}$$

$$\hat{u}^{\tau}_{j,t} = X_{j,t}\,\beta^{\tau} + p_{j,t}\,\alpha^{\tau} + \xi^{\tau}_{j} \tag{21}$$

Equation 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 21 shows conceptually the decomposition of mean flow utility values $\hat{u}$ on local prices and amenity levels. The full decomposition equation employed in this estimation, accounting for the previous normalization of $\tilde{V}^{\tau}_{t}$, is detailed in Appendix Section A.1.

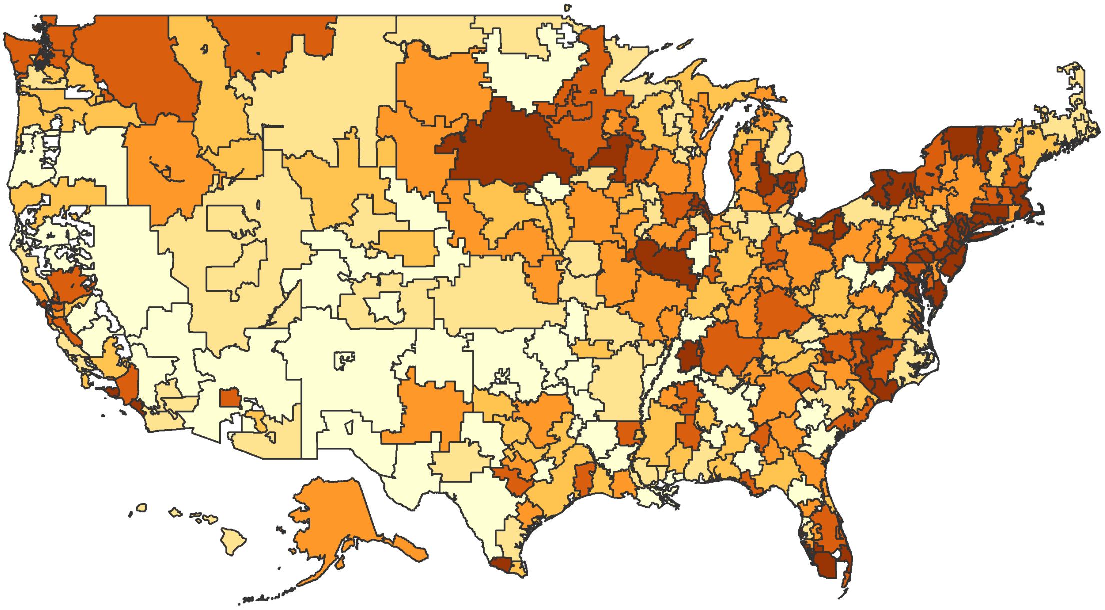
6. Results

6.1. Survival and Health Fixed Effects

Figure 3 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.

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 306 available locations. Figure 4 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

[20]A plot of the first and second principal component can be found in Appendix Figure 9. Places that are plotted close to each other are similar in amenities.



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

Figure 3: ESTIMATED PLACE-FIXED EFFECTS ON SURVIVAL

is larger than the variation in median life expectancy across health types at age 65.

6.2. Moving Cost Parameter Estimates

Moving costs and mean lifetime utility values are estimated separately for each age and health type. To develop intuition, Table 8 reports the moving cost parameters from a pooled estimation over all types. A complete set of heterogeneous moving cost parameters by type with bootstrapped standard errors is reported in the Appendix Table 13.

Table 8 shows that moves of relatively short distances are relatively expensive, indicating a high fixed utility cost of moving. An in-state move between 100 and 500 km is estimated to cost 4.91 utils, which is larger than the range of mean lifetime utils across space (-2.56, 1.80). The distance parameters add up sequentially. For example, an in-state move of 501 km is estimated

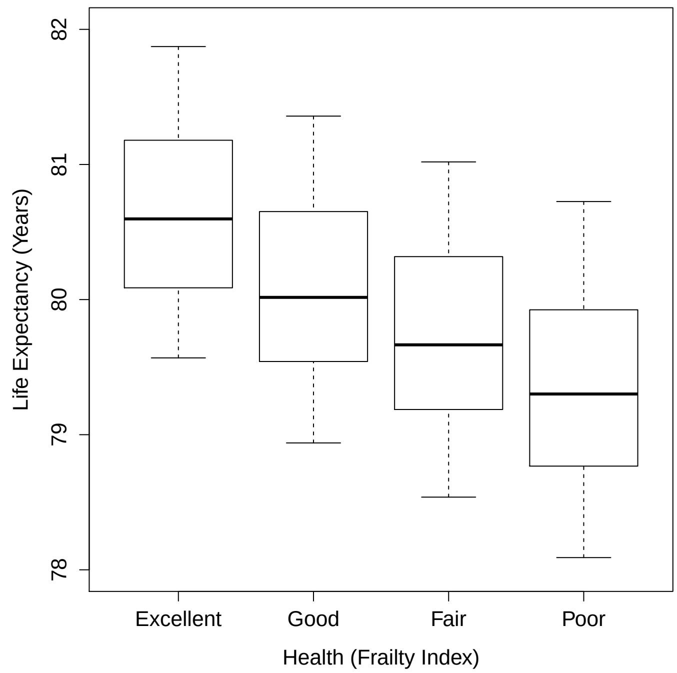


Figure 4: SPATIAL VARIATION IN LIFE EXPECTANCY AT AGE 65

Table 8: MOVING COST PARAMETER ESTIMATES

Cross state	3.14
Distance indicator	
>100 km	4.91
>500 km	0.25
>1,000 km	-0.08
>1,500 km	-0.51
>2,000 km	0.88
Origin-destination combinations	
Northeast-Midwest	1.36
Northeast-South	-0.06
Northeast-West	0.19
Midwest-South	0.32
Midwest-West	0.03
South-West	0.21

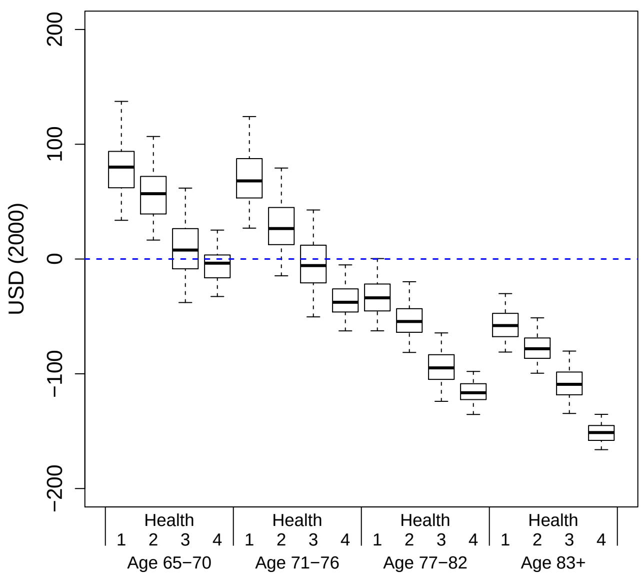
Estimated moving cost parameters of Equation 15 for full sample, model period 2001-2006. For full table of all types see Table 13 to cost 5.16 utils. Moving across state lines increases costs further. Moving costs increase in distance at a decreasing rate and decrease between 1,000 and 2,000 km, suggestive of concave moving costs up on a moving distance until 2,000 km. Moving longer distances than 2,000 km appears to again be more costly. 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 slightly negative additional moving cost for moves from the Northeast to the South reflects the popularity of the South as a destination for seniors from the Northeast (Table 12).

6.3. Willingness to Pay for Local Amenities

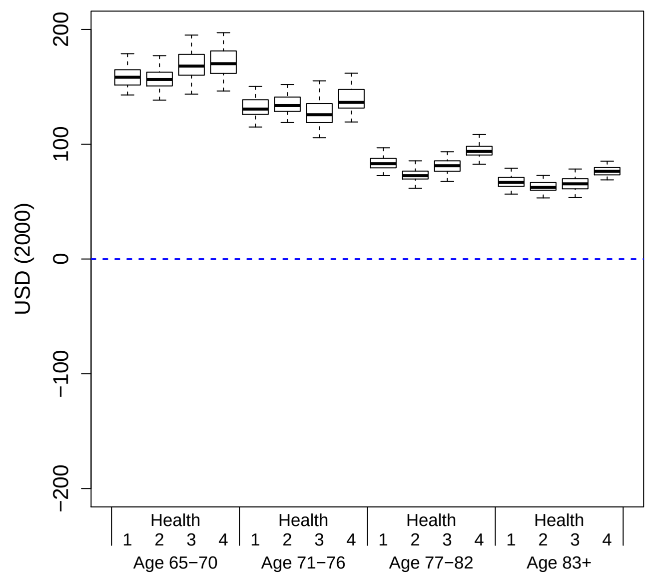
Amenities are an important determinant of individual location decisions.[21] Figure 5 shows the estimates for annual marginal willingness to pay (WTP) for climate amenities in 2000 USD. More precisely, these are estimates for the annual WTP to change climate in the current period.

For higher summer temperatures, the younger and healthier types even have positive valuations. The WTP estimates for summer temperature have a distinct trend in age and in health: older and sicker types exhibit WTP to avoid summer heat, other than younger and healthier types who appreciate it. For example, for the youngest types aged 65-70, annual WTP for a 1C increase in summer temperature ranges from 80 dollars for the healthiest types to -4 for the sickest types. For the oldest type aged 83 and older, the analogous range is -58 dollars to -151 dollars.

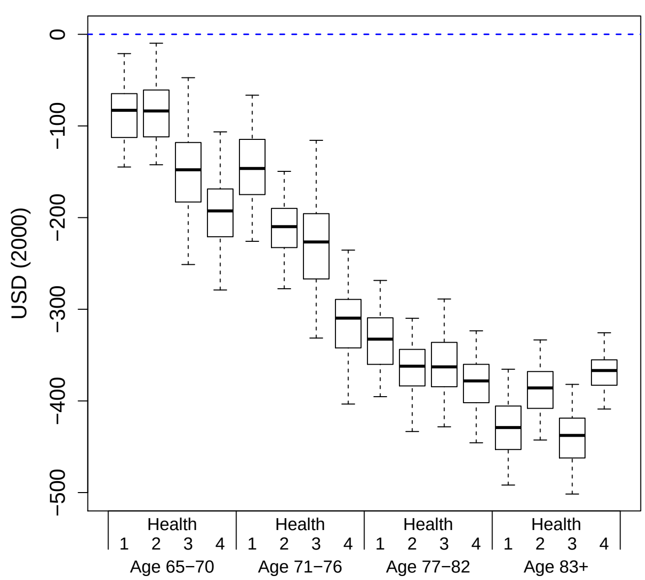
[21] The adjusted R^2 is higher than 50 percent for all second stage decompositions.



(a) Summer temperature (C)



(b) Winter temperature (C)



(c) Daily precipitation (mm)

Figure 5: ANNUAL MWTP FOR AMENITIES BY AGE AND HEALTH TYPE

Whisker plots with 95 percent Confidence Intervals from $B = 200$ bootstrap resamples.

For higher winter temperatures, the estimated valuation appears to be consistently positive across all types. 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 and ranges between 62 and 170 dollars.

Valuation for humidity - proxied with average daily precipitation - is consistently negative for all types. Relatively younger and healthier types seem to be less sensitive to humid climate, but view humidity increasingly as a disamenity as health worsens and as they get older. The annual WTP for 1mm increase in daily precipitation ranges from -83 dollars for the youngest and healthiest to -367 dollars for the oldest types. These numbers might seem quantitatively more important than the WTP for changes in temperature, but a 1mm daily rainfall would in fact mean a notable increase since the average daily rainfall is 2.7mm.

Results of WTP for non-climate amenities are mostly intuitive. For example, the annual WTP to reduce PM 2.5 by one microgram ranges from 265 dollars for the youngest types to 67 dollars for the oldest types. Valuation for social amenities like golf courses, movie theaters, apparel stores and dining places also appears to be reassuringly positive. For tractability, the WTP for amenities other than climate is restricted to vary only by age type.[22]

6.4. Model Fit

The estimated model does a reasonable job in predicting moves compared to Bayer et al. (2016) who focused on a single metropolitan area. Using the same diagnostic measures of

[22] A complete set of marginal utility estimates for all types and amenities with standard errors is reported in Appendix Table 14.

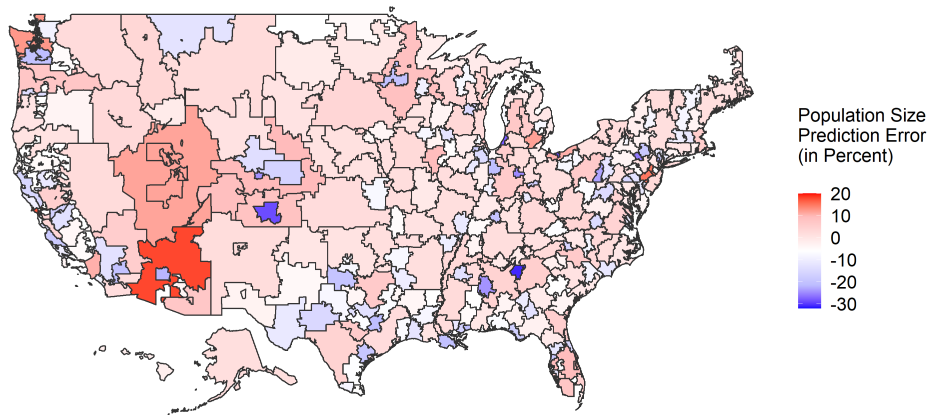


Figure 6: MODEL FIT PER LOCATION

Predicted population size relative to actual population size per HRR for model period 2001-2006

model fit as their study I find that, across the full sample, 96 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 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 65 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.

Figure 6 provides a map of predicted population size relative to actual population size per HRR, resulting from fitted location choices in model period 2001-2006. The median prediction error in population size across locations is -3.5 percent.

7. 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 climate 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[23], 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. 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 2 shows a map of the implied changes to average summer temperature, winter temperature, and average daily precipitation.

7.1. 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 6 and

[23]World Climate Research Programme Database CMIP6 ScenarioMIP SSP585

7 are regressed on all observed amenities. Notice that the resulting coefficients are not causal estimates, they merely describe how the location-specific fixed effects co-vary with local characteristics. The location-specific fixed effects in question are $\gamma_j^{tr,\tau}$ from Equation 3 and γ_j from Equation 2. The regression coefficients are reported in Table 9. Higher temperatures are found to be associated with higher mortality and morbidity. Humidity, proxied by precipitation, has 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. Since both the survival rates (Equation 10) and the health transition rates (Equation 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 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 22. The terminal period is defined to be the period after age type 4. In this terminal period, the individual consumes only their flow utility and dies with certainty at the end of the period. This restriction provides a reasonable approximation to the data in which less than one percent of seniors are older than 95 years[24].

Lifetime utility of age type 4 is constructed for each possible health type, as outlined in

[24]According to the Population Pyramid Project, the share of 95+ year olds among the senior population (65+) was 0.96 percent in the year 2000.

Table 9: MARGINAL EFFECTS OF AMENITIES ON PLACE-SPECIFIC HEALTH AND MORTALITY

	Mortality	Health
Rentindex (USD 2000)	-0.0001	0.0003
	(0.0000)	(0.0000)
Summer (C)	0.0016	0.0010
	(0.0013)	(0.0024)
Winter (C)	0.0025	0.0032
	(0.0005)	(0.0010)
Precipitation (mm)	-0.0102	0.0282
	(0.0034)	(0.0066)
Apparel stores (log)	-0.0588	0.0596
	(0.0128)	(0.0248)
Dining places (log)	0.0622	0.0223
	(0.0150)	(0.0291)
Golf courses (log)	-0.0048	0.0364
	(0.0062)	(0.0120)
Movie theaters (log)	-0.0002	-0.1357
	(0.0080)	(0.0155)
PM 2.5 (mg per m^2)	-0.0018	0.0206
	(0.0013)	(0.0026)
Ambulatory care-sensitive hospital stays	-0.0003	0.0633
(per 1,000 Medicare enrollees)	(0.0035)	(0.0068)
Constant	-0.0571	-0.8676
	(0.0620)	(0.1199)
N	306	1,224
R^2	0.40	0.41
Adjusted R^2	0.38	0.40

Notes: Dependent variables: Causal place fixed effects for mortality $\hat{\delta}_j$ and health transition $\hat{\delta}_j^{\tau}$. Place fixed effects on health transition are pooled across initial health types. Higher values imply higher mortality and higher rates of transition to worse states of health. Standard errors in parentheses.

Equation 22. The 'future' lifetime utility of age type 4 is simply the flow utility of the terminal period, less moving costs, depending on the current location, weighted by the probability of transitioning to a different state of health. Next, the flow utility of age type 3 is calculated for each possible health type, as the sum of the current flow utility plus the discounted lifetime utility of age type 4, which is the lifetime utility in the next period, again less moving costs, and weighted by the probability of transitioning to a different health type. This recursive structure is applied 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 and average rent index levels in the period 2007-2012 when making their location decisions in the period 2001-2006. 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. As part of this counterfactual, it is only relevant what individuals assume in the period 2001-2006 with respect to the period 2007-2012. In this counterfactual, there are no more decisions being made in the period 2006-2012 that could be affected by shifted expectations due to the housing bust in this period.

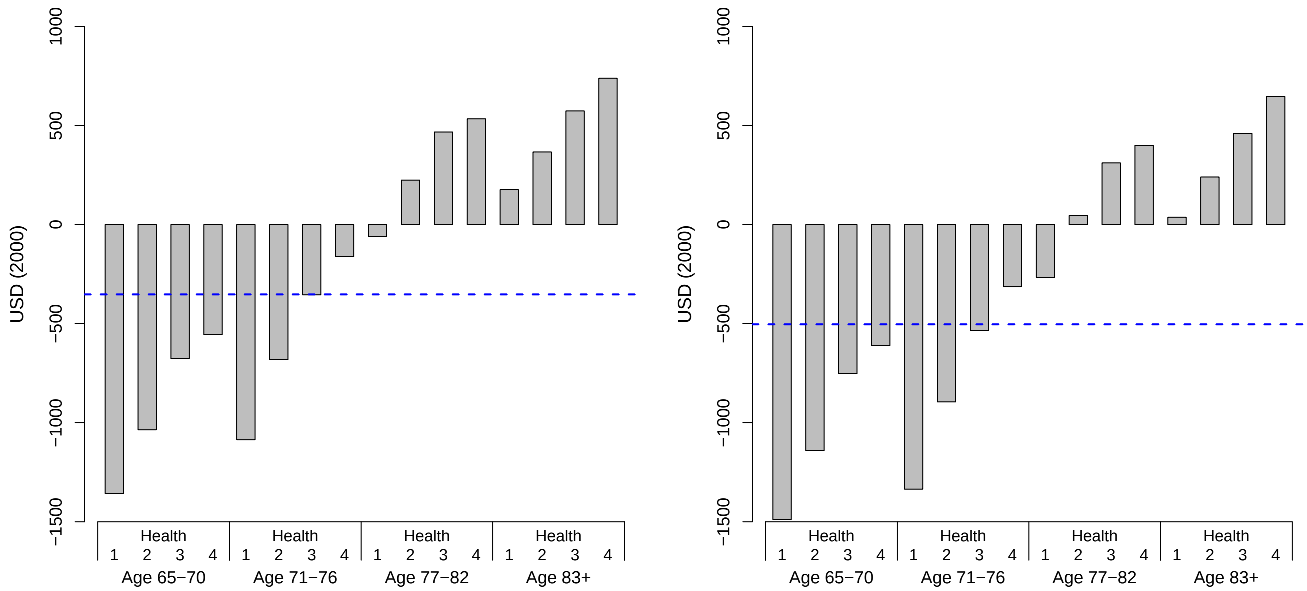
$$\hat{V}^{\tau}_{j,t} = \hat{u}^{\tau}_{j,t} + \beta\; \hat{s}^{\tau}_{j,t}\; E^{\tau}_{j,t} \left[c_{EM} + \log \sum_{k} \exp(\hat{V}^{\tau'}_{k,t+1} - \hat{MC}^{\tau'}_{t+1}(k,j)) \right] + \beta\; (1 - \hat{s}^{\tau}_{j,t})\; \theta \tag{22}$$

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

7.2. Welfare Implications

The annual willingness to pay (WTP) to avoid this climate change scenario varies across health types, ages types, and initial locations, ranging from $1,431 to -$3,813. Negative numbers amount to a welfare benefit from the climate change scenario. Perhaps surprisingly, the population weighted average WTP is negative (-$352); 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 7a 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 $1,357. This stems from their relatively strong preferences for warmer winters, their weaker preferences for warmer summers, and their relative indifference to additional precipitation (Figure 5a and 5c). In contrast, older, sicker types are affected relatively negatively by hotter summers and higher precipitation.

Figure 7 decomposes the mechanisms underlying the WTP measures by contrasting the average WTP to avoid the climate change scenario (Figure 7a) with an the average WTP from an alternative scenario that ignores climate change's effects on health and survival (Figure 7b). The dashed horizontal lines show the population-weighted averages. If there were no effects on health and mortality, the WTP for the changes in climate would be as high as $1,488 for the youngest and healthiest types, which is $131 higher than when health and survival effects are taken into account. The difference in the population-weighted average WTP between climate change affecting only enjoyment of amenities versus also affecting health and survival is $151. Younger and healthier types are somewhat less vulnerable to the averse health effects



(a) CLIMATE CHANGE

(b) AMENITY EFFECT ONLY

Figure 7: WTP TO AVOID CLIMATE CHANGE BY AGE AND HEALTH TYPE

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 $2,085. In the scenario with climate change, the annualized welfare cost of not being able to move is $2,092. This comparison provides a quantification for the role of migration in adaptation to climate change within one model period of six years. Individuals are strictly worse off and incur large welfare costs if they are not able to re-optimize their location choice, but not being able to move in response to climate change adds only $7

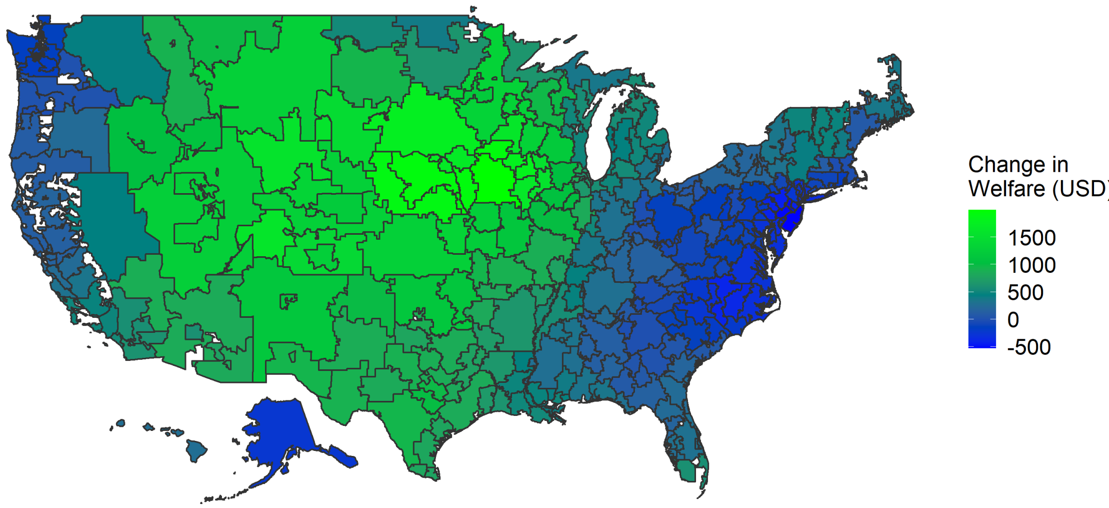


Figure 8: SPATIAL DISTRIBUTION OF WELFARE GAINS FROM CLIMATE CHANGE UNDER "BUSINESS AS USUAL"

compared to the welfare cost of not being able to move at all. This result is due to the enormous utility cost of re-optimizing, i.e. moving. While the climate change scenario clearly generates non-zero welfare effects, these welfare effects are not sufficient to justify large moving responses. Very few individuals would actually alter their location choices in response. Therefore, adaptation to climate change through moving is found to play a quite small role, at least within the time horizon of one model period. Across types, the welfare cost of not being able to adjust is higher for younger and healthier types. 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 accordingly, life expectancy at age 65 reduces by 0.18 years on average. Due to the small migration responses in the counterfactual, this change in life expectancy is not mitigated by migration.

Finally, Figure 8 shows a spatial map of population-weighted aggregate gains and losses.

Green indicates welfare gains, blue indicates welfare losses. Notice that the regions that most stand to gain are those with large expected increases in winter temperature, modest expected increases in summer temperature, and lower or unchanged precipitation levels.

7.3. 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 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 contrast 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 14 dollars per individual and 117 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. One important difference that drives the difference in results is the definition of a move. While Sinha et al. (2018b) define a move whenever the current location of an individual is unequal to their location of birth, I define a move when the location in the beginning of 2007 is different from the location in the beginning of 2001. This means that my definition of moves captures recent decisions and, given that location decisions are subject to substantial inertia, reflect current preferences over location characteristics among seniors. The 'lifetime' definition of moves covers moves that might have occurred a long time ago during childhood or due to past job opportunities.

7.4. 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).

8. 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. The framework I built is highly flexible and can be applied to any setting in which the welfare effects of changes in local amenities need to be quantified. 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 relatively strong preferences for warmer climates. 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. I add to the literature by exploring how the welfare effects of climate change vary systematically with individual characteristics and across space. 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.

References

Albouy, D., Graf, W., Kellogg, R., and Wolff, H. (2016). Climate amenities, climate change, and american quality of life. *Journal of the Association of Environmental and Resource Economists*, 3(1):205–246.

Aldy, J. E. and Viscusi, W. K. (2008). Adjusting the value of a statistical life for age and cohort effects. *The Review of Economics and Statistics*, 90(3):573–581.

Banzhaf, S. and Farooque, O. (2013). Interjurisdictional housing prices and spatial amenities: Which measures of housing prices reflect local public goods? *Regional Science and Urban Economics*, 43:635–648.

Barreca, A., Clay, K., Deschênes, O., Greenstone, M., and Shapiro, J. S. (2015). Convergence in adaptation to climate change: Evidence from high temperatures and mortality, 1900-2004. *American Economic Review*, 105(5):247–51.

Bayer, P., Ferreira, F., and McMillan, R. (2007). A unified Framework for Measuring Preferences for Schools and Neighborhoods. *Journal of Political Economy*, 115(4):588–638.

Bayer, P., Keohane, N., and Timmins, C. (2009). Migration and hedonic valuation: The case of air quality. *Journal of Environmental Economics and Management*, 58(1):1–14.

Bayer, P., McMillan, R., Murphy, A., and Timmins, C. (2016). A dynamic model of demand for houses and neighborhoods. *Econometrica*, 84(3):893–942.

Bayer, P., McMillan, R., and Rueben, K. (2004). An equilibrium model of sorting in an urban housing market. *NBER Working Paper*, 10865.

Bayer, P. and Timmins, C. (2007). Estimating equilibrium models of sorting across locations. *The Economic Journal*, 117(518):353–374.

Berry, S. T. (1994). Estimating discrete-choice models of product differentiation. *The RAND Journal of Economics*, pages 242–262.

Bishop, K. C., Ketcham, J. D., and Kuminoff, N. V. (2018). Hazed and confused: The effect of air pollution on dementia. Working Paper 24970, National Bureau of Economic Research.

Burgess, R., Deschenes, O., Donaldson, D., and Greenstone, M. (2014). The unequal effects of weather and climate change: Evidence from mortality in india. *Cambridge, United States: Massachusetts Institute of Technology, Department of Economics. Manuscript*.

Calabrese, S., Epple, D., Romer, T., and Sieg, H. (2006). Local public good provision: Voting, peer effects, and mobility. *Journal of Public Economics*, 90(6-7):959–981.

Chamberlain, S. (2019). *rnoaa: 'NOAA' Weather Data from R*. R package version 0.8.4.

Chay, K. Y. and Greenstone, M. (2003). The impact of air pollution on infant mortality: evidence from geographic variation in pollution shocks induced by a recession. *The quarterly journal of economics*, 118(3):1121–1167.

Chay, K. Y. and Greenstone, M. (2005). Does air quality matter? evidence from the housing market. *Journal of political Economy*, 113(2):376–424.

Chetty, R., Stepner, M., Abraham, S., Lin, S., Scuderi, B., Turner, N., Bergeron, A., and Cutler, D. (2016). The association between income and life expectancy in the United States, 2001-2014. *Jama*, 315(16):1750–1766.

Currie, J., Davis, L., Greenstone, M., and Walker, R. (2015). Environmental health risks and housing values: evidence from 1,600 toxic plant openings and closings. *American Economic Review*, 105(2):678–709.

Currie, J. and Walker, R. (2015). Does living along a busy highway increase premature births? *Chicago, IL: MacArthur Foundation.*

Deryugina, T., Heutel, G., Miller, N. H., Molitor, D., and Reif, J. (2019). The mortality and medical costs of air pollution: Evidence from changes in wind direction. *American Economic Review*, 109(12):4178–4219.

Deryugina, T. and Molitor, D. (2020). Does When You Die Depend on Where You Live? Evidence from Hurricane Katrina. *American Economic Review*, 110(11):3602–33.

Diamond, R. (2016). The determinants and welfare implications of us workers' diverging location choices by skill: 1980-2000. *American Economic Review*, 106(3):479–524.

Epple, D. and Platt, G. J. (1998). Equilibrium and local redistribution in an urban economy when households differ in both preferences and incomes. *Journal of Urban Economics*, 43(1):23–51.

Epple, D. and Sieg, H. (1999). Estimating equilibrium models of local jurisdictions. *Journal of Political Economy*, 107(4):645–681.

Eyring, V., Bony, S., Meehl, G. A., Senior, C. A., Stevens, B., Stouffer, R. J., and Taylor, K. E. (2016). Overview of the coupled model intercomparison project phase 6 (cmip6) experimental design and organization. *Geoscientific Model Development*, 9(5):1937–1958.

Finkelstein, A., Gentzkow, M., and Williams, H. L. (2021). Place-based drivers of mortality: Evidence from migration. *American Economic Review*, forthcoming.

Galiani, S., Murphy, A., and Pantano, J. (2015). Estimating neighborhood choice models: Lessons from a housing assistance experiment. *American Economic Review*, 105(11):3385–3415.

Goggins, W. B., Woo, J., Sham, A., and Ho, S. C. (2005). Frailty index as a measure of biological age in a chinese population. *The Journals of Gerontology Series A: Biological Sciences and Medical Sciences*, 60(8):1046–1051.

Gompertz, B. (1825). Xxiv. on the nature of the function expressive of the law of human mortality, and on a new mode of determining the value of life contingencies. in a letter to francis baily, esq. frs &c. *Philosophical transactions of the Royal Society of London*, 1(115):513–583.

Grossman, M. (1972). On the concept of health capital and the demand for health. *Journal of Political Economy*, 80(2):223–255.

Hamilton, T. L. and Phaneuf, D. J. (2015). An integrated model of regional and local residential sorting with application to air quality. *Journal of Environmental Economics and Management*, 74:71–93.

Holland, S. P., Mansur, E. T., Muller, N. Z., and Yates, A. J. (2016). Are there environmental benefits from driving electric vehicles? the importance of local factors. *American Economic Review*, 106(12):3700–3729.

Hosseini, R., Kopecky, K. A., and Zhao, K. (2021). The evolution of health over the life cycle. *Working Paper*.

Hotz, V. J. and Miller, R. A. (1993). Conditional choice probabilities and the estimation of dynamic models. *The Review of Economic Studies*, 60(3):497–529.

Isen, A., Rossin-Slater, M., and Walker, W. R. (2017). Every breath you take—every dollar you'll make: The long-term consequences of the clean air act of 1970. *Journal of Political Economy*, 125(3):848–902.

Kuminoff, N. V., Smith, V. K., and Timmins, C. (2013). The new economics of equilibrium sorting and policy evaluation using housing markets. *Journal of Economic Literature*, 51(4):1007–62.

McMichael, A. J., Wilkinson, P., Kovats, R. S., Pattenden, S., Hajat, S., Armstrong, B., Vajanapoom, N., Niciu, E. M., Mahomed, H., Kingkeow, C., et al. (2008). International study of temperature, heat and urban mortality: the 'isothurm'project. *International journal of epidemiology*, 37(5):1121–1131.

Menne, M., Durre, I., Korzeniewski, B., McNeal, S., Thomas, K., Yin, X., Anthony, S., Ray, R., Vose, R., Gleason, B., and Houston, T. (2012a). Global historical climatology network - daily (ghcn-daily), version 3.26. Technical report, NOAA National Climatic Data Center.

Menne, M., Durre, I., Vose, R., Gleason, B., and Houston, T. (2012b). An overview of the global historical climatology network-daily database. *Journal of Atmospheric and Oceanic Technology*, 29:897–910.

Mitnitski, A., Song, X., Skoog, I., Broe, G. A., Cox, J. L., Grunfeld, E., and Rockwood, K. (2005). Relative fitness and frailty of elderly men and women in developed countries and their relationship with mortality. *Journal of the American Geriatrics Society*, 53(12):2184–2189.

Murphy, A. (2018). A dynamic model of housing supply. *American Economic Journal: Economic Policy*, 10(4):243–67.

O'Neill, B. C., Tebaldi, C., van Vuuren, D. P., Eyring, V., Friedlingstein, P., Hurtt, G., Knutti, R., Kriegler, E., Lamarque, J.-F., Lowe, J., Meehl, G. A., Moss, R., Riahi, K., and Sanderson, B. M. (2016). The scenario model intercomparison project (scenariomip) for cmip6. *Geoscientific Model Development*, 9(9):3461–3482.

Pope III, C. A., Burnett, R. T., Thun, M. J., Calle, E. E., Krewski, D., Ito, K., and Thurston, G. D. (2002). Lung cancer, cardiopulmonary mortality, and long-term exposure to fine particulate air pollution. *Jama*, 287(9):1132–1141.

Schlenker, W. and Walker, W. R. (2015). Airports, air pollution, and contemporaneous health. *The Review of Economic Studies*, 83(2):768–809.

Sieg, H., Smith, V. K., Banzhaf, H. S., and Walsh, R. (2004). Estimating the general equilibrium benefits of large changes in spatially delineated public goods. *International Economic Review*, 45(4):1047–1077.

Sinha, P., Caulkins, M. L., and Cropper, M. L. (2018a). Do discrete choice approaches to valuing urban amenities yield different results than hedonic models? Working Paper 24290, National Bureau of Economic Research.

Sinha, P., Caulkins, M. L., and Cropper, M. L. (2018b). Household location decisions and the value of climate amenities. *Journal of Environmental Economics and Management*, 92:608–637.

Tiebout, C. M. (1956). A pure theory of local expenditures. *Journal of Political Economy*, 64(5):416–424.

A. Appendix

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 across locations 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 23 rewrites Equation 18 with $\tilde{V}^\tau = V^\tau - m^\tau$ to illustrate the relationship between the estimated $\tilde{u}$ and the true u.

$$\begin{aligned}
\tilde{u}_{j,t}^\tau &= \underbrace{V_{j,t}^\tau - s_{j,t}^\tau \cdot \beta E_{j,t}^\tau \left[c_{EM} + \log \sum_k \exp(V_{k,t+1}^{\tau'} - MC_{t+1}^{\tau'}(k,j)) \right]}_{= u_{j,t}^\tau + \beta(1 - s_{j,t}^\tau)\theta} - \underbrace{(m_t^\tau - s_{j,t}^\tau \cdot \beta E_{j,t}^\tau \left[m_{t+1}^{\tau'} \right])}_{\text{normalization bias}} \\
\tilde{u}_{j,t}^\tau &= X_{j,t}\beta^\tau + p_{j,t}^\tau \alpha^\tau + \beta(1 - s_{j,t}^\tau)\theta - (m_t^\tau - s_{j,t}^\tau \cdot \beta E_{j,t}^\tau \left[m_{t+1}^{\tau'} \right])
\end{aligned} \tag{23}$$

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 24). The regression is run separately for each age type. To address component (2), the product of survival probabilities $\hat{s}^{\tau}_{j,t}$ 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. $m^{\tau}_{t} = m^{\tau}_{t+1}$), 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, without the possibility of moving. Equation 24 specifies the estimation equation for decomposing $\tilde{u}$.

$$\tilde{u}^{\tau}_{j,t} = \beta^{\tau} X_{j,t} + \alpha^{\tau} p_{j,t} + \sum_{\tau' \neq \tau} m^{\tau'} \cdot (\beta \; \hat{s}^{\tau}_{j,t} \; \hat{P}_{j,t}(\tau,\tau')) + m^{\tau} \left(\beta \; \hat{s}^{\tau}_{j,t} \; \hat{P}_{j,t}(\tau,\tau) - \mathbb{1}\right) + \beta \; (1 - \hat{s}^{\tau}_{j,t})\theta \quad (24)$$

Table 10: SHARE OF INDIVIDUALS PER HEALTH TYPE, CONDITIONAL ON AGE IN 2001

	Health Type				
Age	1	2	3	4	Total
65-70	50.1	28.2	8.9	12.8	100.0
71-76	31.6	32.5	13.0	22.9	100.0
77-82	23.7	31.0	14.5	30.8	100.0
83+	18.7	29.1	14.8	37.3	100.0

Table 11: NUMBER OF INDIVIDUALS PER TYPE IN 2001

	Health Quintile			
Age	1	2	3	4
65-70	675,300	380,104	120,312	172,025
71-76	404,100	414,987	165,996	291,872
77-82	246,765	322,642	150,853	320,983
83+	158,902	247,236	125,932	316,848

Table 12: CROSS-REGION MIGRATION FLOWS 2001-2006

	Destination				
Origin	Northeast	Midwest	South	West	Total
Northeast	55.0	4.0	34.9	6.1	100.0
Midwest	2.5	61.9	24.8	10.9	100.0
South	10.7	12.2	70.3	6.8	100.0
West	2.8	8.9	13.2	75.2	100.0

Full sample observed in 2001, conditional on moving once between 2001 and 2006, by region of origin.

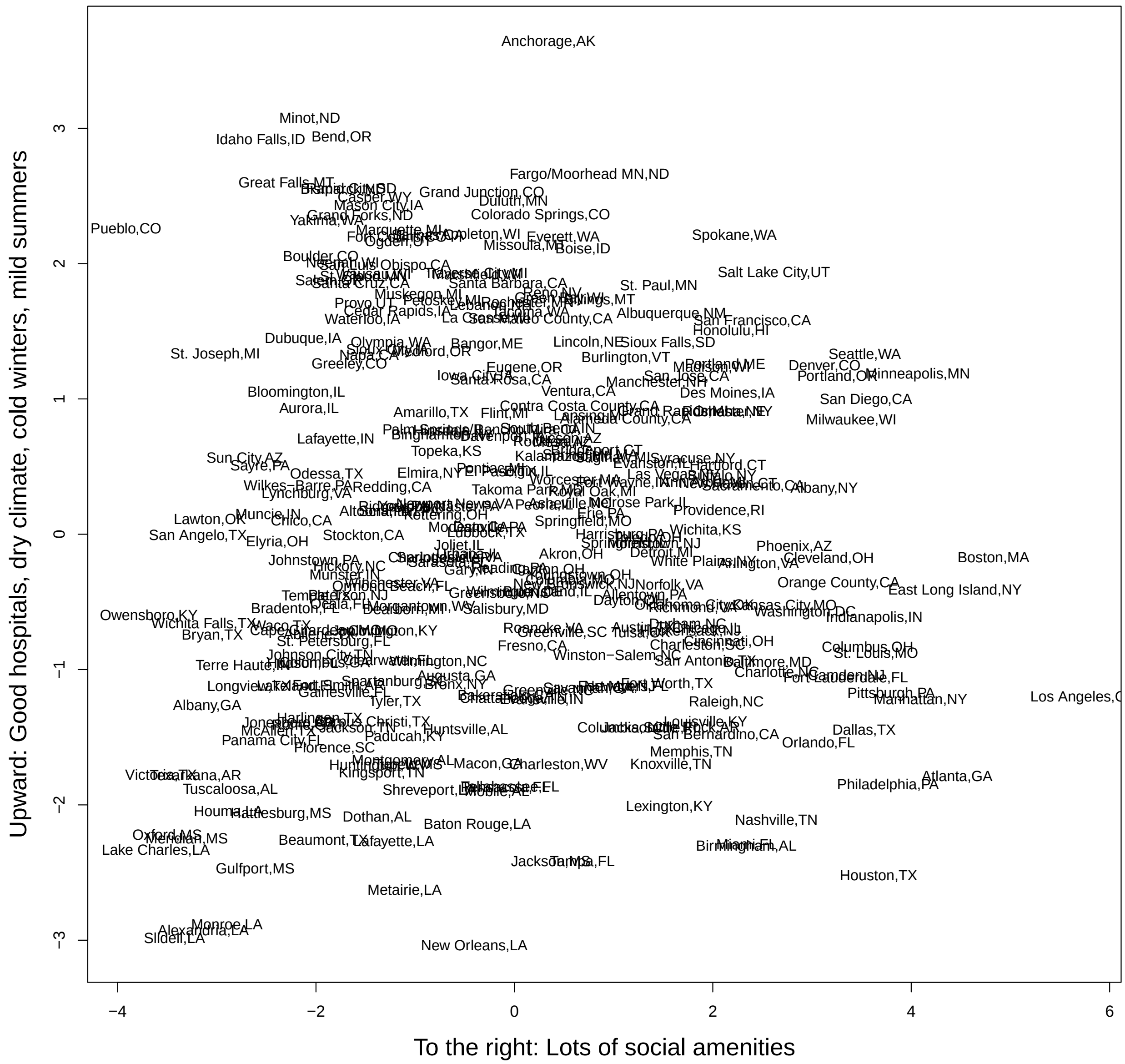


Figure 9: SIMILAR PLACES IN AMENITY SPACE - PRINCIPAL COMPONENT ANALYSIS

Table 13: MOVING COST PARAMETER ESTIMATES BY AGE AND HEALTH TYPE

Age	Health	Cross state	Distances in km					Origin-Destination Combinations of Census Regions					
			>100	>500	>1,000	>1,500	>2,000	Northeast -Midwest	Northeast -South	Northeast -West	Midwest -South	Midwest -West	South -West
65-70	Excellent	3.12	4.97	0.18	-0.06	-0.35	0.81	1.63	0.09	0.28	0.42	0.04	0.13
		(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.05)	(0.02)	(0.05)	(0.02)	(0.03)	(0.03)
65-70	Good	3.17	5.04	0.17	-0.05	-0.50	0.84	1.74	0.03	0.38	0.30	0.05	0.26
		(0.01)	(0.01)	(0.02)	(0.03)	(0.03)	(0.03)	(0.07)	(0.03)	(0.07)	(0.03)	(0.04)	(0.04)
65-70	Fair	3.21	5.01	0.29	-0.20	-0.51	0.97	1.43	-0.04	0.08	0.31	-0.01	0.21
		(0.02)	(0.02)	(0.04)	(0.05)	(0.04)	(0.06)	(0.10)	(0.04)	(0.12)	(0.05)	(0.09)	(0.08)
65-70	Poor	3.17	4.96	0.31	-0.14	-0.51	0.97	1.55	-0.06	0.14	0.23	-0.12	0.16
		(0.02)	(0.02)	(0.03)	(0.04)	(0.04)	(0.05)	(0.10)	(0.03)	(0.10)	(0.04)	(0.06)	(0.06)
71-76	Excellent	3.21	5.06	0.15	-0.08	-0.43	0.78	1.48	0.00	0.27	0.39	0.02	0.20
		(0.01)	(0.01)	(0.02)	(0.03)	(0.03)	(0.03)	(0.06)	(0.03)	(0.06)	(0.02)	(0.04)	(0.04)
71-76	Good	3.24	5.06	0.15	-0.10	-0.55	0.89	1.53	-0.09	0.31	0.31	0.11	0.33
		(0.01)	(0.01)	(0.02)	(0.02)	(0.03)	(0.03)	(0.06)	(0.02)	(0.06)	(0.02)	(0.04)	(0.04)
71-76	Fair	3.27	5.01	0.22	-0.18	-0.58	0.93	1.45	-0.12	0.20	0.21	0.10	0.30
		(0.02)	(0.02)	(0.03)	(0.04)	(0.04)	(0.05)	(0.09)	(0.04)	(0.09)	(0.03)	(0.07)	(0.06)
71-76	Poor	3.24	4.94	0.29	-0.15	-0.63	0.99	1.32	-0.16	0.09	0.19	-0.01	0.27
		(0.01)	(0.01)	(0.02)	(0.03)	(0.03)	(0.03)	(0.07)	(0.02)	(0.06)	(0.03)	(0.05)	(0.05)
77-82	Excellent	3.08	4.91	0.29	0.02	-0.39	0.71	1.33	0.05	0.28	0.28	-0.02	0.13
		(0.01)	(0.01)	(0.03)	(0.04)	(0.03)	(0.04)	(0.07)	(0.03)	(0.07)	(0.03)	(0.05)	(0.05)
77-82	Good	3.09	4.87	0.26	-0.03	-0.46	0.85	1.24	0.02	0.10	0.34	0.05	0.24
		(0.01)	(0.01)	(0.02)	(0.03)	(0.03)	(0.04)	(0.05)	(0.02)	(0.06)	(0.03)	(0.04)	(0.04)
77-82	Fair	3.13	4.84	0.29	-0.04	-0.51	0.89	1.22	-0.12	-0.08	0.25	-0.06	0.19
		(0.02)	(0.01)	(0.03)	(0.04)	(0.04)	(0.05)	(0.08)	(0.04)	(0.09)	(0.04)	(0.07)	(0.06)
77-82	Poor	3.16	4.80	0.33	-0.09	-0.61	0.99	1.21	-0.17	0.03	0.26	-0.00	0.15
		(0.01)	(0.01)	(0.02)	(0.03)	(0.03)	(0.03)	(0.05)	(0.02)	(0.07)	(0.03)	(0.05)	(0.04)
83+	Excellent	2.99	4.78	0.33	0.10	-0.35	0.77	0.95	-0.03	-0.12	0.32	-0.13	0.08
		(0.02)	(0.01)	(0.03)	(0.04)	(0.04)	(0.04)	(0.07)	(0.04)	(0.09)	(0.04)	(0.06)	(0.06)
83+	Good	2.99	4.73	0.39	0.11	-0.51	0.80	1.05	-0.07	0.21	0.34	-0.03	0.29
		(0.01)	(0.01)	(0.02)	(0.03)	(0.03)	(0.04)	(0.06)	(0.03)	(0.07)	(0.03)	(0.05)	(0.05)
83+	Fair	3.05	4.76	0.39	0.02	-0.45	0.85	0.88	-0.14	-0.01	0.28	-0.10	0.19
		(0.02)	(0.02)	(0.04)	(0.04)	(0.04)	(0.05)	(0.07)	(0.04)	(0.09)	(0.04)	(0.07)	(0.07)
83+	Poor	3.09	4.74	0.48	-0.07	-0.55	1.00	1.03	-0.23	-0.18	0.28	-0.23	0.09
		(0.01)	(0.01)	(0.02)	(0.03)	(0.03)	(0.04)	(0.05)	(0.02)	(0.06)	(0.03)	(0.04)	(0.04)

Estimates from Equation 15 for the model period 2001 to 2006, by health and age type. Standard errors are bootstrapped with $B = 200$, in parentheses.

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 14. Note that $\hat{m}^\tau$ equals $-V^\tau$.

Table 14: MARGINAL UTILITY ESTIMATES - DECOMPOSITION OF FLOW UTILITY VALUES

	Age 65-70	Age 71-76	Age 77-82	Age 83+
Summer (degrees Celsius)	0.0235	0.0184	-0.0120	-0.0234
	(0.0062)	(0.0058)	(0.0064)	(0.0063)
Summer (Health type 2)	-0.0068	-0.0112	-0.0073	-0.0081
	(0.0039)	(0.0043)	(0.0053)	(0.0060)
Summer (Health type 3)	-0.0212	-0.0199	-0.0217	-0.0206
	(0.0061)	(0.0060)	(0.0065)	(0.0069)
Summer (Health type 4)	-0.0246	-0.0286	-0.0294	-0.0376
	(0.0054)	(0.0050)	(0.0057)	(0.0057)
Winter (degrees Celsius)	0.0465	0.0353	0.0296	0.0269
	(0.0017)	(0.0023)	(0.0023)	(0.0026)
Winter (Health type 2)	-0.0006	0.0008	-0.0037	-0.0018
	(0.0018)	(0.0023)	(0.0024)	(0.0028)
Winter (Health type 3)	0.0029	-0.0013	-0.0006	-0.0005
	(0.0029)	(0.0031)	(0.0027)	(0.0036)
Winter (Health type 4)	0.0035	0.0016	0.0038	0.0039
	(0.0025)	(0.0024)	(0.0024)	(0.0026)
Precipitation (mm per m^2)	-0.0244	-0.0395	-0.1184	-0.1729
	(0.0104)	(0.0118)	(0.0134)	(0.0140)
Precipitation (Health type 2)	-0.0002	-0.0171	-0.0105	0.0174
	(0.0111)	(0.0117)	(0.0130)	(0.0161)
Precipitation (Health type 3)	-0.0191	-0.0217	-0.0108	-0.0035
	(0.0157)	(0.0158)	(0.0161)	(0.0179)
Precipitation (Health type 4)	-0.0323	-0.0441	-0.0162	0.0251
	(0.0136)	(0.0127)	(0.0142)	(0.0148)
Ambulatory care-sensitive hospital stays	0.0312	0.0406	-0.0598	-0.1373
(per 1,000 Medicare enrollees)	(0.0175)	(0.0171)	(0.0170)	(0.0140)
$PM_{2.5}$ (μg per m^3)	-0.0777	-0.0616	-0.0328	-0.0269
	(0.0029)	(0.0024)	(0.0030)	(0.0027)
Apparel stores (log # per location)	0.0473	-0.0197	0.1380	0.2595
	(0.0391)	(0.0354)	(0.0362)	(0.0318)
Golf (log # per location)	0.4276	0.3406	0.1307	-0.0230
	(0.0311)	(0.0287)	(0.0308)	(0.0255)
Movie (log # per location)	0.1534	0.1342	0.1333	0.0844
	(0.0135)	(0.0117)	(0.0149)	(0.0131)
Dining places (log # per location)	0.0765	0.2689	0.3831	0.5144
	(0.0262)	(0.0263)	(0.0316)	(0.0252)
Correction (Health type 1)	-2.6585	-3.6806	-4.7417	-5.1867
	(1.4220)	(0.8989)	(0.7307)	(0.5943)
Correction (Health type 2)	-2.0892	-2.8710	-3.9695	-4.3794
	(1.4006)	(0.8561)	(0.6893)	(0.5491)
Correction (Health type 3)	-1.3937	-2.3130	-3.2241	-3.5293
	(1.3949)	(0.8843)	(0.6782)	(0.5209)
Correction (Health type 4)	-1.0134	-1.6340	-2.4436	-2.5012
	(1.4252)	(0.8697)	(0.6633)	(0.4719)
Rentindex (USD 2000)	-0.0035	-0.0032	-0.0043	-0.0048
	(0.0003)	(0.0002)	(0.0002)	(0.0002)
Intercept	-1.4714	-1.4597	-0.3619	0.3837
	(0.4362)	(0.3541)	(0.3727)	(0.3879)
N	1224	1224	1224	1224
R^2	0.5623	0.5483	0.5360	0.5077
Adjusted R^2	0.5540	0.5396	0.5271	0.4983

Notes: Results from estimating Equation 24. Decomposition of flow utility values on amenities, rent indices, and variables to correct normalization in the first stage of the estimation. Climate variables are interacted with health type dummies for types 2-4, therefore the coefficients are relative to the coefficients of type 1. Rentindices are instrumented with amenity variables of similar but distant locations. Standard errors are bootstrapped with $B = 200$, in parentheses.