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Household residential location choice in retirement: The role of climate amenities☆

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ABSTRACT

The paper examines the relationship between climate amenities and locational choices in retirement. Using data from 2017 release of the American Community Survey, I construct a household residential location choice model and value climate amenities from the trade-offs among housing cost, climate amenities, and other locational attributes in a metropolitan statistical area (MSA). On average, a retired household is willing to pay $1209 for a 1 °C drop in average summer temperature, $1114 for a 1 °C increase in average winter temperature, and $486 for a 1 °C decrease in temperature variability. The values of climate amenities vary with household demographic characteristics, and older households with a higher retirement income and disability have a higher marginal willingness to pay for a favorable climate. Moreover, among the retired population, there exists a positive preference-based sorting across MSAs, where those favoring the preferred temperatures more than the average live in places with a more friendly climate. Using the estimated preference parameters, I compute the values of projected climate amenities and find that retired households would be willing to pay nearly 3.3% of their annual income to avoid a standard future projected climate scenario. Simulation results suggest that over 2% of retired households would relocate in response to this level of climate change, resulting in an overall northbound shift in the retired population.

1. Introduction

Locational choices among the retired population have long been a focal point in the analysis of social welfare. The large-scale migration resulting from millions of household relocations for retirement life can have a long-term impact on local population composition and thus become an important demographic and social phenomenon. During the past decade in the United States, migration contributed substantially to the aging of Florida and Arizona. These retirement migrations are expected to become even more salient as the population of baby boom generation continues to age. The members who were born during 1946–1964, the baby boom period, will pass the retirement age of 65 in 2020–2030, which makes the pool of potential retirement migrants reach a peak in the near future. The growing public attention on the upcoming retirement migration motivates the study of residential location choices of retired households in this paper.

In addition to living costs and income, a household locational choice depends on many location-specific amenities. Among them, climate amenities can play an important role in choosing a residential location for retired households, given large geographical variations across climate regions in the United States. On account of large impacts on comfort, daily outdoor activity, and health, e.g., mortality risk, local climate amenities affect the desirability of different locations and the quality of life (Deschênes and Greenstone, 2011; Barreca et al., 2015). Households always prefer to retire in a place with favorable climate amenities, *ceteris paribus*. Thus, given their considerable influence on locational choices and household welfare, this paper conceptualizes the migration decision-making process driven by climate amenities and seeks to estimate dollar values retired household place on climate amenities. Past research has focused mainly on the middle-age or entire population, with relatively less attention paid to retired households who are more sensitive to climate amenities, especially temperature-related amenities

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(Albouy, 2016). Moreover, after retirement, household preferences for certain location-specific attributes, e.g., employment opportunities, can be different from younger working households (Chen and Rosenthal, 2008). However, no past research, to the best of my knowledge, has ever investigated retirement migration driven by climate amenities at the household level. In an attempt to fill the gap, this paper uses the newly released U.S. Census data to comprehensively analyze how locational decisions made by retired households are influenced by climate, with a focus on temperature-related amenities. In addition to temperature levels, retired elderly people may be sensitive to daily changes in the temperature. Given the rich information in available temperature data, this is the first paper that considers another temperature-related amenity, variability of temperature, and provides the relevant empirical evidence.

Unlike regular commodities that can be freely traded, climate amenities, as public goods, cannot be purchased separately and thus priced directly. Due to the lack of formal markets for them, estimating these values poses an econometric challenge since the evaluations of a friendly climate would be entangled with many other local site characteristics. Given the development in estimation techniques, there are two main methodologies widely used in estimating climate amenities. The first is a hedonic pricing model assuming that decision-makers trade-off among economic variables, e.g., living cost, and other locational attributes, including climate amenities in choosing alternative locations (Rosen, 1974; Malpezzi, 2002). These estimated hedonic values are the empirical results as a consequence of a market equilibrium based on revealed preferences. However, these equilibrium outcomes obtained from the reduced-form hedonic models usually do not account for potential migration costs, leading to biased estimates of preference parameters in modeling locational choices. Therefore, a hedonic pricing model is unable to accurately measure climate values if the influence of migration costs is significant. This shortcoming motivates the use of the second approach, discrete choice model, that internalizes the high moving cost in a utility-consistent setting (McFadden, 1973). Under a utility maximization framework, the discrete choice modeling describes the choice behavior of retired households and yields unbiased estimates on values of climate amenities.

To account for potential preference heterogeneity in climate amenities, I construct a random coefficient logit model to value all primary climate amenities and examine how the marginal willingness to pay (MWTP) for temperature-related amenities varies with socio-demographic groups and residential location. It is found that, for a retired household, the average MWTP for a cooler summer by a 1 °C is around $1,209, while the MWTP for a warmer winter by a 1 °C is $1114. Other than the mean temperatures, this paper reports the MWTP for a less variable temperature that older people may also favor and finds that they are willing to pay $486 for a 1 °C drop in the average difference between daily maximum and minimum temperatures. This paper contributes to existing literature by further going deep down to the demographic categorization and examines the variations by age groups, household income levels, health status. It is found that older and wealthier retired households with a disability, *ceteris paribus*, have a higher MWTP for preferred temperature amenities.[1] In addition to heterogeneous preferences by demographic attributes, I explore the geographical variations and find that households favoring the preferred temperatures more than the average live in places with a more friendly climate. As part of the estimation results, this paper updates the estimates of economic values for quality of life (QOL) in the U.S. metropolitan statistical areas (MSA) (Albouy et al., 2016). It shows that MSAs located on the east and west coasts have a better life quality, due mainly to a friendly climate and improved urban facilities, and the difference in the quality of life between two MSAs can be as large as $3,800, as measured in a dollar value.

Apart from the current generation, climate amenities can have a substantial long-term impact on the future retired population. The projected global climate change, however, can have an ambiguous impact on the desirability of local climate amenities in the United States. Due to rising temperatures driven by global warming, households suffer from hotter summers but benefit from milder winters. The changes in temperatures also depend on where households are located. Given the estimated value of temperature amenities and future temperature projections, I compute the value of projected changes in temperature amenities in 2050 and 2100 and find that households on average are willing to pay nearly 3.3% of their annual retirement income to avoid the future climate scenarios, conditional on current locations. Moreover, I simulate the location decisions of numerous retired households in new climate amenities and analyze the further residential sorting driven by the changing local climate. The simulation results forecast that hotter summers would overwhelm the warmer winters for future retired population and cause an overall northbound migration from the South climate region. Valuing future climate amenities not only advances the understanding of how climate affects social welfare but also the potential large-scale migration among the retired population. Ultimately, these findings have profound implications for local urban planning, e.g., urban facilities for retired population, in response to changing demographic compositions through the long-term residential sorting.

The remainder of this paper is organized as follows. Section 2 presents a brief review of relevant literature. The econometric framework of a household locational choice model and empirical strategies are contained in section 3. The data used for empirical study are discussed in section 4. Section 5 presents the empirical results. In section 6, I value the projected changes in temperatures and simulate the residential sorting in response to climate changes. The paper concludes with a summary of key findings and policy implications in section 7.

2. Literature review

A household location choice model regularly characterizes the selection of residential location by weighting site characteristics of each location for an economically rational household (McFadden, 1978). Typically, it assumes that a household utility is comprised of locational attributes, coupled with unobserved idiosyncratic errors, and estimates the hedonic value of some attribute through housing price or wage differentials across alternative locations. Previous studies have mainly focused on a couple of apparent motivations that affect household moving and location decisions. A large number of factors with some predictive power have been examined under the framework of random utility maximization (RUM) theory. Existing research has found that residential location choices can be motivated primarily by employment opportunity (Greenwood et al., 1991), education resources (Benabou, 1993), and transportation service (Anas, 1982).

In addition to urban facilities, the last few years have seen an increasing focus on natural amenities, especially climate amenities, in modeling residential locational choices. It is since, when living standard advances rapidly, climate amenities become much more prominent in evaluating the quality of life. A substantial body of literature, using a hedonic pricing analysis, has shown that households respond to climatic differences and value the favorable climate amenities (Rehdanz, 2006; Butsic et al., 2011). However, some authors point out that high migration costs can introduce stickiness in a location choice and thus bias the estimates of climate values in a hedonic price model (Bayer and Timmins, 2007). In an attempt to incorporate the moving cost when estimating climate values, many studies have overcome the challenge and established a linkage between climate and household location choice. Poston et al. (2009) find that extreme temperatures have a large impact on migration flows and confirm that more friendly climates are

[1] Compared to other studies that only roughly separate the entire population by a single cutoff of the age and the decision of relocation, this paper examines variations by other demographic attributes in more detail (Sinha et al., 2018).

positively correlated with in-migration rates. By constructing an inter-metropolitan residential location choice model, Plantinga et al. (2013) provide some estimates on the values of favorable changes in mean January and July temperatures. Sinha and Cropper (2013), using the U.S. census data, also characterize household locational choices among metro areas and provide empirical results about the influence of climate amenities on the desirability of alternative locations.

In a separate strand of literature, the driving force and motives of retirement migration have been fully explored, and many papers have analyzed how retirees make location decisions (Duncombe et al., 2001). The rationale behind these analyses is that, conditional on affordable moving costs, retired households vote with their feet and choose the utility-maximizing location by evaluating all locational attributes, including, among other things, climate amenities. As for socioeconomic characteristics, retired households are found to value low tax rates, crime rates, and low living costs, on the one hand (Longino, 1995). On the other hand, older retired persons have been shown to be attracted to locations with favorable natural amenities, such as sunny climates (Conway and Houtenville, 1998), access to coast (Bures, 1997), water area (Schneider and Green, 1992), and public parks (Duncombe et al., 2000). These findings provide guidance for choosing the main locational attributes that have a large influence on retired household utility in this paper.

The above-mentioned literature in the residential location choice model has been facilitated by the improved econometric techniques in discrete choice modeling. Over the past decades, the modeling methods of residential household location choice have been largely developed (Hensher et al., 2005) and thus substantially contribute to the proliferation of researches in this area. Since the seminal paper by McFadden (1973), the multinomial logit (MNL) model has been the most common approach to modeling home location choice, due to a closed-form probability formula. The MNL model imposes an assumption of independence of irrelevant alternatives (IIA) among alternatives, which makes cross-elasticity across each pair of choice alternatives equivalent. Yet, the IIA assumption is violated if households perceive some destination alternatives as closer substitutes (Daly and Zachary, 1978). To address the issue of IIA constraint, a nested logit model (NL) allows alternatives to be grouped in a manner with correlations within, though not between, nests (Ben-Akiva et al., 1985). Soon after, to reflect a more flexible substitution pattern among alternatives, some more advanced discrete choice models are developed, such as ordered generalized extreme value (OGEV) model (Small, 1987), cross-nested logit (CNL) (Vovsha, 1997), and paired combinatorial logit (PCL) model (Wen and Koppelman, 2001). Despite a complex substitution pattern among alternatives, none of the discrete choice models consider potential heterogeneous preferences for certain attributes. To accommodate random tastes, McFadden and Train (2000) propose a mixed logit model that allows random coefficients. This flexible model features a framework that captures an unrestricted substitution pattern and individual-specific preference for some locational attributes in the decision-making process. Since then, due to its appealing property, the mixed logit model has been widely adopted in modeling a discrete choice in different contexts, including types of recreational activity episodes (Bhat and Gossen, 2004), electricity supplier (Revelt and Train, 2000), and drivers' parking (Chaniotakis and Pel, 2015) and driving behavior (Behnood et al., 2016). However, few papers have sought to model residential location choice with preference heterogeneity in some site attributes (Mistiaen and Strand, 2000). To fill the gap and contribute to the existing literature in residential location choice, the empirical analysis in this paper employs a mixed logit model that allows the coefficients on climate amenities to vary by households. This state-of-the-art modeling method fully reveals heterogeneous preferences for climate amenities and estimates household-specific hedonic values of these favorable climate amenities.

3. Household locational choice model

3.1. Utility function specification

To value climate amenities and examine their impacts on the decision of where to retire, I model household residential location choices under a random utility framework. Following the seminal work by McFadden (1973), retired households are assumed to be utility maximizers who attain utility through the selection of a preferred Metropolitan Statistical Area (MSA) in the United States. A household i, facing all alternative locations in the choice set ($j \in \mathbf{J}$), selects the location j and obtains a certain level of utility, U_{ij}, if and only if this alternative yields the highest utility, i.e., $U_{ij} > U_{il}, \forall\, l \neq j$. U_{ij} is a stochastic variable that can be decomposed into a systematic utility, V_{ij}, and a random part, ϵ_{ij}. The systematic component, V_{ij}, is a function of all observable attributes of alternatives and household characteristics, while ϵ_{ij} captures heterogeneity in preferences that are unobserved. This paper assumes that the utility of a retired household is dependent upon retirement income, housing cost, expense on non-housing services, climate and other locational amenities of the chosen residence, and moving cost in the relocation. Specifically, the utility that household i receives when living in MSA j is given by:

$$U_{ij} = V_{ij} + \epsilon_{ij} = \alpha(Y_i - H_{ij} - Q_{ij}) + \mathbf{\Pi}_j \beta_i + \mathbf{\Gamma}_j \lambda + MC_{ij} + \eta_j + \epsilon_{ij}, \tag{1}$$

where Y_i is the total income household i can receive in retirement. H_{ij} represents the housing expense and Q_{ij} denotes the cost of other non-housing services. In the baseline model, the household utility is assumed to be linear in the Hicksian bundle, $Y_i - H_{ij} - Q_{ij}$. The constraint of linearity in the Hicksian bundle is imposed to simplify the computation of welfare measures. I relax this assumption with some non-linear specifications to check the robustness, as shown in Table 10 in Appendix A. $\mathbf{\Pi}_j$ is a vector of observed location-specific amenities whose values vary across households. $\mathbf{\Gamma}_j$ represents locational attributes for which households have the same preference. Going forward, MC_{ij} is the general moving cost of a relocation that involves both economic and psychic costs. η_j is a locational fixed effect at the MSA level that controls for all unobserved location-specific amenities. ϵ_{ij} is the error term that incorporates unobserved utility-related preference heterogeneity.

To further elaborate the specification, some utility determinants are specified as follows. The total household retirement income, Y_i, is composed of negative incomes and assumed to be unrelated to locational choice.[2] The location-specific cost of other non-housing services, Q_{ij}, varies by household size. Housing expenditure, H_{ij}, is determined by the housing choice made by household i in MSA j. For simplicity, I predict the alternative housing expenditure with the assumption that a household consumes the same bundle of housing services. To test the validity of this assumption, I estimate the average number and standard deviations of some critical housing characteristics, e.g., the number of bedrooms and household tenure choice, across the MSAs for different demographic groups.[3] I find no significant variations in housing choices across MSAs in each group, which is in line with the conclusion by Sinha et al. (2018).[4] Thus, the alternative housing expense for each household i in MSA j is estimated and predicted based on the following hedonic housing equations for each MSA:

$$\ln H_{ij} = \boldsymbol{Z}_i \boldsymbol{\beta}^j + \epsilon_{ij}, \forall j = 1, \dots, J, \tag{2}$$

[2] The total household income involves all types of negative income, including retirement income, public assistance income, supplementary security income, and social security income.

[3] According to American Housing Survey, there exist small variations ($\leq 5\%$) in average bedroom size across metro areas. See: https://www.census.gov/programs-surveys/ahs.html.

[4] Specifically, I use one sample t-test for each housing characteristic and fail to reject the null hypothesis of the same housing choice for each demographic group.

where H_{ij} is the annual housing cost of household i in MSA j. $\boldsymbol{Z}_i$ is the vector of housing choices and dwelling characteristics, and $\boldsymbol{\beta}^j$ are the MSA-specific coefficients for these housing attributes. Summary statistics of the estimation results of these hedonic housing equations are presented in Table 9 Appendix A.

When making a locational decision, moving cost is expected to deter a long-distance relocation and influence the utility of choosing each alternative location. To fully control for its impact, this paper adopts a more generalized form of moving cost involving both psychic cost of moving in various ranges (Davies et al., 2001) and economic cost.[5] Some papers set the birthplace of a householder as the origin of movement (Bayer et al., 2009; Fan et al., 2016). However, this assumption might not well apply to retired households, due to the fact that they are older and have less connection to the environment where they grew up. Instead, this paper takes the residence in which a household lived one year ago as the origin of movement. Specifically, based on geographic boundaries shown in Fig. 1, the general moving cost is represented as follows:

$$MC_{ij} = \lambda_1 I_{ij}^{\text{Metro}} + \lambda_2 I_{ij}^{\text{State}} + \lambda_3 I_{ij}^{\text{Region}} + \lambda_4 d_{ij} + \lambda_5 d_{ij}^2, \tag{3}$$

where I_{ij} is a set of dummy variables reflecting the psychic cost in each range of movement. The dummy variables equal one if a household has to move out of certain MSA, state or region for an alternative location j. d_{ij} denotes the moving distance, and its quadratic form is used to proxy for the economic cost in the moving process.

3.2. Estimation strategy and choice probability

To estimate heterogeneous preferences for climate amenities, I construct a mixed logit model that accommodates random coefficients (McFadden and Train, 2000). This paper mainly focuses on temperature amenities, and thus I allow the coefficients on three temperature-related attributes, i.e., $\boldsymbol{\beta}_i = (\beta_i^{ST}, \beta_i^{WT}, \beta_i^{VT})$, to vary across retired households. β_i^{ST} and β_i^{WT} are the coefficients on average summer and winter temperatures. The paper also incorporates another temperature-related amenity, the variability of temperature, as a climate amenity and its coefficient β_i^{VT} is assumed to be random as well. It is due to the fact that, generally, retired elderly people may be sensitive to daily changes in the temperature and its influence can vary across age groups.

To get around the potential bias from omitted locational and climate attributes in estimating the model, this paper adopts a two-stage estimation strategy (Murdock, 2006). The first stage is to estimate a mixed logit model where the systematic utility, V_{ij}, incorporates the Hicksian bundle, household-specific values for temperature-related amenities, general moving cost, and MSA fixed effects as below:

$$V_{ij} = \alpha(Y_i - \widehat{H_{ij}} - Q_{ij}) + \text{WT}_j\beta_i^{WT} + \text{ST}_j\beta_i^{ST} + \text{VT}_j\beta_i^{VT} + MC_{ij} + \eta_j, \tag{4}$$

where $\widehat{H_{ij}}$ is the predicted housing cost. WT_j and ST_j are the average MSA-specific winter and summer temperatures. VT_j is the variability in the temperature, which is the average daily difference between the maximum and minimum temperatures in each MSA. All other variables are defined as the same as before. The three coefficients in $\boldsymbol{\beta}_i$ are assumed to be jointly normally distributed, with the mean vector $\boldsymbol{\mu}$ and variance-covariance matrix Σ, i.e., $\boldsymbol{\beta}_i \sim N(\boldsymbol{\mu}, \Sigma)$. The matrix Σ is estimated in the first stage, while the means of $\boldsymbol{\beta}_i$ are restricted to be zeros. The mean coefficients of the three attributes, $\boldsymbol{\mu}$, can only be estimated in the second stage, since MSA fixed effects, η_j, technically absorb all the average influences of locational attributes. In the second stage, I regress the estimated MSA fixed effects on all climatic and locational attributes to estimate the mean coefficients of three temperature and other amenities as follows:

$$\widehat{\eta}_j = \boldsymbol{\Pi}_j\boldsymbol{\mu} + \boldsymbol{\Gamma}_j\lambda + \omega_j, \tag{5}$$

where $\widehat{\eta}_j$ are the estimated MSA fixed effects. $\boldsymbol{\Pi}_j$ are the three temperature variables, i.e., WT_j, ST_j, and VT_j. $\boldsymbol{\Gamma}_j$ denote all other amenities and locational attributes for which households have homogeneous preferences, λ. ω_j is the idiosyncratic error. This approach essentially treats the MSA fixed effect as a quality of life (QOL) index, which is equal to a weighted sum of climate amenities and other location-specific attributes (Albouy, 2016).

Assuming that the idiosyncratic errors, ϵ_{ij}, are independently and identically distributed with Type I extreme values, the probability of household i choosing MSA j is given by:

$$P_{ij} = \int \frac{\exp(\boldsymbol{\Pi}_j\boldsymbol{\beta}_i + \boldsymbol{Z}_{ij}\boldsymbol{\theta})}{\sum_{j=1}^{J}\exp(\boldsymbol{\Pi}_j\boldsymbol{\beta}_i + \boldsymbol{Z}_{ij}\boldsymbol{\theta})} f(\boldsymbol{\beta}_i|\boldsymbol{\mu},\Sigma)d\boldsymbol{\beta}_i, \tag{6}$$

where $f(\boldsymbol{\beta}_i|\boldsymbol{\mu},\Sigma)$ is the density function of $\boldsymbol{\beta}_i$ that follows the multivariate normal distribution. Z_{ij} is the vector of all other variables for which households have the homogeneous preferences. Then, the parameters of equation (4) are estimated by maximizing the following simulated log-likelihood (*SLL*) function (Hole, 2007):

$$SLL = \sum_{i=1}^{N} \ln\left\{\frac{1}{R}\sum_{r=1}^{R}\prod_{j=1}^{J}\left[\frac{\exp(\boldsymbol{\Pi}_j\boldsymbol{\beta}_i^{[r]} + \boldsymbol{Z}_{ij}\boldsymbol{\theta})}{\sum_{j=1}^{J}\exp(\boldsymbol{\Pi}_j\boldsymbol{\beta}_i^{[r]} + \boldsymbol{Z}_{ij}\boldsymbol{\theta})}\right]^{y_{ij}}\right\}, \tag{7}$$

where $\boldsymbol{\beta}_i^{[r]}$ is the r-th draw from the joint normal distribution. R is the number of draws of random coefficients for each household. y_{ij} equals 1 if the household i selects alternative j and 0 otherwise.

4. Data

This section presents the data used in estimating the hedonic housing model and household locational choice model. This paper adopts a unique dataset, comprised of the U.S. census data and several other data sources.

4.1. Census data

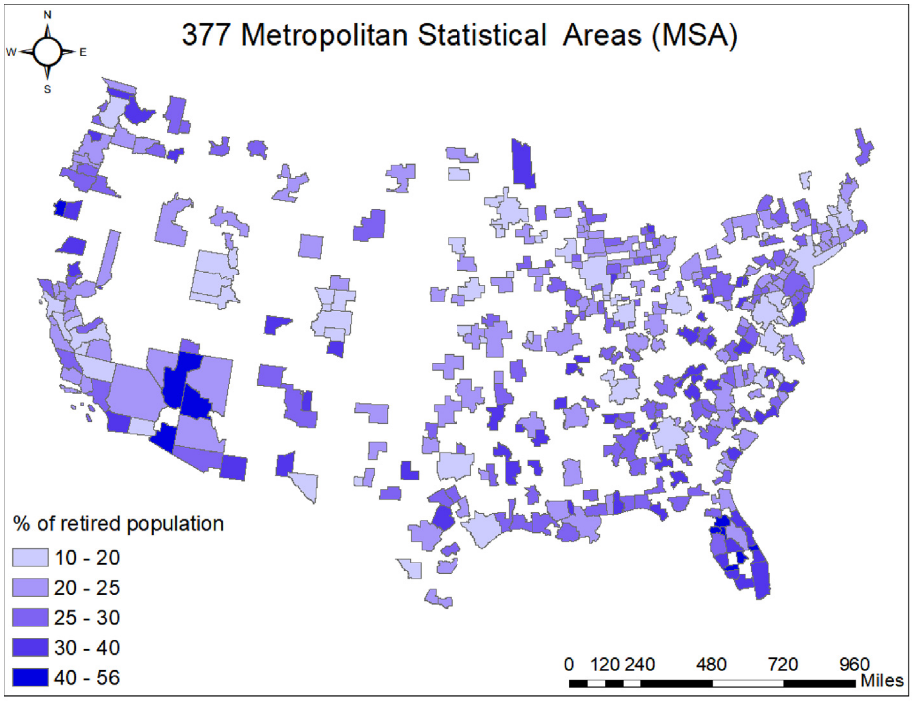
The main source of data used for the empirical analysis is the Public Use Microdata Sample (PUMS) from the American Community Survey (ACS).[6] It is a very detailed and comprehensive survey describing household socioeconomic and demographic characteristics. It covers around 1% of the entire population in the U.S at the household level on a yearly basis. Since climate amenities in each place typically change slowly within a couple of years or even decades, I select the newly released census data in 2017 to estimate location choice models.

4.2. Geography of the choice set

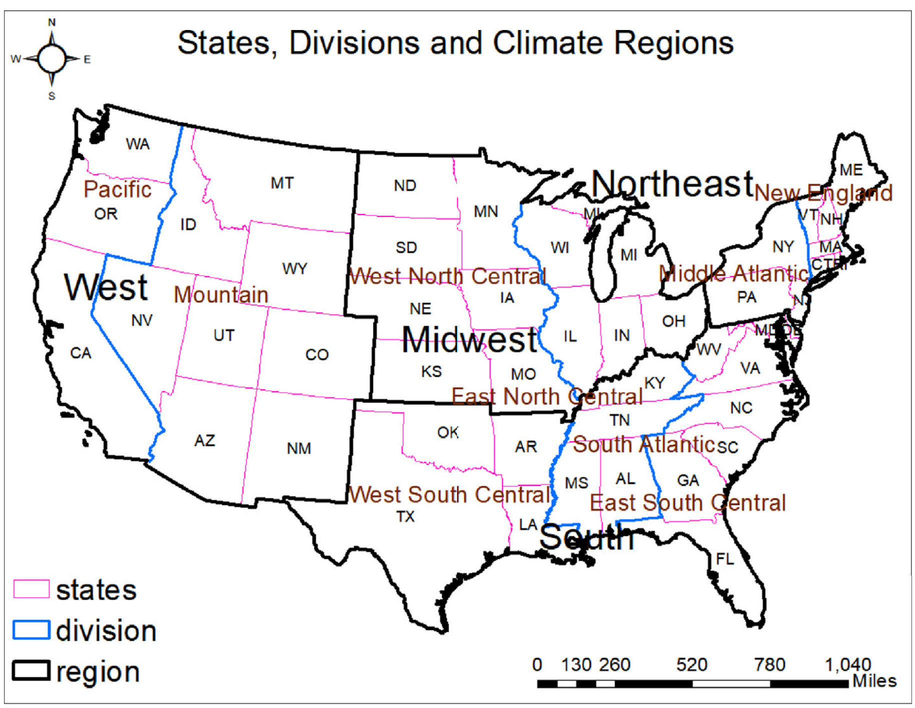
The study area of this paper is the entire continental United States, and I mainly focus on households residing in metropolitan areas. The study sample is chosen for two reasons. First, Hawaii, Alaska, and Puerto Rico are separate regions, and households have different preferences for climate amenities. This forms a household substitution pattern among alternative locations that are not comparable with the mainland United States. Secondly, the real moving cost between those regions and the continental U.S. cannot be well defined as that in the moving within the continental U.S., which may largely bias estimates on preference parameters in a locational choice model. Lastly, there exist rich data of urban amenities and locational attributes. The lowest level of identifiable location in PUMS is Public Use Microdata Area (PUMA), a statistical geographic area containing at least 100,000 people. Given

[5] The psychic cost includes the loss of social network and familiarity with the surrounding environment, while the economic cost relates to what a household pays for a relocation.

[6] https://www.census.gov/programs-surveys/acs/.



(a) Geographic profile of MSAs



(b) States, divisions and climate regions

Fig. 1. (a) Geographic profile of MSAs (b) Geographic boundaries of states, divisions, and regions.

that climate amenities do not vary significantly at a small geographic scale and most locational attributes are measured at the level of metro areas, this paper selects a metropolitan statistical area (MSA) as a choice unit by aggregating PUMAs into discrete MSAs. To map PUMA locations to the choice set of MSAs, I assign each PUMA to the MSA that overlaps its boundary. For the PUMA that belongs to several MSAs, I randomly assign the households into each MSA with the population-weighted probabilities. All 377 MSAs contain nearly 86 percent of the total U.S. population in 2017.[7]

Fig. 1 illustrates the geography of the study area. Panel (a) shows that each retired household can choose among 377 MSAs to live. The

[7] The total of population estimate as of July 1 in those MSAs is 279.7 million, and the entire population in the U.S. in 2017 is 325.7 million.

Table 1
Summary statistics of household demographics and locational choices.

Variable	Description	N	Mean	SD	Min	Max
Demographics						
Age	Age of household head	306,714	73.64	8.79	55	95
Household size	# of household members	306,714	1.63	0.55	1	2
High	High school graduate	306,714	0.90	0.30	0	1
College	College graduate	306,714	0.39	0.48	0	1
Female	Female household head	306,714	0.38	0.49	0	1
White	White household head	306,714	0.61	0.48	0	1
Dis	With a disability	306,714	0.17	0.47	0	1
White	White household head	306,714	0.61	0.48	0	1
Y	Household income	306,714	42,002.17	34,821.73	2000	413,200
Q	Non-housing cost	306,714	25,073.09	8083.76	2939.60	35,484.87
H	Housing expenditure	306,714	16,051.13	12,091.21	504	160,704
Locational Choice						
I^{Metro}	Move out of a metro area	36,299[a]	0.31	0.40	0	1
I^{State}	Move out of a state	36,299	0.08	0.42	0	1
I^{Region}	Move out of a region	36,299	0.05	0.37	0	1
Moving distance	in miles	36,299	31.14	76.73	0	785.63

Note: The summary statistics are calculated by 306,714 retired households surveyed in 2017.
[a] Among 306,714 retired households, 36,299 (12%) households moved in the previous year. Among All economic variables are measured in 2017 U.S. dollars.

color represents the percentage of the retired population in each MSA, which is the percent of retired households in the local population. It can be seen that the popular retirement spots are mainly concentrated in Southern California, Florida, and Texas. The metropolitan area, Villages in Florida, has the largest percentage of the retired population (56%). Panel (b) shows the geographic boundaries at various levels. Each MSA lies in a state that belongs to a division, and several divisions constitute a climate region. There are a total of 48 states plus District of Columbia, nine divisions, and four climate regions in the continental United States.[8] These boundaries divide the entire continent into several parts to estimate region-specific values of climate amenities. In addition, the geographical boundaries are delineated to calculate the psychic cost in the moving process.

4.3. Sample selection and demographics

This paper mainly focuses on the influence of climate amenities on the life in retirement. I restrict the sample households to those who have retired as the decision-makers.[9] Households moving from areas other than the continental U.S. are dropped since they may have different preferences for certain attributes from local residents, leading to inconsistent estimates. Table 1 describes the characteristics of sample households. There are a total of 306,714 retired households, aged between 55 and 95 years old. I select only the households composed of a retired couple, a widowed or single retired person and drop multi-generational households (Lee and Painter, 2014). It is due to the fact that, if living with the next generation, locational choices of retired members can be constrained by other younger members, making the estimation of their preference parameters biased. It can be seen that most retired householders have a high school degree and over a third of them graduated from a college. Nearly 61% of respondents come from white households, while 17% of households have a disability. In terms of economic variables, it is shown that retired households on average have a household income of $42,002, lower than the entire population.[10] The average non-housing and housing expenses are almost 2/3 and 1/3 of their total retirement income. The data of livable non-housing expenses comes from Living Wage Calculator, a database that reports all expenses for a decent quality of life. It involves all basic needs, including food, childcare, health care, transportation, other necessities, and taxes.[11] The expenses vary by household size and are measured at the county level. To make living costs compatible with locational choices, they are converted into MSA level, weighted by population. Regarding the locational choices, it is seen that around 31% of retired households moved out of the previous metro area, and 8% moved out of a state. Only 5% of them relocated to a different climate region in 2017. The moving distances are the Euclidean distances between population-weighted centroids of two MSAs.[12] On average, each retired household moved to a residence 31.14 miles away from where they lived a year ago.

4.4. Housing choice

As an important utility determinant, the housing service that a household attains has a large influence on locational choices. Table 2 presents the summary statistic of housing choices and property characteristics occupied by retired households. A retired household on average spends $16,051 per year ($1337 per month) on housing, whose components depend on the tenure choice. The housing cost paid by renters includes the rent, insurance, and utility fees, while the cost for homeowners involves property tax, homeowner association fee, insurance, utility fees, and, if applicable, home mortgage payment. Around 70% of households stay in their own dwellings, rather than renting. The percent of homeownership is slightly higher than that in the entire population, largely due to the higher wealth retired households have accumulated in the past.[13] Almost half of the dwelling units occupied by retired households are single-family houses and, on average, they need two

[8] Northeast region consists of New England and Middle Atlantic divisions. The South Atlantic, West South Central, and East South Central divisions constitute the South region. The West North Central and East North Central comprise the Midwest region. The West region is composed of Mountain and Pacific divisions.

[9] Households are defined to be retired if they do not participate in the labor force and have no wage income.

[10] The average household income was $63,644 in the U.S. in 2017. I drop the sample whose household incomes are below $2000 since their location choice can be very limited due to the budget constraint.

[11] http://livingwage.mit.edu/.

[12] Due to large geographical variations in population density within each MSA, I calculate the geographic coordinates weighted by population density. https://www.census.gov/geo/reference/centersofpop.html.

[13] The percent is around 62% of the entire population. It agrees with the life-cycle hypothesis that the elderly more likely have bought a real property, rather than rent, for the late time of residency (Green and Lee, 2016).

Table 2
Summary statistics of housing characteristics of retired households.

Variable	Description	N	Mean	SD	Min	Max
Housing Choice						
H	Housing expenditure	306,714	16,051.13	12,091.21	504	160,704
Own	Owner-occupied unit	306,714	0.70	0.46	0	1
Property Characteristics						
house	Single-family house	306,714	0.51	0.49	0	1
bed	# of bedrooms	306,714	1.98	1.05	1	7
kit	Complete kitchen	306,714	0.93	0.08	0	1
plm	Complete plumbing	306,714	0.97	0.05	0	1
rwat	Running water	306,714	0.98	0.04	0	1
bath	Bathtub or shower	306,714	0.99	0.04	0	1
acr10	House on ten or more acres	306,714	0.03	0.17	0	11
year	Age of dwelling unit	306,714	12.37	11.05	0	74

Note: The summary statistics of housing choices and property characteristics are calculated over 306,714 retired households.

bedrooms in each unit. Most of the dwelling units have complete facilities of kitchen, plumbing, running water, bathtub, and shower, which is important for the elderly. Nearly 3% of houses have a total lot size of more than ten acres. The average age of these housing units is 12 years.

Following the hedonic housing equation (2), I estimate the MSA-specific coefficients using the entire sample of 1,203,865 housing units in the study area.[14] The estimation results of these hedonic equations are presented in Table 9 Appendix A. It is shown that the means of most estimated coefficients are consistent with the conventional wisdom, even if they vary significantly across MSAs. Thus, housing costs need to be estimated separately across housing markets. Given the estimated coefficients and household housing choices, I predict the alternative housing expenditures for households have they lived in another place.

4.5. Climatic and locational attributes

In addition to the census data, climatic and locational attributes are attained to model household location choices. Among various climate amenities, temperature proves to be a primary concern for households (Schlenker and Roberts, 2009; Deschênes and Greenstone, 2011). This paper considers both mean and variability in temperature-related amenities. The mean temperature in winter is measured over the three months from December to February, while the mean temperature in summer is the average from June to August.[15] The temperature variability is the average daily difference between the maximum and minimum temperatures. The three temperature-related attributes pick up most temperature impacts. Since climatic variables change slowly over decades and households mainly focus on the temperature in recent years, this paper computes the temperature variables over the past three years, i.e., 2015, 2016 and 2017. The climate data comes from GHCN-Daily, a dataset that contains daily maximum and minimum temperatures provided by the NOAA National Climatic Data Center of the United States (Durre et al., 2010).[16] The top panels (a) and (b) in Fig. 2 illustrate the mean temperatures in summer and winter seasons measured in degrees Celsius, showing that there exist large variations in the average summer and winter temperatures across climate regions. The South region and southern Arizona in the West region experienced higher summer and winter temperatures than the rest of the continental United States. The average summer temperature across 377 MSAs is 23.3 °C with a standard deviation of 3.3 °C. The average winter temperature is 4.7 °C, and the standard deviation is 6.6 °C.[17] The winter temperatures are, on average, more volatile than summer temperatures. Panel (c) displays the variability in the temperature across MSAs, and it can be observed that the West climate region has the largest average difference between daily maximum and minimum temperatures. It is partly because many MSAs are located in the desert climates in the West region. Panel (d) presents the spatial distribution of all 3146 monitors covering the study areas.[18]

The dataset, GHCN-Daily, also reports many other climate attributes, including precipitation, snowfall, wind speed, particulate matter (PM2.5), and percent of possible sunshine. They are all included as utility determinants controlling for influences of these climate amenities. Table 3 summarizes these climate variables and shows the large variations in these climatic attributes across MSAs.

In addition to the common climate attributes, extreme weather and climate-related natural disasters, such as a hurricane in Florida and an earthquake in California, are likely to be considered by retired household in the locational decisions. However, due to the data limitation, it is impossible to collect all the information of many types of extreme weather, and they are barely comparable to each other in terms of the negative impacts. Moreover, retired households are likely to have both biased and heterogeneous perceptions of actual risks in these events, and the influence of extreme weather can be largely controlled for and predicted by climatic attributes, such as variations in temperature, wind, and precipitation.

Given the data availability, many other non-climate locational attributes are also obtained from multiple sources and controlled for in estimating household location choices. I include as many location-specific amenities that retired household care about as possible in the model, as described in Table 3. The data of crime rate at each MSA comes from the FBI's Uniform Crime Reporting (UCR) Program.[19] The scores of education are obtained from WalletHub, a database that evaluates the average quality of educational system across MSAs in the United States.[20] The U.S. Department of Transportation reports trans-

[14] I choose to estimate the housing equation over the entire sample since, from the statistical point of view, it is more accurate to estimate with all housing units, rather than only those occupied by retired households. The housing market is essentially exogenous for every single household. Moreover, I select only the private dwelling units and exclude some special residences, such as group quarters and public places.

[15] Existing literature also adopt the number of heating and cooling days in a year (Gyourko and Tracy, 1991) or the number of days in various temperature bins (Albouy, 2016).

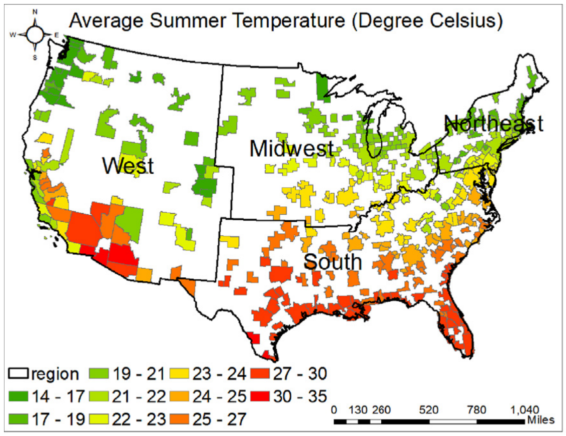
[16] https://docs.opendata.aws/noaa-ghcn-pds/readme.html.

[17] The winter and summer temperatures are highly correlated with the correlation coefficient of 0.87. The correlation coefficient is 0.23 between summer temperature and variability and 0.14 between winter temperature and variability.

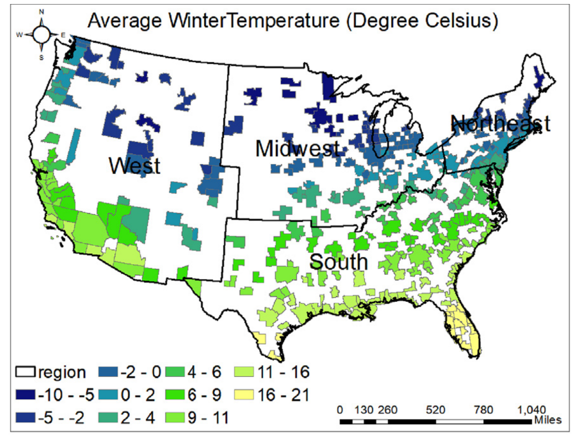
[18] Since the monitors are relatively evenly spread in each MSA, I give the readings of each monitor equal weights for the average climate attributes.

[19] https://ucr.fbi.gov/crime-in-the-u.s/2017/.

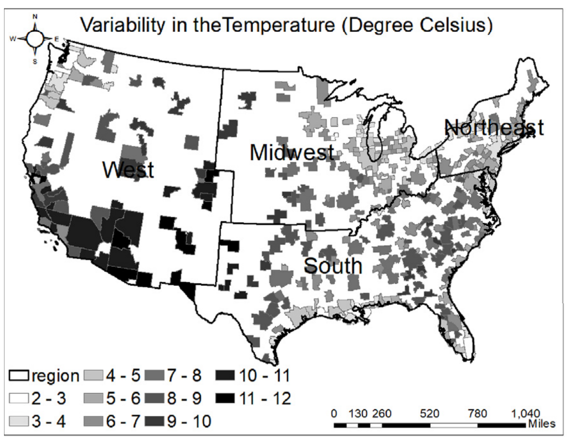
[20] https://wallethub.com/edu/most-and-least-educated-cities/6656/.



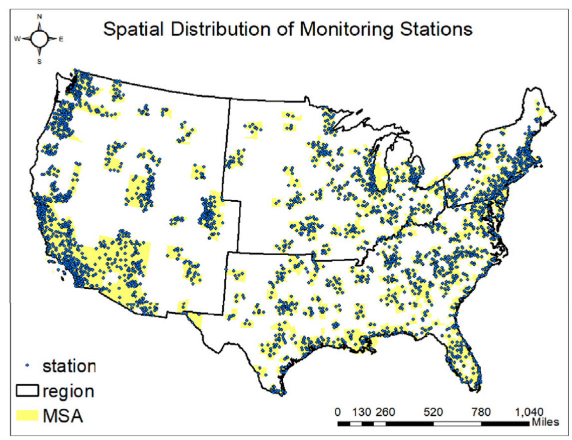
(a) Average summer temperature



(b) Average winter temperature



(c) Temperature variability



(d) Spatial distribution of stations

Fig. 2. The graphs illustrate the mean temperatures in summer and winter seasons, the variability in daily temperatures, and the geographic profile of monitoring stations across regions. Temperatures are measured in degrees celsius.

Table 3
Summary statistics of climatic and locational attributes.

Variable	Description	N	Mean	SD	Min	Max
Climate attributes						
ST	Average summer temperature (°C)	377	23.33	3.31	14.11	34.42
WT	Average winter temperature (°C)	377	4.71	6.67	−10.27	20.92
VT	Variability in temperature (°C)	377	5.41	3.32	2.18	10.88
PRCP	Annual precipitation (inches)	377	39.72	14.81	9.51	60.12
SNOW	Annual snowfall (inches)	377	20.9	21.44	0.00	89.13
AWND	Average daily wind speed (miles/hour)	377	9.75	2.84	6.23	12.53
PSUN	Annual percent of sunshine	377	62.44	7.35	39.01	89.03
PM25	Mean PM2.5 (micrograms/m^2)	377	13.81	2.52	5.16	21.57
Locational attributes						
Elev	Average elevation (miles)	377	0.19	0.23	0.00	1.64
Disc	Distance to the coast (miles)	377	145.61	146.22	0.09	582.70
Pden	Population density (persons/miles^2)	377	246.98	258.61	7.46	2316.02
Pwater	Percent of water area (%)	377	7.55	12.44	0.02	69.80
Trans	Transportation score	377	31.18	0.00	100.00	50.28
Crime	Crime rate per 100,000 inhabitants	377	450.98	208.14	5.87	1300.07
Educ	Education score	377	50.23	25.32	0.00	100.00
Health	Health insurance coverage (%)	377	82.55	12.44	64.02	95.70
Park	Park area (miles^2)	377	201.10	382.31	1.13	797.61

Note: The summary statistics of climatic and locational attributes are measured at the MSA level in 2017. Temperature amenities are calculated over 2015–2017.

Table 4
Estimation results of the household location choice model.

Variables	Estimates (*util*)	Std Err	MWTP ($)	Std Err ($)
The first-stage estimation				
Dependent variable: deterministic utility, V_{ij}, in equation (4)				
Std Dev of β_i^{ST}	0.0763***	0.0018		
Std Dev of β_i^{WT}	0.0867***	0.0027		
Std Dev of β_i^{VT}	0.0332***	0.0081		
Correlation coefficient				
$\rho(\beta_i^{ST}, \beta_i^{WT})$	−0.9111***	0.0134		
$\rho(\beta_i^{ST}, \beta_i^{VT})$	−0.4341***	0.0287		
$\rho(\beta_i^{WT}, \beta_i^{VT})$	0.3127***	0.0170		
Hicksian bundle	4.7621e-5***	1.1862e-5		
Moving out of metro	−0.0801***	0.0176	−1683.18	369.83
Moving out of state	−0.0426***	0.0075	−886.76	156.11
Moving out of region	−0.0198***	0.0065	−416.09	136.60
Moving distance	−3.8706e-4***	8.7036e-6	−7.9811	0.1794
Moving distance squared	−5.2321e-5***	3.3006e-7	−1.0987	0.0069
# of observations = 115,631,178, # of decision makers = 306,714				
The second-stage estimation				
Dependent variable: the estimated MSA fixed effects, $\hat{\eta}_j$, in equation (5)				
Mean summer temperature	−0.0576**	0.0290	−1209.97	611.09
Mean winter temperature	0.0531**	0.0250	1114.09	525.51
Variability in temperature	−0.0231*	0.0128	−486.13	270.07
Annual precipitation	0.0052*	0.0028	109.09	60.60
Annual snowfall	−0.0189**	0.0094	−398.12	199.06
Average daily wind speed	−0.0008	0.0006	−18.12	13.93
Annual percent of sunshine	0.0047*	0.0026	98.24	54.57
Mean PM2.5	−0.1528**	0.0764	−3210.01	1605.01
Average elevation	−0.0002	0.0002	−5.12	5.12
Distance to the coast	−0.0013**	0.0006	−28.23	14.11
Population density	0.0043	0.0053	91.42	114.27
Percent of water area	0.0375*	0.0208	789.21	438.45
Transportation score	0.0391**	0.0195	821.13	410.56
Crime rate	−0.0052**	0.0026	−109.27	54.63
Education score	0.0014	0.0017	29.56	36.95
Health insurance coverage	0.0104**	0.0051	218.09	108.50
Park area	0.0230***	0.0058	483.87	124.07
# of observations = 377, Adjusted R^2 = 0.4769				

Notes: The marginal willingness to pay (MWTP) is calculated by normalizing the coefficients on Hicksian bundle, measured in 2017 dollars. Robust standard errors are reported in the right columns, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

portation scores by MSAs in 2017.[21] The percents of the population with health insurance are estimated by the U.S. Census Bureau.[22] The data concerning park areas are provided by The Trust for Public Land, an organization reporting urban park statistics.[23] The values of non-climate locational attributes, in addition to climate amenities, are estimated with equation (5) in the second stage of the locational choice model.

5. Empirical results

This section presents the empirical results of the household locational choice model. I then investigate the preference heterogeneity in temperature amenities and the resulting residential sorting.

5.1. The household locational choice model

Given the choice set composed of 377 alternative locations for each of 306,714 retired households, I need to estimate the location choice model over 115,631,178 observations. To address the computational challenges, some papers adopt the sampling of alternatives that reduces the number of alternatives in the mixed logit model. It has been shown that a sampling strategy can theoretically produce consistent parameter estimates, but it loses some efficiency (Guevara and Ben-Akiva, 2013). By virtue of sufficient computing power in a computer server, the preference parameters in the household location choice model are estimated over the full choice set.[24] The model estimation is executed in PandasBiogeme, a free package for discrete choice modeling (Bierlaire, 2003).

Table 4 shows the estimation results of the household location choice model following the two-stage estimation strategy. In the first stage, the mixed logit model restricts the mean of $(\beta_i^{ST}, \beta_i^{WT}, \beta_i^{VT})$ to be zeros and allows the coefficients on three temperature-related variables to be jointly normally distributed. Therefore, only the standard deviations and correlations of the three coefficients can be estimated. It is seen that the level of preference heterogeneity in the winter temperature is slightly higher than that in the summer temperature, while the variation of coefficients on temperature variability is smaller than that in the mean temperatures. As for correlation coefficients, the winter and summer temperature coefficients are negatively correlated (−0.91). It suggests that retired households who prefer a warmer winter also favor a cooler summer, while those favoring a colder winter can sustain a hotter summer. In addition, the negative correlation between summer

[21] https://cms.dot.gov/transportation-health-tool/indicators.
[22] https://www.census.gov/topics/health/health-insurance/data.html.
[23] https://www.tpl.org.

[24] Specifically, the model is estimated in C5 instance in the Amazon server. It performs in 3.0 GHz Intel Xeon Platinum processors, offering 72 vCPU and 144 GiB of memory.

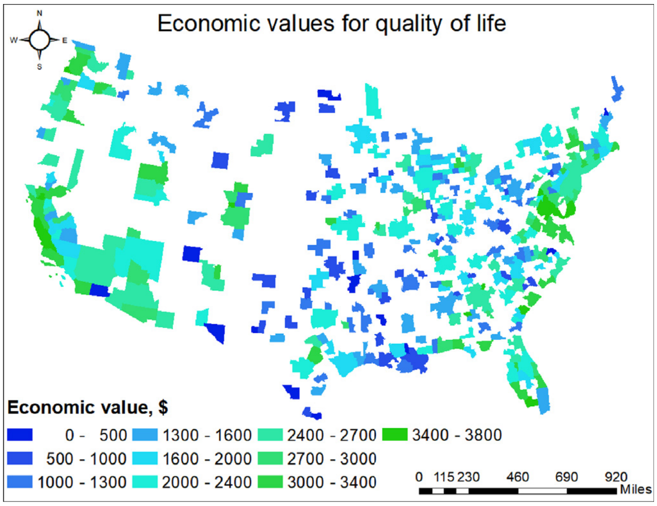


Fig. 3. Economic values for the quality of life across MSAs.

temperature and temperature variability implies that households who prefer cooler summers are more sensitive to changes in the outdoor temperature. Similarly, the preferences for milder winters are positively correlated with temperature variability, showing that households who value warmer winters more than others would like less volatile temperatures more than the average. Other than the statistics of household-specific coefficients, the first-stage model estimation yields the coefficients on the Hicksian bundle and generalized moving cost. I calculate the marginal willingness to pay (MWTP) on moving cost, climate and other location-specific attributes by dividing the associated coefficients by the coefficient on the Hicksian bundle, i.e., $E(\text{MWTP}^k) = -\frac{E(\beta^k)}{\alpha}$. It is estimated that the psychic costs of moving out of the MSA, state, and region in which a household lived before are \$416, \$887, and \$1,683, respectively. In terms of an economic cost in the relocation, it is observed that there exists nonlinearity in the relationship between a moving distance and an economic cost and a household pays \$1313 for a movement on average.[25]

As the group of coefficients estimated in the first stage, the estimates on locational fixed effects at the MSA level can be considered as overall evaluations for the quality of life in the metro areas. Fig. 3 shows the economic values for the MSAs, among which Laredo in Texas state has the lowest estimate and is taken as the reference group due to its extremely hot summers. The economic values for quality of life are the estimated WTP for the differences between the reference location and any particular MSA. It is shown that, generally, MSAs located on the east and west coasts have a better life quality. Generally, retired households favor some popular retirement spots in Southern California, Florida, and Maryland more than other places. Salinas in California is given the highest dollar value, i.e., \$3,750, compared to the reference group, largely due to its friendly climate, coastal attractions, and relatively high-quality urban facilities.

In the second stage, the estimated MSA fixed effects are regressed on climatic and locational variables. The bottom panel in Table 4 reports both coefficients and MWTP on these local attributes. It shows that retired households view higher winter temperatures and lower summer temperatures as preferred climate amenities. On average, they are willing to pay \$1209 for a 1 °C decrease in average summer temperature. This large MWTP should be interpreted as the value of a cooler summer during the entire three months. On the other hand, cold winter is considered a disamenity and retired households are willing to pay \$1114 for 1 °C increase in the winter temperature. The MWTP of temperature amenities are nearly 2.9% and 2.7% of average annual household incomes among the retired population. By comparison, the percents are much higher than those in the classic and well-cited paper by Albouy et al. (2016). They find that the WTPs to reduce an additional heating degree and cooling degree are 0.8% and 1.9% of income in the entire population. The considerable difference is largely due to the fact that residents become more sensitive to temperature and thus value them more highly when getting older.[26] It can also be the case that retired households care less about other attributes, like employment opportunities and school education for the next generation, and thus put a higher weight on climatic amenities than younger households in a locational decision (Lee, 2018). Moreover, the mean MWTP for a decrease of 1 °C in the daily difference between the maximum and minimum temperatures is \$486, nearly a half as much as that for a change of 1 °C in the summer and winter temperature. This new evidence suggests that retired households also value daily temperature change. Apart from average temperatures in summer and winter seasons, the second-stage estimation yields the coefficients and MWTPs for other attributes. The empirical results show that retired households view a higher level of precipitation, a larger percent of sunshine, proximity to the coast as valuable natural amenities, while a higher level of snowfall and air pollution, higher wind speed, and higher elevation are taken as disamenities. In terms of locational attributes, they prefer a higher population density, larger percent of water area, an advanced transportation facility, and lower local crime rate. As opposed to climatic attributes that are exogenous, some might be concerned that there exist general equilibrium effects of a climate-driven migration. It is due to the fact that numerous locational choices made by retired households, in the aggregate, can influence the local locational attributes, such as the density of retired population, that, in return, have an impact on locational decisions. The potential endogeneity arising form the reverse causality can bias the estimation results. To address the concern, I extend the model by adding two more variables related to the local age distribution, the percent of the retired population and density of the retired population, in estimating the main mixed logit model. However, having controlled for the local population density, none of the two variables are statistically significant.[27] Furthermore, retired households also favor a better medical system and more parks in an MSA, while, as expected, they barely have any preference for local education quality. Among these site characteristics, the coefficients on air quality, convenient transport, coast amenity, public safety, health system, and park facilities are statistically significant, showing that retired households have stronger preferences for these attributes. The estimated preferences for some attributes conform to the features of life in retirement.

The baseline model with the utility specification 4 assumes that 1) retired households have identical preferences for marginal changes in economic variables and 2) moving cost depends on the moving distance and the place where you lived one year ago. Table 10 in Appendix reports the robustness check of the value of temperature amenities to the setting of economic components and moving cost. Specifically, the Model 2 relaxes the linearity in the Hicksian bundle and allows the coefficients on the retirement income net of housing cost and non-housing cost to be different. It is shown that the relaxation of linearity in the Hicksian bundle has no significant influence on the estimates of the coefficients in Model 2. Following the setting of moving cost with the

[25] The economic moving cost with an average moving distance is $7.9811*31.14 + 1.0987*31.14^2 \approx \$1313.94$.

[26] Another similar evidence comes from the study by Sinha et al. (2018). They estimate that the MWTP for summer and winter temperatures are \$873 (1.4%) and \$709 (1.1%), respectively.

[27] Admittedly, some other urban facilities in the supply side might be endogenous, such as an increased supply level of housing for the retired population that influences local housing expenses. For instance, some retired households do not like to be surrounded by many retired households but prefer living with younger people.

Table 5
Heterogeneous preferences for temperature amenities by demographic groups.

MWTP ($)	Mean summer temp	Mean winter temp	Variability in temp
Age group[a]			
55–65	−1071.72	994.19	−387.31
66–75	−1223.15	1043.91	−499.12
76–85	−1423.11	1344.97	−548.22
86–95	−1119.93	1074.21	−423.49
Household income			
1%–25% ($2000-$18,400)	−1129.73	914.26	−246.21
25%–50% ($18,400-$32,300)	−1285.06	1181.75	−316.89
50%–75% ($32,300-$54,100)	−1289.37	1224.45	−435.84
75%–100% ($54,100-$413,200)	−1310.89	1243.12	−587.09
Health status			
With a disability	−1313.42	1244.29	−656.71
Without a disability	−1167.56	1002.24	−386.36
All	−1209.92	1114.11	−486.10

Notes.
[a] The age group is categorized by the average age of household members.

birthplace of a householder as the origin (Bayer et al., 2009; Fan et al., 2016), Model 3 checks how the hedonic values for temperature amenities can be influenced by moving cost. The alternative moving cost becomes $MC_{ij} = \pi_1 I_{ij}^{\text{Metro}} + \pi_2 I_{ij}^{\text{State}} + \pi_3 I_{ij}^{\text{Region}}$, where the dummy variables, I_{ij}, equal one if choosing a place different from the birthplace in each range. It is observed that the magnitudes of MWTP for staying in the same birthplace are much lower than those for the same current residence and the estimated values of temperature amenities are also lower than those in the baseline model. The large differences show the importance of moving costs in a locational choice. Retired households value the recent residential area more highly than their birthplace since they have less connection to the environment of birthplace when they retire. Therefore, it is reasonable to keep the setup of the baseline model with a linear Hicksian bundle and moving cost determined by the previous living area for the rest of the empirical analysis.

5.2. Heterogeneous preferences for temperature amenities

Among the retired households, values of temperature amenities can differ depending on demographic attributes and other unobserved preferences. The random coefficients on the temperature-related variables in the mixed logit model enable the exploration of preference heterogeneity in these amenities. Conditional on the household location choice, y_{ij}, and observable household and locational attributes, Z_{ij}, the conditional distribution of the random coefficients can be derived using the Bayes rule (Revelt and Train, 2000):

$$h(\boldsymbol{\beta}|y_{ij}, \boldsymbol{Z}_{ij}, \boldsymbol{\mu}, \Sigma) = \frac{P(y_{ij}|\boldsymbol{Z}_{ij}, \boldsymbol{\beta}) f(\boldsymbol{\beta}|\boldsymbol{\mu}, \Sigma)}{P(y_{ij}|\boldsymbol{Z}_{ij}, \boldsymbol{\mu}, \Sigma)} \tag{8}$$

where $f(\boldsymbol{\beta}|\boldsymbol{\mu}, \Sigma)$ is the overall distribution of random parameters. y_{ij} equals one if alternative j is chosen by household i. Then, the household-specific means of the parameters become:

$$E(\boldsymbol{\beta}_i|y_{ij}, \boldsymbol{Z}_{ij}, \boldsymbol{\mu}, \Sigma) = \int \boldsymbol{\beta}_i h(\boldsymbol{\beta}|y_{ij}, \boldsymbol{Z}_{ij}, \boldsymbol{\mu}, \Sigma) d\beta. \tag{9}$$

Intuitively, the expected $\boldsymbol{\beta}_i$ can be thought of as the conditional means of the coefficient distribution for the subsample who have the identical household demographics and make the same locational choice. In practice, the conditional expectations can be approximated using simulation (Revelt and Train, 2000) as follows:

$$\widehat{\boldsymbol{\beta}}_i = \frac{\frac{1}{R}\sum_{r=1}^{R} \boldsymbol{\beta}_i^{[r]} \prod_{j=1}^{J} \left[\frac{\exp(\boldsymbol{\Pi}_j \boldsymbol{\beta}_i^{[r]} + Z_{ij}\theta)}{\sum_{j=1}^{J} \exp(\boldsymbol{\Pi}_j \boldsymbol{\beta}_i^{[r]} + Z_{ij}\theta)} \right]^{y_{ij}}}{\frac{1}{R}\sum_{r=1}^{R} \prod_{j=1}^{J} \left[\frac{\exp(\boldsymbol{\Pi}_j \boldsymbol{\beta}_i^{[r]} + Z_{ij}\theta)}{\sum_{j=1}^{J} \exp(\boldsymbol{\Pi}_j \boldsymbol{\beta}_i^{[r]} + Z_{ij}\theta)} \right]^{y_{ij}}}, \tag{10}$$

where $\boldsymbol{\beta}_i^{[r]}$ is the r-th draw for household i from the estimated distribution of $\boldsymbol{\beta}$. This paper takes 100 draws for each household to calculate the household-specific coefficients on temperature-related variables.

The MWTP for temperature amenities may be influenced by age and health status due to their close relations with the desire for a friendly climate in doing outdoor activities. Moreover, the budget constraint can also have an impact on how much a household is willing to pay for a preferred temperature. Table 5 reports the means of the conditional MWTP that are averaged across all households in each subgroup divided by age, income level, and health condition. It can be seen that older retired households do favor a friendly temperature more than the younger retired groups, confirming the stronger desire for warmer winters, cooler summers, and steady weather for outdoor activities. This trend lasts until households turn the 90s, partially because they stay longer in the rooms and thus no longer need the preferred outdoor temperature that much. In another aspect, household income has a significant influence on the MWTP for temperature amenities. This positive relationship between income level and MWTP reflects a higher cost richer households are willing to pay for climate amenities and related well-being. In terms of health status, the mean MWTP for preferable temperature amenities is higher for disabled households than those without a disability, due to the fact that, generally, a disability makes it harder to do daily outdoor activities in a bad climate.[28]

5.3. Residential sorting for temperatures

Apart from the preference heterogeneity across demographic groups, there could exist a residential sorting based on the preferences for temperature-related amenities among retired households. Given the household locational choices, I calculate and average the household-specific coefficients on temperatures for each MSA, in order to examine how households in retirement sort across locations with their tastes for temperature amenities.

Fig. 4 shows the relationship between temperature amenities and average household MWTP for them across the MSAs. Each dot represents an MSA, and they are categorized by climate regions and represented by various symbols and colors. As seen in Panel (a), there exists a strong negative correlation between MWTP for cooler summers and MSA summer temperatures. It indicates a residential sorting pattern across cities. Holding other factors equal, households with a higher MWTP for lower summer temperatures tend to retire in a cooler

[28] The defined disability in the census data does not specify the type of physical features, which thus relates to an overall impact.

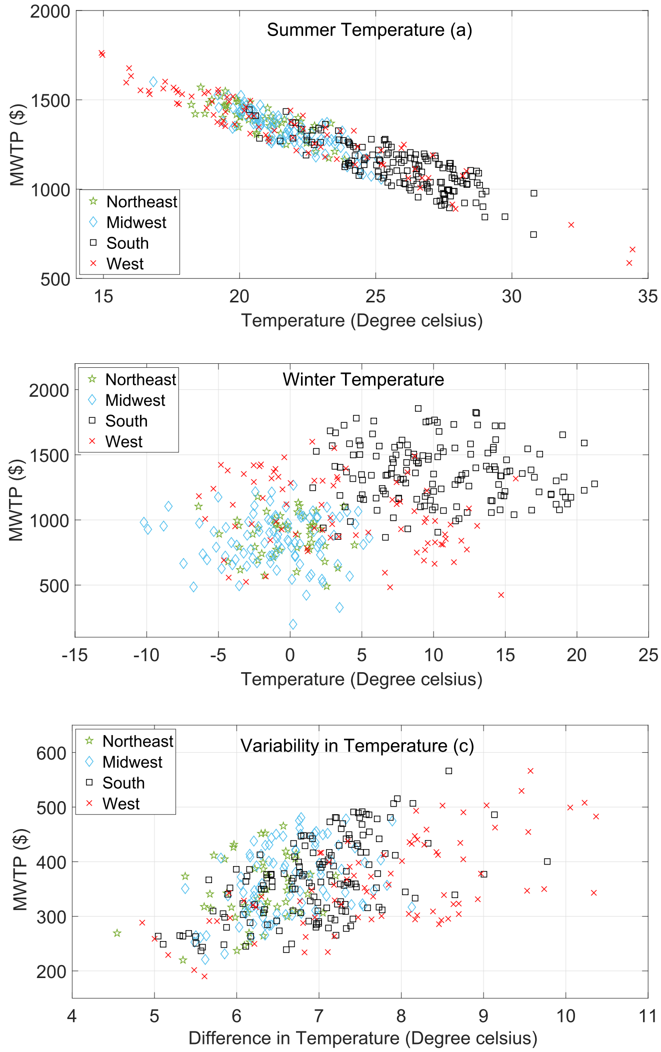


Fig. 4. The graphs illustrate residential sorting across MSAs based on temperature amenities.

city in summer, while those with a lower MWTP have resided in hotter cities. The three salient metropolitan areas on the top bottom corner are Phoenix, Yuma, and El Centro in Arizona and California. It is intuitive since these places located in the desert experience the highest temperatures during summer days with no precipitation. Retired households who choose to stay there thus have a higher ability to endure hot summers and do not have much incentive to move out, based on their revealed preferences. The Panel (b) illustrates the taste-based sorting for winter temperatures, and we can observe a positive relationship between winter temperature and its average MWTP across climate regions. Specifically, retired households residing in the South climate region with higher winter temperatures typically favor and thus are willing to pay more for warmer winters than those living in other climate regions. It largely explains why households who have a higher MWTP for warmer winters are more likely to overcome a moving cost and choose to live in the South region for retirement. On the contrary, many MSAs in the Midwest, Northeast and West regions (Northern part of the continental U.S.) feature lower winter temperatures, some of which are even below 0 °C. These urban areas are mainly inhabited by retired households who are willing to pay less than the average for warmer winters. As to the daily variability in temperature presented in Panel (c), there exists a less obvious sorting pattern, and retired households barely have significantly different MWTPs for this temperature amenity across MSAs. Some MSAs in western regions, located in the top right corner, feature higher average differences in daily temperature. However, households who choose to retire there have a similar MWTP for temperature variability to other MSAs, suggesting that temperature variability is not the primary driver for climate-related migration.

Table 6 reports the temperature amenities and calculates MWTP conditional on the locational choices across climate regions. The MWTPs for temperature-related amenities are first averaged across all households in an MSA and then weighted by the MSA population to obtain region-level values. It can be seen that, due to the preference-based sorting across MSAs, the population-weighted MWTPs for summer and winter temperatures are higher than those without sorting. The average MWTPs for a warmer winter and cooler summer are higher in the South region than the rest, while the average MWTP for variability in temperature does not vary mainly by climate regions.

In sum, there exist significant preference-based sorting patterns for both summer and winter temperatures, while the taste-based sorting does not exist for the variability in temperature. Retired households who favor the preferred temperatures more than the average live in places with a more friendly climate, while those who can endure a hot summer and cold winter retire in residences with less preferred climate amenities. The revealed preferences in the locational choices are used to solicit household MWTP for these climate amenities, showing that residences with preferred temperatures are indeed inhabited by retired households who are willing to pay more for these amenities. The MWTP for a better temperature in some MSAs can be four times ($2000 vs. $500) as high as that in other MSAs, which implies retired households have very different valuations for climate amenities across the United States. Thus, taste-based sorting should not be ignored when estimating the aggregate value of climate amenities.

6. Values of projected temperature changes

Using the estimated preference parameters for temperature amenities, this section provides the empirical estimates on values of future temperature changes for retired households.

6.1. Projections of temperature amenities

Many projections of future temperatures have been made by climate scientists under various climate scenarios and models. To value changes in the temperature amenities, I apply the most commonly used climate projection dataset, NASA Earth Exchange Global Daily Downscaled Projections (NEX-GDDP).[29] This NEX-GDDP dataset includes downscaled projections from the 21 models and scenarios for which daily scenarios are produced and distributed under the Coupled Model Intercomparison Project Phase 5 (CMIP5) (Taylor et al., 2012). It presents the global climate projections of daily temperature over the periods from 1950 through 2100 at very small scales.[30] Specifically, I select two typical time points, the year 2050 and 2100, under the scenario of RCP45.[31] The average summer and winter temperatures are then calculated in these two years for each MSA. A total of 4349 locations with projections spatially overlap with the MSAs. The values are averaged over all spots in each MSA. Fig. 5 illustrates the projected changes in summer and winter temperatures under various situations. It can be seen that, in 2050 and 2100, both the summer and winter temperatures are projected to be higher, which implies that we will experience warmer winters and hotter summers this century. The temperature projections for the continental United States do not largely differ

[29] https://cds.nccs.nasa.gov/nex-gddp/.

[30] The spatial resolution of the dataset is 0.25° (−25 km × 25 km), and there are a total of 1,036,800 spots with projections across the globe.

[31] RCP is short for Representative Concentration Pathways. Another common climate scenario is RCP85. The two climate scenarios vary by the projected concentration of greenhouse gas emissions but with an only slight difference in projected temperatures (Karl et al., 2009).

Table 6
Temperature amenities and MWTP by climate regions.

Region	Midwest	Northeast	West	South	All
Temperature amenities					
Summer temperature	21.3	17.8	27.8	30.2	23.8
Winter temperature	−3.5	−4.6	6.8	10.7	4.5
Variability in temperature	5.0	4.9	5.9	4.7	5.3
Marginal willingness to pay (MWTP)					
MWTP for summer temperature	−1313.1	−1210.9	−1494.5	−1565.1	−1416.1
MWTP for winter temperature	1041.5	1144.3	1342.0	1412.0	1294.3
MWTP for temperature variability	−474.1	−461.7	−459.4	−479.9	−472.1

Notes: The temperature-related variables and MWTPs are first averaged across all households in an MSA and then weighted by MSA populations to gain region-specific values.

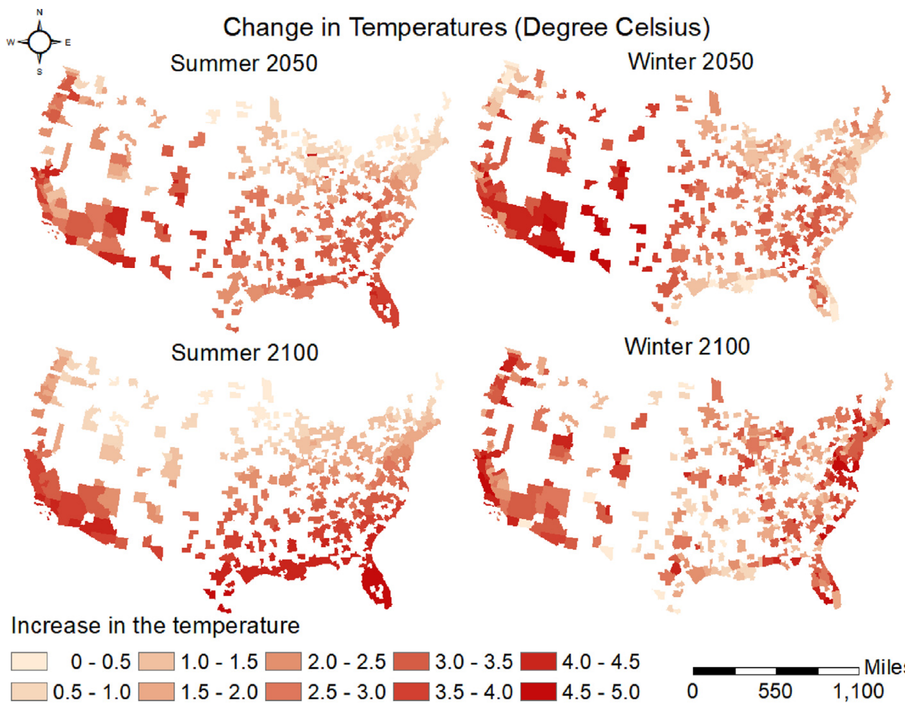


Fig. 5. Δ°C in 2050 and 2100 across MSAs.

between the two periods. In the coming 2050, there will be an average increase of 3.1 °C in summer temperature and 2.9 °C in winter temperature, which are slightly lower than those in 2100 (3.6 °C in summer and 3.3 °C in winter). The average temperature variability almost remains the same change over decades, and thus its calculated WTP is not reported. As for the variations across climate regions, summers in the future would become much higher in the South region, compared to the rest, while the West region will experience warmer winter than other climate regions. Therefore, the changing temperature amenities caused by long-lasting global warming in the 21st century can have location-specific impacts on retired households. I calculate the dollar values of these climate changes to evaluate its influence on daily life and welfare.

6.2. *WTP for temperature change with current locations*

Given the coefficients on temperature amenities and projected change in the temperatures, I compute WTP by multiplying the MWTP for summer and winter temperatures in each MSA by the size of the temperature change, conditional on household location choices. The population-weighted WTPs in each climate region and the entire U.S. are also computed for each climate scenario. Table 7 presents the changes in temperatures across regions and the WTP for each situation conditional on locational choices. The WTP equals the value of warmer winters, net of the disvalue of hotter summers. It is seen that, in terms of the entire U.S., the overall WTP for climate change is negative, implying that global warming will cause aggregate damage to the wellbeing of the retired population. A retired household on average is willing to pay $890 (nearly 2.1% of an annual retirement income) to avoid the climate scenario projected to occur in 2050 and $1379 (3.3% of their annual income) in 2100. The empirical estimates show that retired households are willing to pay a higher percentage of their income for a favorable climate amenity than the rest of the pollution.[32] Moreover, there exist large geographic variations in estimated values. Retired households distaste the future temperature changes in most climate regions, except for the Northeast region where households are willing to pay for the changes. It implies that, in the majority of urban areas, the benefits from warmer winters are outweighed by hotter summers, while the value of warmer winters exceeds hotter summers in the Northeast region. The positive impact of global warming on future retired households in the Northeast region primarily comes from the mitigation of the coldest climate.

[32] The values of a similar and more friendly climate scenario are found to be around 1%–1.4% of household income for the entire U.S. population (Sinha et al., 2018).

Table 7
Temperature changes and WTP in current locations in 2050 and 2100.

Region	Midwest	Northeast	West	South	All
Year 2050					
Δ°C in summer temperature	2.9	1.6	3.8	4.2	3.1
Δ°C in winter temperature	2.5	2.9	3.2	3.2	2.9
WTP for the change	−723.6	1294.9	−1032.8	−1516.8	−890.1
Year 2100					
Δ°C in summer temperature	3.1	2.9	4.1	4.6	3.6
Δ°C in winter temperature	2.7	3.6	3.8	3.1	3.3
WTP for the change	−742.8	501.8	−1227.1	−2112.2	−1.379.4

Notes: The changes in temperatures and WTPs are weighted by the MSA populations in each region. The WTP amounts to the willing to pay for warmer winters, net of hotter summers.

Table 8
Temperature changes and compensating variations in 2050 and 2100.

Region	Midwest	Northeast	West	South	All
Year 2050					
Δ°C in summer temperature	2.9	1.6	3.8	4.2	3.1
Δ°C in winter temperature	2.5	2.9	3.2	3.2	2.9
E(*CV*) for the change	−413.3	891.2	−738.4	−1092.2	−602.3
Year 2100					
Δ°C in summer temperature	3.1	2.9	4.1	4.6	3.6
Δ°C in winter temperature	2.7	3.6	3.8	3.1	3.3
E(*CV*) for the change	−640.3	202.2	−321.3	−1238.2	−992.5

Notes: The temperature changes and E(*CV*) are weighted by the MSA population across climate regions. The absolute values of negative numbers are the amounts a household needs to be compensated with a new climate scenario.

6.3. *Welfare evaluation with mobility and household relocations*

The previously calculated values for various climate scenarios are conditional on current locations, without considering the potential averting behaviors. Households are assumed to stay in their current MSA and not move in response to temperature changes over time. However, given the heterogeneous preferences for temperature amenities across socio-demographic groups, there can exist further residential sorting driven by the projected climate change over the long period. Retired households may overcome a moving cost and relocate to another place, even if the adjustments should be relatively rare given the small changes in the temperature. Thus, to calculate an exact welfare measure of temperature changes, I take into account the possibility of migration and allow each retired household to choose the utility-maximizing residence again under new climate scenarios. Given locational attributes and household-specific preferences for temperature-related amenities, the exact welfare change is measured by a household compensating variation (CV), which is implicitly solved in the following equation:

$$U_{ij} = \max_j \left(V_{ij}^0 + \epsilon_{ij} | Y_i, \mathrm{ST}_j^0, \mathrm{WT}_j^0, \mathrm{VT}_j^0 \right) \tag{11}$$

$$= \max_j \left(V_{ij}^1 + \epsilon_{ij} | Y_i - CV_i, \mathrm{ST}_j^1, \mathrm{WT}_j^1, \mathrm{VT}_j^1 \right), \tag{12}$$

where ST_j^0, WT_j^0 and VT_j^0 are current temperature amenities and ST_j^1, WT_j^1 and VT_j^1 are projected future temperature amenities. V_{ij}^1 represents the new utility of household i facing a new climate scenario.[33] CV_i denotes the compensating variation that equals the amount household i is willing to pay in exchange for different temperature-related amenities. Given the location choice and household demographics, the expectation of CV_i becomes:

$$E(CV_i | y_{ij}, \boldsymbol{Z}_{ij}, \boldsymbol{\mu}, \Sigma) = \int CV_i h(\boldsymbol{\beta}_i | y_{ij}, \boldsymbol{Z}_{ij}, \boldsymbol{\mu}, \Sigma) d\boldsymbol{\beta}_i, \tag{13}$$

where $h(\boldsymbol{\beta}_i | y_{ij}, Z_{ij}, \boldsymbol{\mu}, \Sigma)$ is the conditional probability of preference parameters, $\boldsymbol{\beta}_i$. In practice, I randomly draw preference parameters and random part of household utility to compute a number of CV_i for household i in equation (11). Then, I repeat the simulation 100 times and take the average of CV_i to calculate the expected compensating variation across all households.

Table 8 reports the expected compensating variations in each scenario across climate regions if all retired households are given full mobility. On average, the average loss of household welfare due to temperature changes is \$602 (1.4% of their annual income) in 2050 and \$993 (2.4% of their annual income) in 2100. The negative numbers equal what a household needs to be compensated for enduring an adverse climate scenario. It can be seen that the preference ranking of various climates remains the same, while the estimates on welfare changes in most cases are lower than WTPs conditional on current locations. The compensation a household requires facing the new climate is on average less than the amount they are willing to pay for staying in the current favorable climate. The differences in estimates arise mainly from the different assumptions on household mobility. When households are free to move, they can improve their welfare by moving to another MSA as long as the utility gain exceeds the generalized moving cost. As a consequence, the actual damage caused by the adverse climate becomes lower due to massive self-adjustments in the residential sorting process.

Given the full mobility and potential household relocations, the retired population in the U.S. can be geographically redistributed over the years in response to changing climate attributes. Fig. 6 in Appendix B shows the time-variant spatial distributions of the retired population in 2050 and 2100. Specifically, the two maps show the percentage changes of retired households in a local population, compared to the year 2017. It can be seen in Panel (a) that, as a

[33] The systematic utility is $V_{ij}^1 = \alpha(Y_i - \widehat{H_{ij}} - Q_{ij} - CV_i) + \mathrm{WT}_j^1 \beta_i^{WT} + \mathrm{ST}_j^1 \beta_i^{ST} + \mathrm{VT}_j^1 \beta_i^{VT} + MC_{ij} + \eta_j$.

result of taste-based sorting, the Northeast region with relatively cooler summers than average would attract more retirees to reside there in 2050. Many retired households will move north from the South region and southern areas in the West region, driven mainly by the upcoming broiling summers. Some MSAs are expected to accommodate 1.5–2.5% more retired households. These estimates are based on the projected changes in outdoor temperatures. Admittedly, some adaptations, such as installing an air conditioner, can largely mitigate the influences of hotter summers. Due to long-term global warming, the pattern of residential sorting will be further intensified over time. As shown in Panel (b) in 2100, a larger portion of retired households move away from southern California, Texas, and south Florida in the South and West regions, contributing to an overall northbound migration pattern.

Given the high moving cost, rational retired households need to forecast the changing climatic and locational attributes when making a locational decision. If they are not forward-looking and thus cannot fully consider the changing temperature amenities, the model estimation is likely to be biased. Using a dynamic computable general equilibrium model in which households incorporate future stream of utilities with time-variant attributes, some recent papers estimate how the long-run climate changes lead to a population redistribution across the United States (Fan et al., 2018). As a robustness check, I reestimate the household locational choice model with projected future temperatures and current locations. The estimation results do not vary significantly, suggesting that retired households are myopic in some sense. However, the potential biasedness is not as worrying as it seems to be. It is due mainly to the fact that retired households make locational decisions for a shorter time horizon and expect to stay in a residence for at most 20 years during which climate attributes would not substantially change. Therefore, it is still reasonable to estimate the model with recent average temperatures.

7. Conclusion

Using the newly released U.S. 2017 census data, this paper documents the relationship between local climate amenities and retired household residential location decisions. The empirical results of the structural sorting model show that climate amenities play an important role in deciding a location in which a retired household chooses to live. It is found that retired households value favorable climate amenities. On average, they are willing to pay $1209 for a 1 °C drop in average summer temperature and $1114 for a 1 °C increase in average winter temperature. The estimated MWTPs by retired households are higher than those by the entire population (Sinha et al., 2018). In addition to the average temperatures, this paper provides the first estimate on the value of another important temperature-related amenity, temperature variability, to account for the particular physical status of retirees. The MWTP for a 1 °C decrease in average difference in daily maximum and minimum temperatures equals $486. In the robustness analysis, I find that these empirical results are robust to the specification of economic component but sensitive to the setup of moving cost. In this paper, the economic values for the quality of urban life are reported and found to be higher, compared to the estimates provided by Albouy et al. (2016). Apart from the mean estimates, I use the random coefficient model to investigate preference heterogeneity in climate amenities. The MWTPs for a favorable climate are found to be higher among older retired households with a higher retirement income and disability. Moreover, in terms of geographic variations, this paper confirms that retired households who live in places with a more friendly climate have a higher MWTP for the preferred temperatures more than the average.

In the economics of climate change, many efforts have been made to analyze how projected changes in climate amenities influence daily household activities. To contribute to literature, this paper also provides some of the first empirical evidence of retired households' WTP to avoid future changes in climate amenities. Conditional on current locations and household preferences for climate amenities, the projected changes in temperatures in the future would cause a welfare loss. On average, households are willing to pay up to nearly 3.3% of their annual retirement income to avoid the upcoming climate scenarios. The calculated household welfare loss caused by unfavorable climate amenities offers much information in the cost-benefit analysis of climate change. Given the large retired population, the large aggregate loss of social welfare motivates the mitigation of global warming.

From an urban planner's perspective, local demographic composition plays a critical role in long-term urban development. The changing climate is important for not only the current generation but also future retired households. It can result in an amenity-driven residential sorting and gradually reshape the geographical distributions of the retired population across localities in the United States. Simulation results forecast the new climate amenities are expected to cause an overall northbound migration of the retired population in the continental United States. This finding is of direct urban policy relevance and has profound implications for local urban planning. Existing literature has shown that retirees are economically beneficial to local areas, due to an increase in the property tax base and a relatively light burden on the public service budget (Duncombe et al., 2001). For policymakers in areas with an upcoming net out-migration, it presents a long-run challenge of providing amenities and other utility enhancing attributes to keep those future retired households. On the contrary, those popular destinations for retirement can start to build more urban facilities, like public parks and nursing homes, to accommodate more retired households.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.regsciurbeco.2019.103489.

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