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HOUSEHOLD LOCATION DECISIONS AND THE VALUE OF CLIMATE AMENITIES

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ABSTRACT

We value climate amenities by estimating a discrete location choice model for US households. The utility of each metropolitan statistical area (MSA) depends on location-specific amenities, earnings opportunities, housing costs, and the cost of moving to the MSA from the household head's birthplace. We use the estimated trade-off among wages, housing costs, and climate amenities to value changes in mean winter and summer temperatures. We find that households sort among MSAs as a result of heterogeneous tastes for winter and summer temperatures. Preferences for winter and summer temperatures are negatively correlated: households that prefer milder winters, on average, prefer cooler summers, and households that prefer colder winters prefer warmer summers. Households in the Midwest region, on average, have lower marginal willingness to pay to increase winter and reduce summer temperatures than households in the Pacific and South Atlantic census divisions. We use our results to value changes in winter and summer temperatures for the period 2020 to 2050 under the B1 (climate-friendly) and A2 (more extreme) climate scenarios. On average, households are willing to pay 1% of income to avoid the B1 scenario and 2.4% of income to avoid the A2 scenario.

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1. Introduction

The amenity value of climate—what people are willing to pay to experience warmer winters or avoid hotter summers—is an important component of the benefits of greenhouse gas mitigation policies. Yet, with the exception of Albouy et al. (2013), the recent literature contains few estimates of the value of climate amenities for the United States. Estimating these values poses an econometric challenge: climate, by definition, changes slowly, so researchers must rely on cross-sectional variation in climate to measure its impact on household location decisions. This paper helps fill this gap by estimating a discrete location choice model in which a household's choice of the city in which to live depends on climate amenities as well as earnings, housing costs, and other location-specific amenities. We use the model to estimate household willingness to pay (WTP) for changes in mean winter and summer temperatures and use these values to assess the welfare effects of temperature changes in cities throughout the United States.

Traditionally, economists have used hedonic wage and property value functions to value climate amenities (Cragg and Kahn 1999; Gyourko and Tracy 1991; Blomquist et al. 1988; Smith 1983). In a world in which households can migrate costlessly across cities, location-specific amenities should be capitalized into wages and property values. In equilibrium, each household will select a city (i.e., a vector of amenities) so that the marginal cost of obtaining each amenity, measured in terms of wages and housing costs, just equals the value it places on the amenity (Roback 1982).[1] This approach has been followed most recently by Albouy et al. (2013), who regress a quality of life (QOL) index—a weighted sum of wage and price indices—for each public-use microdata area (PUMA) on a vector of location-specific amenities, including climate amenities.

An alternate approach to valuing amenities that vary by location is to estimate a discrete choice model of household location decisions (Bayer et al. 2004; Bayer and Timmins 2007; Bayer

[1] Formally, marginal WTP for an amenity equals the sum of the slope of the hedonic wage function with respect to the amenity plus the slope of the hedonic property value function, weighted by the share of income spent on housing, evaluated at the chosen amenity vector (Roback 1982).

et al. 2009; Cragg and Kahn 1997; Klaiber and Phaneuf 2010). Households choose among locations based on the utility they receive from each location, which depends on wages, housing costs, and location-specific amenities. Variations in wages, housing costs, and amenities across locations permit identification of the parameters of the household's utility function.

The discrete choice approach, which we follow here, offers several advantages over the traditional hedonic approach. Most important, it allows the researcher to more easily incorporate market frictions, including the psychological and informational costs of moving.[2] The hedonic approach assumes that consumers are perfectly mobile and hence that the weighted sum of wage and housing price gradients will equal the consumer's marginal willingness to pay (MWTP) for an amenity. Bayer et al. (2009) demonstrate that this equality fails to hold in the presence of moving costs, and they incorporate the psychological and informational costs of leaving one's birthplace into an equilibrium model of household location choice. We also incorporate moving costs from birthplace in our model of location choice and demonstrate that their omission significantly understates the value consumers place on temperature and precipitation.

The discrete choice approach allows us to obtain exact welfare measures for changes in temperature throughout the United States based on two climate scenarios. These welfare measures incorporate both taste sorting based on climate and the opportunity for households to move in response to changes in temperature.

Our Approach

In this paper, we value climate amenities by estimating a model of residential location choice among metropolitan statistical areas (MSAs) for US households in 2000. We model the choice among MSAs based on potential earnings, housing costs, moving costs, climate amenities, and other location-specific amenities. The model is estimated as a mixed logit model, which allows the coefficients on climate amenities to vary among households. We compute the means of these coefficients for each household, conditional on choice of MSA, and then examine how the average conditional means for climate amenities vary across MSAs to describe taste sorting.

[2] Barriers to mobility prevent the sum of wage and housing price gradients from equaling marginal willingness to pay, and they imply that the assumption of national labor and housing markets, which underlies the hedonic approach, may not accurately capture wage and housing costs in different cities.

We use the conditional means in two ways to value future changes in temperature. We compute the value of changes in temperature assuming that each household does not move. This is analogous to the value of temperature changes computed by Albouy et al. (2013) based on local linear estimates of the hedonic price function. We also compute exact welfare measures (i.e., expected compensating variation) using each household's conditional distribution of taste coefficients. These measures implicitly allow households to move in response to temperature changes.

Our paper builds on the work of Cragg and Kahn (1997), who were the first to use a discrete choice approach to value climate amenities.[3] We extend their work, following Bayer et al. (2009), by including moving costs and modeling choices across MSAs. Unlike Bayer et al., however, we cannot use multiple cross sections to difference out unobserved amenities within cities. Historical data indicate that climate changes slowly, forcing us to rely on a single cross section of data rather than data over consecutive decades.[4] We attempt to allay concerns about omitted variable bias by controlling for a wide variety of location-specific amenities other than temperature, especially those that are correlated with temperature.

Our Findings

Our results indicate that households are willing to pay to avoid cold winter temperatures and hot summer temperatures; however, these values vary significantly by residential location. We find a strong positive correlation between MWTP for winter temperature and the temperature of the city in which the household lives: households with the highest MWTP for warmer winters live in Florida, while those with the lowest MWTP live in the Midwest. Preferences for summer temperature and winter temperature are, however, negatively correlated ($\rho = -0.83$). This implies that households that prefer milder winters, on average, also prefer milder summers, while households that prefer colder winters have a lower MWTP to reduce summer temperatures. MWTP to avoid hotter summers is, on average, higher in the South Atlantic and Pacific regions than in the Midwest. At the level of census regions, households in the Midwest and Northeast have lower

[3] Cragg and Khan (1997) value climate amenities by estimating a model of the choice of state in which to live for households that moved between 1985 and 1990.

[4] This is also true of the literature that examines the impact of climate on agriculture (Schlenker and Roberts 2009).

MWTPs to increase winter and reduce summer temperatures than households in the South and West.

We use these estimates to value changes in mean summer and winter temperatures over the period 2020 to 2050 for 284 US cities that contained over 80% of the US population in 2000. The Hadley model projects that, under the B1 climate scenario from the Special Report on Emissions Scenarios (SRES),[5] mean summer temperature (population weighted) will increase, on average, by 3.3°F in these cities and mean winter temperature by 3.4°F. Cities in the New England and Middle Atlantic states will experience larger increases in winter temperature than in summer temperature, although the reverse is true for the East South Central and West South Central census divisions, and also the Pacific and Mountain states. Ignoring sorting overstates the WTP of households in the New England and Middle Atlantic states for the B1 scenario and greatly understates the value of avoiding the B1 scenario to households in the Midwest. On net, allowing for taste sorting increases the average household WTP to avoid the B1 scenario compared with a world in which sorting is ignored.

Allowing for sorting actually decreases the average household WTP to avoid the more severe A2 scenario. The A2 scenario results in very large increases in summer temperature in the East and West South Central divisions and the Midwest region. Ignoring sorting overstates the disamenity of the A2 scenario in the Midwest and South census regions.

Taking sorting into account, the mean household WTP to avoid the B1 scenario in the 2020–2050 timeframe is about 1% of income; it is about 2.4% of income for avoiding the A2 scenario. We note that the latter value is within the range reported by Albouy et al. (2013) for a much more drastic climate scenario in the period 2090–2099.[6] One possible reason for the difference in estimates is that we base our estimates on all households, whereas Albouy et al. (2013) focus on prime-aged households. Our results suggest that the value attached to climate amenities varies with the age of the household head: on average, households with heads over the

[5] To represent a range of driving forces for emissions, such as demographic development, socioeconomic development, and technological change, the Intergovernmental Panel on Climate Change (IPCC) developed a set of emissions scenarios. In the SRES, IPCC (2000) describes these scenarios in more detail. We use projections from a climate-friendly scenario (B1) and a more extreme scenario (A2).

[6] Albouy et al. (2013) focus on the A2 scenario in the period 2090–2099, when it is expected to raise mean temperature in the United States by 8.3˚F compared with the 1970–2000 period.

age of 55 have a MWTP for higher winter temperature and a MWTP to avoid increased summer temperature that is about twice as high as households with heads between 25 and 55 years old. For policy purposes, we focus on results based on all households.

The paper is organized as follows. Section 2 presents the household's location decision and the econometric models we estimate. Section 3 describes the data used in our analysis. Estimation results are presented in Section 4. Section 5 uses these results to evaluate the value of temperature changes projected by the B1 and A2 SRES scenarios. Section 6 concludes the paper.

2. Household Residential Location Model

We model household location in 2000 assuming that each household selected its preferred MSA from the set of MSAs in the United States in 2000. Household utility depends on income minus the cost of housing, location-specific amenities, and moving costs from the birthplace of the household head. Specifically, we assume that the utility that household i receives from city j is given by

$$U_{ij} = \alpha\left(Y_{ij} - P_{ij}\right) + \boldsymbol{A_j}\boldsymbol{\beta}_i + MC_{ij} \tag{1}$$

where Y_{ij} is household i's income and P_{ij} its housing expenditure in city j. MC_{ij} represents the costs—psychological and other—of moving from the head of household's birthplace to city j. $\boldsymbol{A_j}$ is a vector of location-specific amenities. We allow the coefficients on temperature amenities to vary across households. Household income is the sum of the wages of all workers in the household, W_{ij}, plus nonwage income, which is assumed not to vary by residential location. To predict the earnings of household workers in locations not chosen, we estimate hedonic wage and housing price equations for each MSA, as described below.

Moving costs capture the psychological, search, and out-of-pocket costs of leaving a household's place of origin. Seventy-three percent of households in our sample (see Table 1, full sample) live in the census region in which the head was born; 67% live in the same census division. Although households have been moving to warmer weather since the Second World War (Rappaport 2007), family ties and informational constraints may have prevented this from occurring more completely. As shown below, failure to account for these costs significantly alters the value attached to winter and summer temperatures.

Following Bayer et al. (2009), we represent moving costs as a series of dummy variables that reflect whether city *j* is outside of the state, census division, and/or census region in which household *i*'s head was born. Formally,

$$MC_{ij} = \pi_0 d_{ij}^{State} + \pi_1 d_{ij}^{Division} + \pi_2 d_{ij}^{Region} \quad (2)$$

where d_{ij}^{State} denotes a dummy variable that equals one if *j* is in a state that is different from the one in which household head *i* was born, $d_{ij}^{Division}$ equals 1 if location *j* is outside of the census division in which the household head was born, and d_{ij}^{Region} equals 1 if location *j* lies outside of the census region in which the household head was born.

Estimation of the Model

Estimating the location choice model requires information on the wages that a household would earn and the cost of housing in all MSAs. Because wages are observed only in the household's chosen location, we estimate a hedonic wage equation for each MSA and use it to predict W_{ij}. The hedonic wage equation for MSA *j* regresses the logarithm of the hourly wage rate for worker *m* in MSA *j* on variables ($\boldsymbol{X}_{mj}^{w}$) measuring the demographic characteristics—education, experience, and industry and occupation—of worker *m*:

$$\ln w_{mj} = \gamma_j^2 + \boldsymbol{X}_{mj}^{w} \boldsymbol{\Gamma}^{X,2} + \nu_{mj}^2 \quad \forall\, j = 1, \ldots, J \quad (3)$$

Equation (3) is estimated using data on full-time workers in the public use microdata sample (PUMS).[7] The coefficients of equation (3) are used to calculate the earnings of each worker in the sample used to estimate the discrete choice model (see Table 1), under the assumption that individuals work the same number of hours and weeks in all locations. Summing earnings over all individuals in each household, we obtain predicted household wages for household *i* in location *j* ($\hat{W}_{ij}$). Predicted income in city *j*, $\hat{Y}_{ij}$ equals predicted wage income plus non-wage income of household *i* which is assumed not to vay by MSA.

[7] The equation is estimated using data on all persons working at least 40 weeks per year and between 30 and 60 hours per week. Persons who are self-employed, in the military, or in farming, fishing, or forestry are excluded from the sample.

The cost of housing in each location is estimated based on hedonic property value equations for each MSA,

$$\ln P_{ij} = \delta_j^2 + \boldsymbol{X}_{ij}^P \boldsymbol{\Delta}^{X,2} + \omega_{mj}^2 \quad \forall\, j = 1, \ldots, J \tag{4}$$

P_{ij} is the annual cost of owning house i in city j, computed as the sum of the monthly mortgage payment or rent and the cost of utilities, property taxes, and property insurance. $\boldsymbol{X}_{ij}^P$ contains a dummy variable indicating whether the house was owned or rented, as well as a vector of dwelling characteristics. Utility costs are added both to the costs of owning a home and to rents because heating and cooling requirements vary with climate. We wish to separate these costs from climate amenities. Equation (4) is estimated separately for each MSA in our dataset. We predict housing expenditures for household i in city j ($\hat{P}_{ij}$) assuming that the household purchases the same bundle of housing characteristics in city j as it purchases in its chosen city.

The results of estimating the hedonic wage and housing market equations for all cities are summarized in Appendix Tables A-1 and A-2. We find, as do Cragg and Kahn (1997), that the coefficients in both sets of hedonic equations vary significantly across MSAs, suggesting that the assumption of national labor and housing markets made in hedonic studies is inappropriate.

We estimate the discrete location choice model in two stages. The first is a mixed logit model in which the indirect utility function incorporates unobserved heterogeneity in preferences for winter and summer temperature, and MSA fixed effects (δ_j):

$$V_{ij} = \alpha\left(\hat{Y}_{ij} - \hat{P}_{ij}\right) + WT_j\beta_{WT} + ST_j\beta_{ST} + MC_{ij} + \delta_j + \varepsilon_{ij} \tag{5}$$

We assume that the coefficients (β_{WT} and β_{ST}) are jointly normally distributed, with zero mean vector and variance-covariance matrix $\boldsymbol{\Sigma}$. The household's utility function is observed with error term ε_{ij}; that is, $V_{ij} = U_{ij} + \varepsilon_{ij}$. The error term ε_{ij} combines the error in predicting household i's wages and housing expenditures in city j with household i's unmeasured preferences for city j. Assuming that the idiosyncratic errors are independently and identically distributed Type I extreme value, the probability of household i selecting city j is given by the mixed logit model. In the second stage, city-specific fixed effects are regressed on the vector of amenities to estimate the means of the temperature coefficients and the coefficients on other amenities:

$$\delta_j = \boldsymbol{A_j}\Gamma + u_j \tag{6}$$

The parameters of equation (5) are estimated via simulated maximum likelihood techniques, using a choice set equal to the household's chosen alternative and a random sample of 59 alternatives from the set of 284 MSAs.[8]

3. Data

The data used to estimate our location model, hedonic wage equations, and hedonic housing equations come from the 5% PUMS of the 2000 US census as well as other publicly available data sources.

Sample Households

To select the sample used to estimate our location choice models, we focus on households residing in one of the 284 MSAs for which we have complete amenity data. These MSAs contained 80% of the total US population in 2000. To be included, a household must be headed by a person 16 years of age or older who was born in the continental United States. We exclude households with heads in the military or in certain occupations (e.g., logging, mining) that would restrict locational choices. We also eliminate households with members who are self-employed, due to difficulty in predicting their wages, and households with negative Hicksian bundles at their chosen locations.[9]

Table 1 describes the characteristics of our sample households and of subsets of these households. We estimate the discrete choice model for the full sample of households and also for the two subsamples described in Table 1: households with prime-aged heads (i.e., heads between 25 and 55) and households with heads over age 55. Amenity values presented in this paper focus on the full sample. Estimates in the hedonics literature, which use wage and housing cost differentials to value amenities, are usually based on prime-aged adults. The reason for this is clear:

[8] The validity of the McFadden sampling procedure (McFadden 1978) hinges on the independence of irrelevant alternatives, which does not hold in the mixed logit model. We do, however, face computational trade-offs in estimating the mixed logit model using all 284 elements of the universal choice set and a sample large enough to estimate 284 fixed effects with precision. Experiments with the size of the choice set indicated that increasing the size of the choice set beyond 60 MSAs did not significantly alter parameter estimates. In estimating equation (5) the means of β_{WT} and β_{ST} are constrained to be zero.

[9] Households with negative Hicksian bundles may have substantial accumulated wealth (e.g., in real property) that we cannot measure. There are 2,162,570 households in the PUMS that satisfy our criteria for sample inclusion.

98% of households with prime-aged heads have some labor income, and on average, 93% of the income of these households comes from wages. Forty-seven percent of older households have no wage income.

A striking fact in Table 1 is that a large percentage of households continue to live in the area where the household head was born. Fifty-seven percent of all households live in the state where the head was born, 66% in the same census division, and 73% in the same census region. This foreshadows the importance of moving costs in explaining residential location choice.

Climate Variables

The climate variables in our model are summarized in Table 2. All variables are climate normals: the arithmetic mean of a climate variable computed for a 30-year period.[10]

We focus on mean temperature, measured for the winter (December–February) and summer (June–August) seasons. Previous studies of climate amenities have used primarily mean winter and summer temperatures or annual heating and cooling degree days.[11] In studying the impact of climate on agriculture, health, and electricity usage, temperature has been measured by the number of days in various temperature bins (Schlenker and Roberts 2009; Deschenes and Greenstone 2011; Albouy et al. 2013). The advantage of mean winter and summer temperatures is that they capture seasonality, which annual heating and cooling degree days and temperature bins do not. At the same time, correlation between winter and summer temperatures and temperatures during other seasons of the year means that winter and summer temperatures will pick up other temperature impacts: the correlation between mean winter temperature and mean March temperature is 0.97, as is the correlation between mean winter temperature and mean November temperature. Collinearity among mean winter, summer, fall, and spring temperatures, however, makes it impossible to include all four measures in our models.

[10] The temperature and summer precipitation data are for the period 1970 to 2000. July relative humidity, annual snowfall, and percentage possible sunshine are measured for the period 1960 to 1990.

[11] Heating and cooling degree days are computed by the National Climatic Data Center using the average of the high and low temperatures for a day. If this is greater than 65°F, it results in (average temperature − 65) cooling degree days. If the average temperature is less than 65°, it results in (65 − average temperature) heating degree days. Graves and Mueser (1993) and Kahn (2009) use mean January and mean July temperatures; Cragg and Kahn (1997, 1999) use mean February and mean July temperatures. Roback (1982), Blomquist et al. (1988), and Gyourko and Tracy (1991) use annual heating and cooling degree days, as do Albouy et al. (2013).

The precision with which the impact of temperature on location decisions can be estimated depends on temperature variation. Mean winter temperature across the 284 MSAs in our data averages 37°F, with a standard deviation (s.d.) of 12°; summer temperature averages 73°, with an s.d. of 6°. Winter and summer temperatures are highly correlated (r = 0.76).

The models presented in the next section include annual snowfall, mean summer precipitation, and July relative humidity. Mean winter precipitation, which averages 9.4 inches (s.d. = 5 inches), is highest in the Pacific Northwest and the Southeast, where winter precipitation comes in the form of rain. In preliminary analyses, winter precipitation appeared to be a disamenity, but this effect was statistically significant only at low levels of precipitation. This suggested that snowfall should replace winter precipitation: cities with significant snowfall have lower levels of winter precipitation (the correlation between annual snowfall and winter precipitation is −0.36), and snow is likely to be more of a disamenity than rain.

Summer precipitation, which averages 11 inches (s.d. = 5 inches), is heaviest in the southeastern United States. Surprisingly, the correlation between summer precipitation and winter precipitation is very low (r = 0.03), as is the correlation between summer precipitation and annual snow (r = −0.02). Mean July relative humidity is 69% (s.d. = 7%) and is not highly correlated with either winter temperature (r = 0.06) or summer temperature (r = 0.14).

Following the literature, we also include the percentage of possible sunshine, defined as the total time that sunshine reaches the surface of the earth, expressed as a percentage of the maximum amount possible from sunrise to sunset.

Nonclimate Amenities

The nonclimate amenity variables used in the second stage of the model are also summarized in Table 2. These include amenity measures typically used in quality-of-life studies, as well as variables that are likely to be correlated with climate, such as elevation, visibility, and measures of parks and recreation opportunities. Our desire is to be as inclusive as possible. Because climate changes slowly, we cannot use panel data to value climate amenities. We therefore strive to avoid problems of omitted variable bias by including a variety of location-specific amenities in our models.

Many quality-of-life studies include population density as an amenity variable (Roback 1982; Albouy 2012) or city population (Gyourko and Tracy 1991). Population should be used with caution in a discrete choice model, since the model is constructed to predict the share of population in each city (i.e., summing the predicted probability of moving to city *j* across households yields the predicted share of population in city *j*). We therefore do not include population as an amenity, but we do include population density, which may proxy amenities the higher population density supports that are not adequately captured by other amenities (better public transportation, restaurants, and live sporting events). We also estimate models with population density omitted.

Other amenities and disamenities for which we control include air pollution (fine particulate matter [$PM_{2.5}$]), an index of violent crime, visibility (percentage of hours with visibility greater than 10 miles), square miles of parks within the MSA, elevation measured at the population-weighted centroid of the MSA, and distance from the population-weighted centroid of each MSA to the nearest coast. We also include indices from the *Places Rated Almanac* (Savageau and D'Agostino 2000) that measure how well each city functions in terms of transportation, education, health, and recreation opportunities.

4. Estimation Results

Discrete Location Choice Models

Table 3 describes our base model (Model M.1) results for all households, prime-aged households, and households with heads older than 55. The base model is a mixed logit model that allows the coefficients on winter and summer temperatures to be jointly normally distributed and controls for all attributes in Table 2, as well as the Hicksian bundle and moving costs. Coefficients on the climate variables have been converted to MWTP by dividing by the coefficient on the Hicksian bundle. For winter and summer temperatures, we report the mean and standard deviation of the distribution of MWTP, as well as the correlation coefficient between the winter and summer temperature coefficients.[12]

[12] Tables 3 and 4 report MWTP only for climate variables. MWTPs for all model coefficients are reported in Appendix Tables A-3 and A-4. Although we focus on the impacts of summer and winter temperatures, we note that all other amenities except particulate matter and sunshine have expected signs and are statistically significant.

The most striking result in the table is that the mean MWTP for winter and summer temperatures differ significantly across samples. While all groups, on average, view higher winter temperature as an amenity and higher summer temperature as a disamenity, the absolute magnitudes of MWTP are much greater for older households than for prime-aged households. Mean MWTP for a 1° increase in winter temperature is about twice as high for older households as for prime-aged households ($1,035 vs. $518).[13] At the same time, older households are, on average, willing to pay much more to decrease summer temperature than prime-aged households ($1,424 vs. $627). Mean MWTP to increase winter or decrease summer temperature by 1° is about 40% higher using the full sample than prime-aged households. These results underscore the importance of considering all households when evaluating climate impacts for policy purposes.

The models for all three age cohorts indicate considerable variation in tastes for winter and summer temperatures. The standard deviations of the coefficients for winter and summer temperatures are large. For the all-household and older-household samples, there is greater variation in the coefficient on winter than the coefficient on summer temperature. The temperature coefficients in all cases are negatively correlated: most households that prefer milder winters also prefer milder summers, while those that favor colder winters like hotter summers.

The last model in Table 3 is estimated using households that moved between 1995 and 2000. Cragg and Kahn (1997) focus on recent movers to value climate change using the 1990 PUMS. In previous work, we have also focused on recent movers (Sinha and Cropper 2013). Table 3 confirms that movers indeed have different preferences for climate amenities than households in the full sample, which includes households that stayed in the same location. The mean MWTP of movers for winter temperature is, on average, 39% higher than the mean MWTP of households in the full sample and 90% higher than prime-aged households, who more closely resemble movers in terms of demographic characteristics.[14]

[13] In interpreting MWTP, it should be remembered that this represents the value of a 1° increase in temperature each day over three winter months and also captures milder temperatures in adjacent months.
[14] The MWTP of movers for a 1° decrease in summer temperature is 27% higher than in the full sample and 77% higher than in the prime-aged sample.

Calculating the benefits of policies to avoid climate change should be based on the location decisions of all households. We therefore focus on the full sample of households for the remainder of the paper.

Table 4 shows the impact on the coefficients of winter and summer temperatures of alternate specifications of the base model (Model M.1) for the full sample: dropping population density (Model M.2); omitting moving costs (Model M.3); and removing other climate variables (Model M.4). As noted above, MSA population is not included as an amenity because the discrete choice model is a share model—aggregating the probability that city *j* is chosen across all households yields the share of population predicted to live in that city. Population density is included as a proxy for amenities that are made possible by higher population density but not captured by the *Places Rated Almanac*. Nonetheless, population density is correlated with population. Dropping population density leaves the mean MWTP for a 1° change in winter and summer temperatures virtually unchanged. They are $709 and –$873 in Model M.1 and $748 and –$849 in Model M.2.

Model M.3 examines the impact of moving costs on the value of climate amenities. Omitting moving costs reduces (in absolute value) MWTP for winter and, especially, for summer temperatures, as well as precipitation, snowfall, and humidity. These results support Bayer et al.'s (2009) assertion that ignoring moving costs may significantly understate WTP for location-specific amenities. They also suggest that moving costs may have prevented households from moving to warmer weather. Table 4 thus confirms the importance of including moving costs in the discrete choice model.

Model M.4 shows the importance of controlling for other climate variables when valuing temperature. When July humidity, summer precipitation, sunshine, and snowfall are omitted, mean MWTP for winter temperature rises by over 70% (to $1,237), while mean MWTP for summer temperature falls slightly (to –$820). Further sensitivity analyses suggest that when snowfall is omitted, winter temperature picks up its effects, whereas summer temperature is sensitive to July humidity.

Taste-Based Sorting

To examine how households sort across locations in relation to their taste for winter and summer temperatures, we use Model M.1 to calculate the joint distributions of the coefficients of winter and summer temperatures for each household, conditional on the household's choice of location. The means of these conditional distributions are averaged across all sample households in each MSA, divided by the coefficient on the Hicksian bundle, and plotted against MSA temperature in Figures 1 and 2.[15]

There is a strong correlation between MWTP for warmer winters and MSA temperature (the correlation coefficient between MSA winter temperature and mean MWTP is 0.93), indicating that, other things equal, households sort across cities based on preferences for milder winters. The median WTP for a 1° increase in winter temperature in the coldest 142 cities (those with mean winter temperature below 35°) is $223; in the warmest 142 cities, it is $1,184. The city with the lowest MWTP for warmer winters is Fargo, North Dakota; Palm Beach and Naples, Florida, have the highest MWTP.

There is, however, some variation in mean MWTP across cities holding temperature constant. For example, at a mean winter temperature of 40°, households in Oregon and Washington states have a willingness to pay for a warmer winter that is over four times as high as the MWTP of households in Texas. At a mean winter temperature of 50°, households in San Francisco and San Jose, California, are willing to pay approximately $700 more for a 1° increase in warmer winter temperature than households in Charleston, South Carolina.

Preferences for warmer winters vary, on average, by census division, as indicated in Figure 1 and confirmed by Table 5, which shows mean MWTP averaged across the MSAs in each census

[15] When preferences for winter and summer temperatures are forced to be uncorrelated, there is a strong association between MSA mean MWTP for higher temperature and temperature itself—the correlation is 0.96 between MSA mean MWTP for winter temperature and 0.97 between MSA mean MWTP for summer temperature. It appears (incorrectly) that households in warmer cities place higher values on both summer and winter temperatures.

division, weighted by MSA population.[16] MWTP for warmer winters is, on average, negative in the West North Central division; it is also below the mean for the country in the East North Central division and the Middle Atlantic and New England states. MWTP for warmer winters is highest in the Pacific and South Atlantic census divisions. There is, however, considerable variation within divisions. MWTP is higher in California (especially in San Francisco, San Jose, Santa Barbara, and Orange County) than in Oregon and Washington states. It is much higher in Florida, especially in southern Florida, than in the other South Atlantic states; for example, MWTP in Savannah, Georgia, is half that of Miami.

The relationship between MWTP for a 1° increase in summer temperature (Figure 2) and summer temperature is an inverted U. While MWTP for an increase in summer temperature is negative in all cities except Fargo, North Dakota, households in the Pacific and South Atlantic divisions have the greatest MWTP to reduce mean summer temperature by 1°.[17] The disamenity value of a 1° increase in mean summer temperature is greatest in absolute value in Palm Beach and Naples, Florida (–$2,194) and somewhat lower in San Francisco (–$1,825) and San Jose, California (–$1,884). There is also considerable variation in MWTP at a given temperature. At a temperature of 70°, households on the Pacific coast find warmer summers a disamenity; however, this is less so for people in the West North Central division (e.g., the Dakotas). This is also true at mean summer temperatures above 80°F: households in the South Atlantic division find warmer summers a disamenity, but residents of Texas are willing to pay less to avoid hotter summers than residents of Florida.

Figures 1 and 2 and Panel A of Table 5 suggest that, holding temperature constant, MWTP for winter and summer temperatures varies by geographic region: households in the East North

[16] The average MWTP for winter temperature and summer temperature in Table 5 ($819 for winter and –$940 for summer temperature), conditional on location, differ from the unconditional values in Table 3 ($709 for winter and –$873 for summer temperature) because the former are weighted by MSA population. There is a positive correlation between MWTP for winter temperature and city population (0.11) and between MWTP for lower summer temperature and city population (0.10). Weighting by city population thus raises average MWTP. When conditional mean MWTP for winter temperature and summer temperature are averaged across all sample households rather than by city population, the results are $703 and –$875, respectively, which are very close to the unconditional values reported in Table 3.

[17] The correlation between mean summer temperature and MWTP for summer temperature in Figure 2 is –0.38. If we restrict preferences over winter and summer temperatures to be uncorrelated, we find a strong positive correlation between MWTP for summer temperature and the temperature of the city in which the household lives—see footnote 15.

Central census division appear to find hotter summers less of a disamenity than households on the Pacific coast. Households in the Mountain states appear to favor colder winters than households in the Pacific division. Some of this might appear to reflect differences in other climate variables besides temperature, such as summer humidity, precipitation, and snowfall. Our base model, however, controls for summer humidity, precipitation, snowfall, and sunshine. Indeed, Model M.4 indicates the importance of controlling for other climate variables: when they are omitted from the model, the mean of the coefficient distribution on winter temperature increases by 75%.

In summary, although there is considerable variation within census regions, households in the Midwest and the Northeast appear less sensitive to changes in temperature than households in the South and West. This suggests that when valuing changes in climate, ignoring taste sorting may cause warmer winters in the Northeast and Midwest to be overvalued and the value of lowering summer temperature in the South and West to be underestimated.

5. Willingness to Pay for Temperature Changes

We use the results of the location choice model to estimate what households would pay for temperature changes that are projected to occur over the period 2020 to 2050 under two SRES climate scenarios. Specifically, we use the results of the Hadley III model to project mean winter and summer temperatures over the 2020 to 2050 period in our 284 MSAs under the B1 and A2 SRES scenarios.[18] We estimate WTP for these temperature changes, compared with climate averages over the period 1970 to 2000. We first compute WTP by multiplying the conditional mean MWTP for summer and winter temperatures in each MSA by the size of the temperature change. This assumes that households do not move in response to changes in temperature and provides valuations comparable with those produced by hedonic models. We also compute expected compensating variation for temperature changes using distribution of (β_{WT},β_{ST}) for each household, conditional on its location choice.

[18] Data from the Hadley III model were generously provided by Wolfram Schlenker.

The B1 and A2 SRES Scenarios

The B1 SRES scenario, a more climate-friendly scenario than A2, leads to an atmospheric carbon dioxide (CO_2) concentration of 550 parts per million (ppm) in the year 2100, whereas the A2 scenario results in an atmospheric CO_2 concentration of 850 ppm by 2100 (Karl et al. 2009). Over the period 2020 to 2050, however, the temperature projections for the United States do not differ dramatically between the two scenarios.[19] Both scenarios project warmer winters and warmer summers; however, the B1 scenario projects, on average, warmer winters than the A2 scenario for the 284 MSAs—an average increase in winter temperature of 3.4°F under B1 and 2.1°F under A2.[20] Projections of increases in summer temperature for the two scenarios are slightly higher under the A2 scenario (on average, 3.6°F) than under the B2 scenario (3.3°F).

The variation in temperature changes across regions is, however, considerable. Panel B of Tables 5 and 6 show the population-weighted average winter and summer temperature changes for each scenario by census division (Table 5) and census region (Table 6). The Northeast and Midwest regions and the South Atlantic division experience larger increases in winter temperature than increases in summer temperature under the B1 scenario. Cities in the New England and Middle Atlantic states experience the largest increases in winter temperature (4.5°F and 5.1°F, respectively), followed by the Midwest region (East North Central, 3.7°F; West North Central, 3.6°F). The South Atlantic states experience winter temperature increases of about 3.1°F.

The remainder of the South (the West South Central [WSC] and East South Central [ESC] divisions) and the Mountain and Pacific divisions are hurt by the B1 scenario: households in these areas, on average, experience larger increases in summer than in winter temperature. The ESC and WSC divisions (which include Texas, Louisiana, Mississippi, and Alabama) suffer the greatest increases in summer temperature (an average of 5.5°F in the WSC), followed by states in the Mountain and Pacific census divisions. Summer temperatures increase by an average of 3.7°F in the Mountain and 3.1°F in the Pacific census divisions.

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[19] Other authors have focused on the damages associated with climate change at the end of this century, rather than midcentury (Albouy et al. 2013; Deschenes and Greenstone 2011). We focus on smaller, midcentury temperature changes for two reasons. First, changes of the magnitude examined by Albouy et al. (2013) would call for general equilibrium responses that we cannot model. They would result in major changes in wages and housing prices across cities. Second, our model is designed to value marginal temperature changes, rather than nonmarginal changes.

[20] These are population-weighted average temperature changes.

All census divisions experience greater increases in summer than in winter temperature under the A2 scenario; however, the areas that suffer the least are the Northeast and the South Atlantic states. Increases in winter temperature under A2, which average 2.1°F, are fairly uniform geographically. Summer temperature increases are below the national average of 3.6°F in the Northeast and South Atlantic states, approximately equal to the average in the West and Midwest, and highest in the ESC and WSC states.

WTP Conditional on Current Location

Table 5 displays household WTP for each SRES scenario, conditional on the household's current location. For each scenario, we multiply the summer and winter temperature changes in each MSA by the average conditional mean MWTP for that MSA (i.e., by the values shown in Figures 1 and 2). WTP is averaged across MSAs within each census division (weighted by MSA population) and is also computed (population-weighted) for all 284 MSAs. (Table 6 displays the corresponding averages, by census region.) Positive values indicate a positive WTP for the climate scenario, while negative values, indicating WTP to avoid the climate scenario, appear in parentheses. To see how taste sorting affects WTP for temperature changes, we also compute WTP using average household MWTP for summer and winter temperatures (displayed in the last column of Panel A of the table). These values are labeled WTP ignoring sorting.

Averaged across all MSAs, household WTP for the B1 scenario is negative and equal to about 1% of average household income; under the A2 scenario, it is also negative and is equal to about 2.4% of income; however, the distribution of WTP differs greatly across regions. Households in the Middle Atlantic and New England states are willing to pay a positive amount for the B1 scenario; households in the South Atlantic division have the smallest negative WTP for this scenario. This reflects the magnitude of increases in winter temperature in these areas, relative to increases in summer temperature. On the other hand, households in other parts of the South (the West South Central census division) have the highest negative WTP to avoid the B1 scenario, reflecting the much higher average increases in summer than in winter temperature in these states. Households in the East and West South Central divisions also have the highest WTP to avoid the A2 scenario—about 60% more than the MSA average. In general, WTP to avoid the A2 scenario

differs less across regions than under the B1 scenario; however, households in the South Atlantic have a WTP to avoid A2 that is less than half the MSA average.

How would estimates of the value of climate change be altered if sorting were ignored and WTP imputed based on mean MWTP for summer and winter temperatures? Sorting, which implies that MWTP for winter and summer temperatures differ by region, has the biggest impact on the aggregate WTP for climate amenities when temperature changes are unevenly distributed across geographic regions, and areas experiencing extreme temperature changes value them very differently from the mean household. Aggregate climate damages will be understated if temperature changes are negatively correlated with MWTP to increase winter temperature or reduce summer temperature. This is indeed the case in the B1 scenario: the New England, Middle Atlantic, and East North Central divisions are all expected to experience above-average increases in winter temperature, but households in these regions value these changes much less than the mean household. Because the benefits of warmer winters are overstated when sorting is ignored, the resulting aggregate WTP to avoid the B1 scenario is understated—by about 30%.[21]

The impact of sorting on aggregate WTP is less pronounced under the A2 scenario because winter temperature changes are more evenly distributed geographically, and households in the areas that are expected to experience the biggest increases in summer temperatures (the East South Central and West South Central divisions) value these temperature changes about the same as the mean household. Ignoring sorting when valuing the A2 scenario overstates aggregate damages only slightly (by 7%) primarily because ignoring sorting overstates the damages of the A2 scenario in the South Atlantic states.

Exact Welfare Calculations

The WTP estimates in Tables 5 and 6 assume that households must remain in their current MSA when temperatures change. This should, on average, overstate the amount households would pay to avoid the two climate scenarios, given that households can move in response to changes in temperature. We would not, a priori, expect these adjustments to be large, given that we are

[21] This is due primarily to impacts on winter temperature. The areas of the country that experience the greatest increases in summer temperature value them at a rate close to mean MWTP.

evaluating small temperature changes and given the importance of moving costs in the discrete choice model. We do, however, calculate exact welfare measures, which allow for the possibility of migration.

A household's compensating variation for a change in summer and winter temperatures (CV_i) is implicitly defined by the amount that can be taken away from the household when *ST* and *WT* change, as shown in the following equation:

$$\begin{aligned} &\max_j \left[\alpha(\hat{Y}_{ij} - \hat{P}_{ij}) + {WT_j}^0\beta_{WT} + {ST_j}^0\beta_{ST} + MC_{ij} + \delta_j + \varepsilon_{ij}\right] \\ &= \max_j \left[\alpha\left(\hat{Y}_{ij} - \hat{P}_{ij} - CV_i\right) + {WT_j}^1\beta_{WT} + {ST_j}^1\beta_{ST} + MC_{ij} + \delta_j + \varepsilon_{ij}\right] \end{aligned} \quad (7)$$

We compute the expected value of CV_i conditional on the household's choice of MSA—that is, using the distributions of (β_{WT},β_{ST}) and $\{\varepsilon_{ij}\}$ that are conditional on the household's observed choice of MSA:

$$E(CV_i|k\ chosen) = \int CV_i f\left(\beta_i, \varepsilon_i | k\ chosen\right) d\beta_i\, d\varepsilon_i \quad (8)$$

(von Haefen 2003). We simulate $E(CV_i)$ following von Haefen (2003) by taking a draw from the conditional distributions of random coefficients and the vector of error terms ε_{ij} and computing CV_i using equation (7) for each draw. We average these values across 100 draws to compute the household's expected compensating variation.

Table 7 displays $E(CV_i)$ for the B1 and A2 scenarios by census division. As in Table 5, average $E(CV_i)$ is averaged over all households in each MSA; MSA values are then weighted by population to yield census division averages. WTP estimates from Table 5, which are computed assuming that each household cannot change location, are presented for comparison. In all cases, *E(CV)* is less than WTP:[22] households, on average, require less compensation to endure an adverse climate scenario or—in the case of households in the South Atlantic and Middle Atlantic states under B1—are willing to pay more for a climate scenario that they view as an improvement when they can change locations to adjust to the scenario.

[22] McFadden (1999) proves that this result must hold in random utility models employing the generalized extreme value distribution.

The difference between expected compensating variation and WTP conditional on location is, however, small: allowing households to change location lowers the value of avoiding the B1 scenario by about 16% and the value of avoiding the A2 scenario by about 3% compared with Table 5. Averaged across all households, the value of avoiding the climate scenarios using exact welfare measures is $574 for the B1 scenario (0.91% of average household income) and $1,492 for the A2 scenario (2.36% of average household income).

WTP Comparison with the Literature

Our estimates of the welfare losses associated with climate change are larger than those reported by Albouy et al. (2013) using a hedonic approach. Albouy et al. (2013) regress a weighted average of wages (net of taxes) and housing prices on local amenities using data from the 2000 PUMS. They find that households are willing to pay more to reduce cooling degree days than heating degree days and that the marginal disutility to reduce severe heat is not statistically different from the marginal disutility to reduce moderate heat. When these results are used to value temperature changes associated with the A2 scenario in 2090 to 2099—changes that average 8.3°F—welfare losses are 2.24% of household income assuming homogeneous preferences and 2.87% allowing for heterogeneous preferences. We find comparable values for much milder temperature changes, on the order of 4°F.

There are several possible reasons for the difference in magnitude of our results. The hedonic approach uses the capitalization of amenities into wages and housing prices to value amenities. This may work well for prime-aged households that receive most of their income from wages, but it needs to be applied with caution in the case of older households that do not. The discrete choice approach allows for the fact that income may not vary much across MSAs for retirees, who may nevertheless sort across MSAs in response to differences in climate. It is the number of households that have located in each MSA, holding MSA characteristics constant, that identifies the parameters of household utility functions in the discrete choice approach. Our results indicate that it is important to take the preferences of older households (those with heads over 55 years of age) into account when evaluating temperature changes. If we were to base our estimates of the value of avoiding the B1 and A2 scenarios solely on prime-aged households, our estimates would fall by over 37% in the case of the B1 scenario and 34% in the case of the A2 scenario.

A second reason for the difference between the two sets of estimates derives from differences in assumptions about household mobility. Bayer et al. (2009) note that adding moving costs to a hedonic model destroys the equivalence between a household's MWTP for a local amenity and the capitalization of that amenity in wages and housing prices. Whether the capitalization of an amenity into wages and housing prices over- or understates MWTP is an empirical question. We note that removing moving costs from our location choice model causes the absolute value of MWTP for climate amenities to fall, suggesting that moving costs may have prevented climate amenities from being fully capitalized into wages and housing costs. Removing moving costs from our model causes the value of reducing summer temperature to fall by almost 50%.

6. Conclusions

The discrete location choice model that we have estimated for US households indicates that climate amenities play an important role in household location decisions in the United States. The rate of substitution between household income net of housing costs and winter and summer temperatures is statistically significant, holding constant summer precipitation, snowfall, and July humidity. But there is considerable variation in MWTP for winter and summer temperatures across households. In general, households with a higher MWTP for warmer winters have located in MSAs with higher mean winter temperatures, such as MSAs in Florida or California, while those with the lowest MWTP live in the Midwest. Preferences for summer temperature and winter temperature are, however, negatively correlated ($\rho = -0.83$). This implies that households that prefer milder winters, on average, also prefer milder summers, while households that prefer colder winters have a lower MWTP to reduce summer temperatures. MWTP to avoid hotter summers is, on average, higher in the South Atlantic and Pacific regions than in the Midwest. At the level of census regions, households in the Midwest and Northeast have lower MWTPs to increase winter and reduce summer temperatures than households in the South and West.

These sorting patterns have important implications for valuing avoided climate change. Under future warming scenarios, winter temperature is likely to increase the most at northern latitudes, specifically in the Midwest and Northeast. Since these regions have lower-than-average MWTP for warmer winters when allowing for sorting, using average MWTP for warmer winters for the entire United States is likely to overstate the value of warmer winters under most climate

scenarios. At the same time, households' WTP to avoid hotter summers is greatest in the areas that are expected to experience about average increases in summer temperature—the South and parts of Southern California. Thus using average MWTP for cooler summers will understate the value of avoiding hotter summers implied by the A2 and B1 scenarios. Together these results suggest that ignoring taste sorting could understate the value of avoiding climate change.

Taking sorting into account, we estimate the value of avoiding two climate scenarios in the near term (2020–2050). We find that, aggregated over the entire United States, WTP to avoid the more climate-friendly B1 scenario is approximately 1% of household income, while it is approximately 2.4% of household income for the A2 scenario. The A2 scenario we consider would result in an average increase of 3.6°F in summer temperature and of 2.1°F in winter temperature. Estimates for the United States of market-based damages associated with climate change have typically been in the range of 1% of gross domestic product for an increase in mean temperature of 2°C (NRC 2010). Our results suggest that the amenity value of climate could significantly increase estimates of climate damages, even for moderate temperature increases.

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Figures and Tables

Figure 1. Taste-Sorting for Winter Temperature by Metropolitan Area (Base Discrete Choice Model: Model M.1)

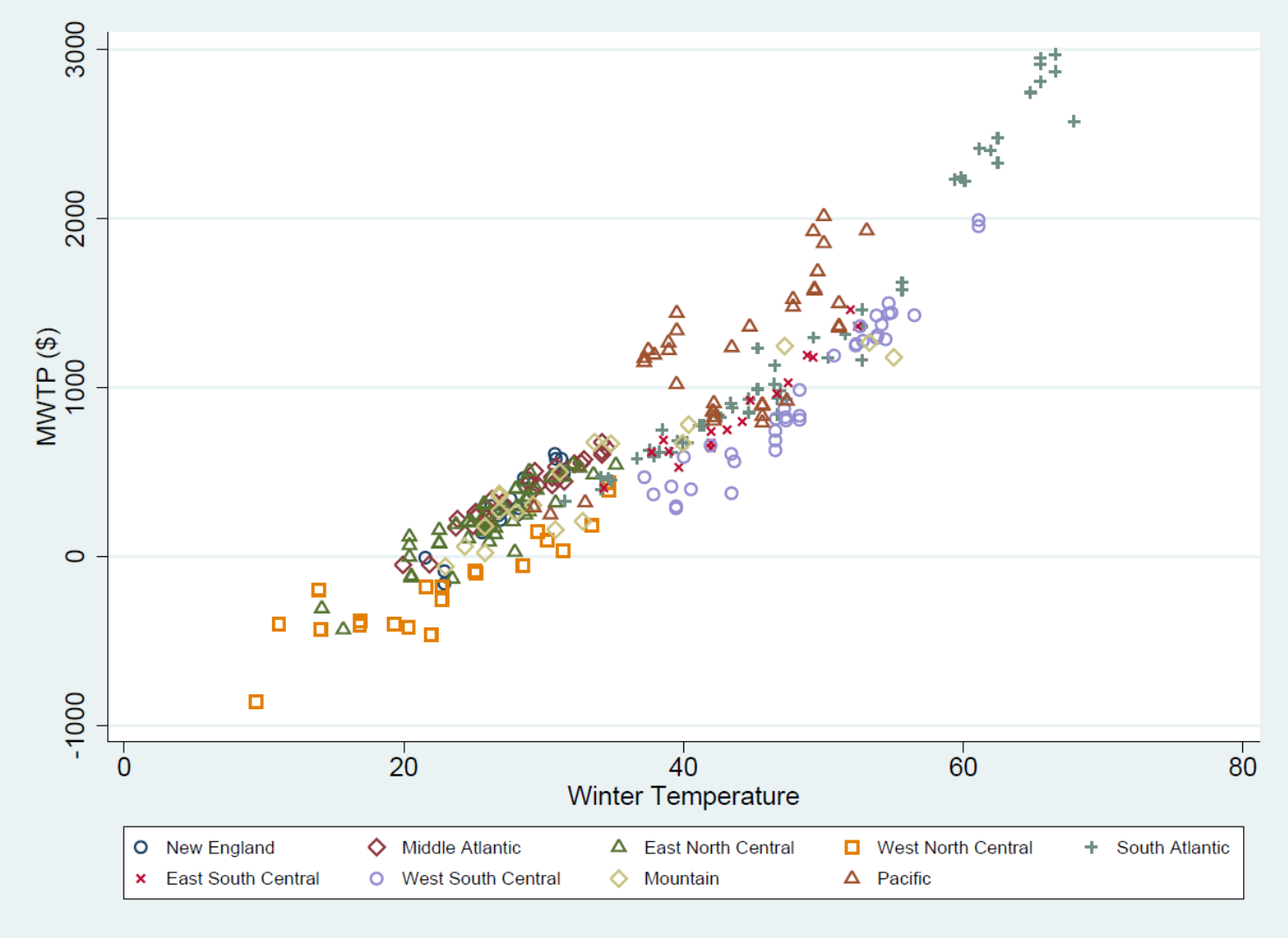

Figure 2. Taste-Sorting for Summer Temperature by Metropolitan Area (Base Discrete Choice Model: Model M.1)

Table 1. Descriptive Statistics for Household Characteristics

		Full sample (N = 54,008)		Prime-aged (N = 33,180)		Greater than 55 (N = 17,643)		Movers (N = 22,759)	
Variable	**Description**	**Mean**	**Std. dev.**	**Mean**	**Std. dev.**	**Mean**	**Std. dev.**	**Mean**	**Std. dev.**
Age of household head (mean)	Age	49.11	17.03	40.79	8.20	69.50	9.41	39.89	15.19
Gender of household head	Male (%)	63.93		67.02		60.60		64.21	
Marital status of household head	Married (%)	52.22		55.43		50.99		46.81	
Race of household head	White (%)	82.70		81.13		87.03		83.86	
	Black (%)	13.11		13.97		10.98		9.97	
	Other (%)	4.20		4.91		1.99		6.16	
Education of household head	No high school (%)	12.86		7.56		23.09		5.77	
	High school (%)	25.96		24.06		29.71		15.22	
	Some college (%)	30.89		33.73		23.65		31.11	
	College graduate (%)	19.33		22.67		12.95		31.12	
	Postgraduate education (%)	10.96		11.99		10.62		16.78	
Household head Movement from place of birth	Left state of birth (%)	42.65		40.99		47.32		66.69	
	Left census division of birth (%)	32.78		31.28		36.86		53.86	
	Left census region of birth (%)	26.55		24.98		30.85		43.68	
Household wage earnings (mean)	Sum of the wage earnings of all household members	$49,960	$54,508	$64,098	$55,106	$26,307	$47,544	$58,208	$60,898
Household wage earnings	Households with zero wage earnings (%)	16.75		2.23		46.94		8.83	
Total household income (mean)	Sum of wage, business, and farm incomes and income from other sources[a] of all household members	$63,312	$58,671	$69,161	$59,723	$57,294	$58,615	$67,532	$65,438

Household annual housing expenditures (mean)	Sum of monthly mortgage payment or rent, cost of utilities, insurance, and property taxes	$15,556	$9,082	$16,193	$9,437	$15,481	$8,560	$14,693	$9,711
Size of household	1 member (%)	26.16		21.05		36.03		29.75	
	2 members (%)	34.69		27.35		47.68		34.87	
	3 or more members (%)	39.15		51.59		16.28		35.38	

[a] Income from other sources would include Social Security income; welfare (public assistance) income; Supplementary Security income; interest, dividend, and rental income; retirement income; and other income.

Table 2. Descriptive Statistics of Amenity Variables

Variable	N	Mean	Std. dev.	Minimum	Maximum	Median
Avg. winter temperature (°F)	284	37.339	12.158	9.442	67.922	34.996
Avg. summer temperature (°F)	284	73.309	5.817	60.848	89.733	72.517
Annual snowfall (inches)	284	20.36	21.366	0	84.05	18.05
Summer precipitation (inches)	284	10.966	5.057	0.44	23.3	11.932
July relative humidity (%)	284	66.246	10.891	22.5	78	70.5
Annual sunshine (% of possible sunshine in 24 hours)	284	60.764	8.323	43	78	58
Avg. elevation (miles)	284	0.197	0.273	0	1.62	0.13
Distance to coast (miles)	284	141.096	169.592	0.009	824.451	91.025
Visibility > 10 miles (% of hours)	284	46.053	19.541	5	85.5	45.5
Mean $PM_{2.5}$ (micrograms/cubic meter)	284	12.829	2.884	5.382	19.535	12.818
Population density (persons per square mile)	284	471.767	983.041	5.4	13,043.60	259.05
Violent crime rate (number of violent crimes per 1000 persons)	284	4.56	2.214	0.069	12.33	4.349
Park area (square miles)	284	192.908	584.303	0	5,477.56	24.893
Transportation score	284	50.37	29.181	0	100	50.28
Education score	284	51.23	29.322	0	100	51.13
Arts score	284	51.137	29.055	0	100	51.14
Healthcare score	284	49.201	28.657	0	98.3	49.43
Recreation score	284	53.342	28.386	0	100	54.245

Table 3. Marginal Willingness to Pay for Climate Amenities (Base Discrete Choice Models)

Sample **PANEL A: 1st Stage Estimates**	**Model M.1 (Full)** All ages (Base model)		**Model M.1 (Prime)** Prime-aged		**Model M.1 (>55)** Over 55 years		**Model M.1 (Movers)** Changed MSA between 1995 and 2000	
Variable	Coef. (std. err.)		Coef. (std. err.)		Coef. (std. err.)		Coef. (std. err.)	
Std. dev.: avg. winter temperature	0.0666		0.0588		0.0742		0.0781	
	(0.0020)		(0.0026)		(0.0039)		(0.0038)	
Std. dev.: avg. summer temperature	0.0522		0.0592		0.0331		0.0698	
	(0.0060)		(0.0068)		(0.0091)		(0.0079)	
Correlation coefficient	–0.8332		–0.6893		–0.9936		–0.8245	
PANEL B: 2nd Stage Estimates								
Variable	Coef. (std. err.)	MWTP (std. err.)	Coef. (std. err.)	MWTP (std. err.)	Coef. (std. err.)	MWTP (std. err.)	Coef. (std. err.)	MWTP (std. err.)
Mean: avg. winter temperature	0.0249	$709	0.0209	$518	0.0375	$1,035	0.0424	$983
	(0.0056)	($160)	(0.0058)	($144)	(0.0070)	($199)	(0.0078)	($184)
Mean: avg. summer temperature	–0.0307	–$873	–0.0253	–$627	–0.0516	–$1,424	–0.0478	–$1,109
	(0.0091)	($260)	(0.0100)	($249)	(0.0106)	($301)	(0.0121)	($283)
July humidity	–0.0269	–$764	–0.0208	–$514	–0.0325	–$896	–0.0316	–$734
	(0.0049)	($142)	(0.0054)	($135)	(0.0054)	($155)	(0.0059)	($139)
Annual snowfall	–0.0166	–$471	–0.0170	–$422	–0.0154	–$425	–0.0215	–$499
	(0.0024)	($70)	(0.0026)	($66)	(0.0026)	($75)	(0.0029)	($69)
Ln(summer precipitation)	0.1408	$376	0.1708	$403	0.0926	$232	0.3279	$741
	(0.0720)	($192)	(0.0768)	($181)	(0.0823)	($206)	(0.0890)	($202)
Annual sunshine	–0.0155	–$441	–0.0149	–$368	–0.0111	–$307	–0.0127	–$296
	(0.0057)	($162)	(0.0060)	($149)	(0.0067)	($185)	(0.0076)	($177)

Note: When entering the regressions nonlinearly, amenity variables are evaluated at population-weighted means in order to compute MWTP.

Table 4. Marginal Willingness to Pay for Climate Amenities (Discrete Choice Model Sensitivities)

Sample **PANEL A: 1st Stage Estimates**	**Model M.1** Base model		**Model M.2** Omit population density		**Model M.3** Omit moving costs		**Model M.4** Omit other climate variables	
Variable	Coef. (std. err.)				Coef. (std. err.)			
Std. dev.: avg. winter temperature	0.0666		Same 1st stage		0.0022		Same 1st stage	
	(0.0020)		estimates as		(0.0148)		estimates as	
Std. dev.: avg. summer temperature	0.0522		Model M.1		0.0210		Model M.1	
	(0.0060)				(0.0278)			
Correlation coefficient	–0.8332				–0.9975			
PANEL B: 2nd Stage Estimates								
Variable	Coef. (std. err.)	MWTP (std. err.)	Coef. (std. err.)	MWTP (std. err.)	Coef. (std. err.)	MWTP (std. err.)	Coef. (std. err.)	MWTP (std. err.)
Mean: avg. winter temperature	0.0249	$709	0.0263	$748	0.0232	$659	0.0435	$1,237
	(0.0056)	($160)	(0.0059)	($169)	(0.0054)	($154)	(0.0047)	($139)
Mean: avg. summer temperature	–0.0307	–$873	–0.0299	–$849	–0.0169	–$478	–0.0288	–$820
	(0.0091)	($260)	(0.0100)	($285)	(0.0090)	($255)	(0.0110)	($313)
July humidity	–0.0269	–$764	–0.0247	–$702	–0.0189	–$535		
	(0.0049)	($142)	(0.0055)	($157)	(0.0044)	($125)		
Annual snowfall	–0.0166	–$471	–0.0152	–$434	–0.0038	–$109		
	(0.0024)	($70)	(0.0026)	($75)	(0.0023)	($66)		
Ln(summer precipitation)	0.1408	$376	0.0969	$258	0.0922	$245		
	(0.0720)	($192)	(0.0769)	($205)	(0.0666)	($177)		
Annual sunshine	–0.0155	–$441	–0.0190	–$540	–0.0100	–$284		
	(0.0057)	($162)	(0.0059)	($168)	(0.0057)	($161)		

Note: When entering the regressions nonlinearly, amenity variables are evaluated at population-weighted means in order to compute MWTP.

Table 5. Temperature, Temperature Changes, and Willingness to Pay Conditional on Current Location, by Census Division

Census region	Northeast		South			Midwest		West		All
Census division	**NE**	**MA**	**SA**	**WSC**	**ESC**	**ENC**	**WNC**	**M**	**P**	**All**
PANEL A: Baseline Values (1970 to 2000)										
Share of population	5%	15%	19%	11%	3%	17%	4%	6%	19%	46%
ST	69	71	78	81	77	71	71	74	71	74
WT	28	30	48	49	43	27	22	37	47	39
MWTP for ST	(711)	(737)	(1215)	(989)	(910)	(617)	(363)	(820)	(1343)	(940)
MWTP for WT	388	466	1324	1017	813	279	(93)	661	1288	819
PANEL B: Projected Values under SRES Scenarios (2020 to 2050)										
Change in ST (A2)	3.1	3.1	3.0	5.2	4.7	3.6	4.1	3.7	3.4	3.6
Change in WT (A2)	1.9	2.2	2.1	2.2	2.2	2.0	1.9	2.7	1.9	2.1
Change in ST (B1)	2.8	2.5	2.7	5.5	4.3	3.3	3.9	3.7	3.1	3.3
Change in WT (B1)	4.5	5.1	3.1	3.0	3.0	3.7	3.6	2.9	2.0	3.4
WTP (A2): based on sorting	(1435)	(1259)	(637)	(2610)	(2421)	(1652)	(1770)	(1534)	(1750)	(1541)
WTP (B1): based on sorting	(202)	552	485	(2281)	(1547)	(936)	(1713)	(1203)	(1231)	(682)
WTP (A2): ignoring sorting	(1318)	(1196)	(1172)	(2941)	(2531)	(1737)	(2201)	(1348)	(1611)	(1662)
WTP (B1): ignoring sorting	802	1385	(173)	(2630)	(1667)	(251)	(868)	(1196)	(1315)	(529)

Notes: MWTP for ST and WT are calculated for each household using coefficient distributions from model M.1, conditional on MSA choice. Values are averaged across all households in an MSA to obtain the average MSA MWTP. WTP is calculated by multiplying MSA MWTP by the relevant temperature change. All division level variables are MSA values weighted by MSA population. NE = New England; MA = Middle Atlantic; SA = South Atlantic; WSC = West South Central; ESC = East South Central; ENC = East North Central; WNC = West North Central; M = Mountain; P = Pacific

Table 6. Temperature, Temperature Changes, and Willingness to Pay Conditional on Current Location, by Census Region

	Northeast	South	Midwest	West	All
PANEL A: Baseline Values (1970 to 2000)					
Share of population	20%	33%	22%	25%	100%
ST	70	79	71	72	74
WT	30	48	26	45	39
MWTP for ST	(730)	(1108)	(567)	(1213)	(940)
MWTP for WT	447	1170	206	1192	819
PANEL B: Projected Values under SRES Scenarios (2020 to 2050)					
Change in ST (A2)	3.1	3.9	3.7	3.5	3.6
Change in WT (A2)	2.1	2.1	1.9	2.1	2.1
Change in ST (B1)	2.6	3.8	3.4	3.3	3.3
Change in WT (B1)	4.9	3.1	3.7	2.2	3.4
WTP (A2): based on sorting	(1302)	(1485)	(1675)	(1697)	(1541)
WTP (B1): based on sorting	368	(660)	(1089)	(1224)	(682)
WTP (A2): ignoring sorting	(1226)	(1910)	(1828)	(1546)	(1662)
WTP (B1): ignoring sorting	1243	(1161)	(372)	(1285)	(529)

Notes: MWTP for ST and WT are calculated for each household using coefficient distributions from Model M.1, conditional on MSA choice. Values are averaged across all households in an MSA to obtain the average MSA MWTP. WTP is calculated by multiplying MSA MWTP by the relevant temperature change. All region-level variables are MSA values weighted by MSA population.

Table 7. Expected Compensating Variation and Willingness to Pay, Holding Location Constant, for Scenarios A2 and B1

Census region	Northeast		South			Midwest		West		All
Census division	**NE**	**MA**	**SA**	**WSC**	**ESC**	**ENC**	**WNC**	**M**	**P**	**All**
E(*CV*) scenario A2	(1423)	(1245)	(613)	(2485)	(2338)	(1623)	(1705)	(1491)	(1673)	(1492)
E(*CV*) scenario B1	(171)	602	589	(2083)	(1447)	(904)	(1665)	(1098)	(1020)	(574)
WTP scenario A2	(1435)	(1259)	(637)	(2610)	(2421)	(1652)	(1770)	(1534)	(1750)	(1541)
WTP scenario B1	(202)	552	485	(2281)	(1547)	(936)	(1713)	(1203)	(1231)	(682)

Notes: *E(CV)* is calculated as described in the text for each household. Values are averaged over all households in an MSA, and MSA averages are weighted by population to yield division averages. MWTP for ST and WT are calculated for each household using coefficient distributions from model M.1, conditional on MSA choice. Values are averaged across all households in an MSA to obtain the average MSA MWTP. WTP is calculated by multiplying MSA MWTP by the relevant temperature change. All division-level variables are MSA values weighted by MSA population. NE = New England; MA = Middle Atlantic; SA = South Atlantic; WSC = West South Central; ESC = East South Central; ENC = East North Central; WNC = West North Central; M = Mountain; P = Pacific

Appendix

Table A-1. Summary of Hedonic Wage Coefficients

Variables (dependent variable: log(wage rate)	Mean of estimates from 297 MSAs	Std. dev. of estimates from 297 MSAs
High school (left-out category is no high school)	0.101	0.040
Some college	0.181	0.047
College graduate	0.387	0.070
Higher education	0.553	0.076
Age	0.051	0.008
Age squared (divided by 100)	−0.049	0.009
Married	0.095	0.022
Male	0.213	0.040
Black (left out category is white)	−0.067	0.075
Other race	−0.054	0.058
Speaks English well	0.111	0.117
Hispanic	−0.043	0.080
Business operations occupation (left-out category is management occupation)	−0.125	0.067
Financial specialists occupation	−0.114	0.078
Computer and math occupation	−0.002	0.090
Engineering occupation	−0.074	0.084
Life, physical, and social sciences occupation	−0.183	0.112
Social services occupation	−0.345	0.085
Legal occupation	−0.040	0.137
Teachers occupation	−0.200	0.091
Other educational occupation	−0.486	0.134
Arts, sports, and media occupation	−0.253	0.098
Healthcare practitioners occupation	0.074	0.077
Healthcare support occupation	−0.323	0.081
Protective services occupation	−0.237	0.106
Food and serving occupation	−0.419	0.076
Maintenance occupation	−0.466	0.079
Personal care service occupation	−0.413	0.112
High-skill sales occupation	−0.135	0.068
Low-skill sales occupation	−0.228	0.064
Office support occupation	−0.298	0.052
Construction trades occupation	−0.239	0.094
Extraction workers occupation	−0.261	0.292
Maintenance workers occupation	−0.185	0.067
Production occupation	−0.310	0.085
Transportation occupation	−0.356	0.074
Construction industry (left-out category is mining and utilities)[a]	−0.178	0.098

Variables (dependent variable: log(wage rate)	Mean of estimates from 297 MSAs	Std. dev. of estimates from 297 MSAs
Manufacturing industry	−0.118	0.108
Wholesale industry	−0.185	0.099
Retail industry	−0.342	0.098
Transportation industry	−0.093	0.110
Information and communications industry	−0.139	0.114
Finance industry	−0.173	0.107
Professional and scientific management services industry	−0.223	0.106
Educational and health social services industry	−0.274	0.096
Recreation and food services industry	−0.378	0.114
Other services industry	−0.361	0.101
Public administration industry	−0.131	0.100

[a] Because these two industries have very few observations, we bundled them together as the omitted category.

Table A-2. Summary of Hedonic Housing Coefficients

Variables (dependent variable: log(user costs including insurance and utility costs))	Mean of estimates from 284 MSAs	Std. dev. of estimates from 284 MSAs
House is owned	0.464	0.144
3 bedrooms (left-out category is less than three bedrooms)	0.160	0.061
4 bedrooms	0.208	0.082
5 bedrooms	0.324	0.110
More than 5 bedrooms	0.500	0.163
2 rooms (left-out category is less than two rooms)	0.080	0.133
3 rooms	0.053	0.140
4 rooms	0.075	0.146
5 rooms	0.126	0.154
6 rooms	0.218	0.156
More than 6 rooms	0.413	0.176
Complete kitchen	–0.104	0.261
Complete plumbing	0.221	0.212
1 to 10 acres	0.246	0.140
0 to 1 year old (left-out category is over 60 years old)	0.428	0.157
2 to 5 years old	0.404	0.158
6 to 10 years old	0.358	0.150
11 to 20 years old	0.247	0.127
21 to 30 years old	0.150	0.122
31 to 40 years old	0.093	0.113
41 to 50 years old	0.039	0.089
51 to 60 years old	–0.011	0.075
Number of units in structure: single-attached (left-out category is single family detached)	–0.082	0.105
2 units in structure	–0.089	0.107
3 to 4 units in structure	–0.135	0.095
5 to 9 units in structure	–0.167	0.106
10 to 19 units in structure	–0.132	0.127
20 to 49 units in structure	–0.154	0.151
Over 49 units in structure	–0.190	0.207

Table A-3. Marginal Willingness to Pay for All Location-Specific Amenities (Base Discrete Coice Models)

Sample **PANEL A: 1st Stage Estimates**	**Model M.1 (Full)** All ages (base model)		**Model M.1 (Prime)** Prime-aged		**Model M.1 (>55)** Over 55 years		**Model M.1 (Movers)** Changed MSA between 1995 and 2000	
Variable	Coef. (std. err.)		Coef. (std. err.)		Coef. (std. err.)		Coef. (std. err.)	
Std. dev.: avg. winter temperature	0.0666		0.0588		0.0742		0.0781	
	(0.0020)		(0.0026)		(0.0039)		(0.0038)	
Std. dev.: avg. summer temperature	0.0522		0.0592		0.0331		0.0698	
	(0.0060)		(0.0068)		(0.0091)		(0.0079)	
Correlation coefficient	–0.8332		–0.6893		–0.9936		–0.8245	
PANEL B: 2nd Stage Estimates								
Variable	Coef. (std. err.)	MWTP (std. err.)	Coef. (std. err.)	MWTP (std. err.)	Coef. (std. err.)	MWTP (std. err.)	Coef. (std. err.)	MWTP (std. err.)
Mean: avg. winter temperature	0.0249	$709	0.0209	$518	0.0375	$1,035	0.0424	$983
	(0.0056)	($160)	(0.0058)	($144)	(0.0070)	($199)	(0.0078)	($184)
Mean: avg. summer temperature	–0.0307	–$873	–0.0253	–$627	–0.0516	–$1,424	–0.0478	–$1,109
	(0.0091)	($260)	(0.0100)	($249)	(0.0106)	($301)	(0.0121)	($283)
July humidity	–0.0269	–$764	–0.0208	–$514	–0.0325	–$896	–0.0316	–$734
	(0.0049)	($142)	(0.0054)	($135)	(0.0054)	($155)	(0.0059)	($139)
Annual snowfall	–0.0166	–$471	–0.0170	–$422	–0.0154	–$425	–0.0215	–$499
	(0.0024)	($70)	(0.0026)	($66)	(0.0026)	($75)	(0.0029)	($69)
Ln(summer precipitation)	0.1408	$376	0.1708	$403	0.0926	$232	0.3279	$741
	(0.0720)	($192)	(0.0768)	($181)	(0.0823)	($206)	(0.0890)	($202)
Annual sunshine	–0.0155	–$441	–0.0149	–$368	–0.0111	–$307	–0.0127	–$296
	(0.0057)	($162)	(0.0060)	($149)	(0.0067)	($185)	(0.0076)	($177)
Ln(population density)	0.2283	$7	0.2094	$6	0.2939	$9	0.2535	$6
	(0.0452)	($1)	(0.0494)	($1)	(0.0521)	($2)	(0.0592)	($2)
Mean $PM_{2.5}$	0.0708	$2,014	0.0572	$1,416	0.0990	$2,731	0.0767	$1,779
	(0.0159)	($455)	(0.0164)	($408)	(0.0182)	($519)	(0.0202)	($471)

Violent crime rate	0.0045	$129	0.0006	$15	0.0115	$316	–0.0090	–$208
	(0.0136)	($386)	(0.0142)	($352)	(0.0166)	($458)	(0.0173)	($402)
Transportation score	0.0093	$263	0.0105	$259	0.0081	$223	0.0038	$88
	(0.0015)	($42)	(0.0015)	($39)	(0.0018)	($51)	(0.0018)	($42)
Education score	0.0034	$97	0.0043	$106	0.0011	$29	0.0053	$123
	(0.0015)	($44)	(0.0016)	($41)	(0.0017)	($48)	(0.0018)	($41)
Arts score	0.0048	$136	0.0043	$106	0.0048	$132	0.0034	$79
	(0.0017)	($49)	(0.0018)	($46)	(0.0020)	($55)	(0.0021)	($50)
Healthcare score	0.0005	$13	0.0002	$4	0.0004	$11	0.0016	$37
	(0.0012)	($33)	(0.0012)	($31)	(0.0014)	($39)	(0.0015)	($34)
Recreation score	0.0131	$374	0.0124	$307	0.0150	$414	0.0156	$363
	(0.0015)	($44)	(0.0016)	($41)	(0.0018)	($54)	(0.0019)	($46)
Park area	0.0002	$4	0.0001	$4	0.0002	$5	0.0002	$4
	(0.0001)	($2)	(0.0001)	($1)	(0.0001)	($2)	(0.0001)	($2)
Visibility > 10 miles	0.0078	$222	0.0073	$180	0.0094	$259	0.0093	$216
	(0.0032)	($92)	(0.0033)	($82)	(0.0038)	($106)	(0.0037)	($87)
Ln(elevation)	0.0810	$13,069	0.0895	$12,450	0.0873	$14,273	0.1468	$17,898
	(0.0441)	($7,126)	(0.0481)	($6,706)	(0.0475)	($7,798)	(0.0547)	($6,683)
Distance to coast	–0.0025	–$45	–0.0020	–$25	–0.0035	–$65	–0.0034	–$52
	(0.0007)	($15)	(0.0007)	($14)	(0.0008)	($18)	(0.0009)	($15)
(Distance to coast)^2	0.0000		0.0000		0.0000		0.0000	
	(0.0000)		(0.0000)		(0.0000)		(0.0000)	
No. of obs. (MSAs)	284		284		284		284	
Adjusted R-squared	0.84		0.82		0.82		0.78	

Notes: When entering the regressions nonlinearly, amenity variables are evaluated at population-weighted means in order to compute MWTP. Nonlinear covariates: population density, summer precipitation, and elevation enter in log form, while distance to the coast enters the model quadratically.

Table A-4. Marginal Willingness to Pay for All Location-Specific Amenities (Discrete Choice Model Sensitivities)

Sample	**Model M.1**		**Model M.2**		**Model M.3**		**Model M.4**	
PANEL A: 1st Stage Estimates	Base Model		Omit Population Density		Omit Moving Costs		Omit Other Climate Variables	
Variable	Coef. (std. err.)				Coef. (std. err.)			
Std. dev.: avg. winter temperature	0.0666 (0.0020)		Same 1st Stage Estimates as Model M.1		0.0022 (0.0148)		Same 1st Stage Estimates as Model M.1	
Std. dev.: avg. summer temperature	0.0522 (0.0060)				0.0210 (0.0278)			
Correlation coefficient	–0.8332				–0.9975			
PANEL B: 2nd Stage Estimates								
Variable	Coef. (std. err.)	MWTP (std. err.)	Coef. (std. err.)	MWTP (std. err.)	Coef. (std. err.)	MWTP (std. err.)	Coef. (std. err.)	MWTP (std. err.)
Mean: avg. winter temperature	0.0249 (0.0056)	$709 ($160)	0.0263 (0.0059)	$748 ($169)	0.0232 (0.0054)	$659 ($154)	0.0435 (0.0047)	$1,237 ($139)
Mean: avg. summer temperature	–0.0307 (0.0091)	–$873 ($260)	–0.0299 (0.0100)	–$849 ($285)	–0.0169 (0.0090)	–$478 ($255)	–0.0288 (0.0110)	–$820 ($313)
July humidity	–0.0269 (0.0049)	–$764 ($142)	–0.0247 (0.0055)	–$702 ($157)	–0.0189 (0.0044)	–$535 ($125)		
Annual snowfall	–0.0166 (0.0024)	–$471 ($70)	–0.0152 (0.0026)	–$434 ($75)	–0.0038 (0.0023)	–$109 ($66)		
Ln(summer precipitation)	0.1408 (0.0720)	$376 ($192)	0.0969 (0.0769)	$258 ($205)	0.0922 (0.0666)	$245 ($177)		
Annual sunshine	–0.0155 (0.0057)	–$441 ($162)	–0.0190 (0.0059)	–$540 ($168)	–0.0100 (0.0057)	–$284 ($161)		
Ln(population density)	0.2283 (0.0452)	$7 ($1)			0.2872 (0.0401)	$9 ($1)	0.1924 (0.0472)	$6 ($1)
Mean $PM_{2.5}$	0.0708 (0.0159)	$2,014 ($455)	0.0937 (0.0158)	$2,666 ($454)	0.0627 (0.0145)	$1,779 ($412)	0.0935 (0.0166)	$2,659 ($477)
Violent crime rate	0.0045 (0.0136)	$129 ($386)	0.0192 (0.0145)	$545 ($411)	–0.0139 (0.0148)	–$394 ($420)	0.0127 (0.0147)	$361 ($417)

Transportation score	0.0093	$263	0.0084	$240	0.0105	$296	0.0106	$302
	(0.0015)	($42)	(0.0016)	($46)	(0.0014)	($41)	(0.0016)	($47)
Education score	0.0034	$97	0.0044	$125	0.0025	$71	0.0029	$83
	(0.0015)	($44)	(0.0016)	($46)	(0.0016)	($44)	(0.0017)	($48)
Arts score	0.0048	$136	0.0081	$231	0.0035	$99	0.0064	$181
	(0.0017)	($49)	(0.0018)	($51)	(0.0015)	($43)	(0.0018)	($53)
Healthcare score	0.0005	$13	0.0001	$2	0.0008	$23	–0.0003	–$10
	(0.0012)	($33)	(0.0012)	($35)	(0.0012)	($33)	(0.0013)	($38)
Recreation score	0.0131	$374	0.0137	$390	0.0127	$361	0.0101	$288
	(0.0015)	($44)	(0.0016)	($48)	(0.0015)	($43)	(0.0017)	($48)
Park area	0.0002	$4	0.0001	$3	0.0001	$3	0.0002	$7
	(0.0001)	($2)	(0.0001)	($1)	(0.0000)	($1)	(0.0001)	($2)
Visibility > 10 miles	0.0078	$222	0.0112	$317	0.0028	$79	0.0150	$427
	(0.0032)	($92)	(0.0034)	($96)	(0.0033)	($93)	(0.0031)	($90)
Ln(elevation)	0.0810	$13,069	0.0484	$7,810	0.0993	$15,974	0.0398	$6,422
	(0.0441)	($7,126)	(0.0455)	($7,350)	(0.0376)	($6,066)	(0.0446)	($7,207)
Distance to coast	–0.0025	–$45	–0.0033	–$61	–0.0014	–$25	–0.0011	–$11
	(0.0007)	($15)	(0.0007)	($16)	(0.0007)	($15)	(0.0007)	($16)
(Distance to coast)^2	0.0000		0.0000		0.0000		0.0000	
	(0.0000)		(0.0000)		(0.0000)		(0.0000)	
No. of obs. (MSAs)	284		284		284		284	
Adjusted R-squared	0.84		0.82		0.83		0.80	

Notes: When entering the regressions nonlinearly, amenity variables are evaluated at population-weighted means in order to compute MWTP. Nonlinear covariates: population density, summer precipitation, and elevation enter in log form, while distance to the coast enters the model quadratically.