ABSTRACT

Title of Dissertation: TWO ESSAYS ON
VALUING CLIMATE AMENITIES

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Chapter 2: Household Location Decisions and the Value of Climate Amenities

I value climate amenities by estimating a discrete location choice model for U.S. 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. I use the estimated trade-off among wages, housing costs, and climate amenities to value changes in mean winter and summer temperatures. I 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. I use my 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 percent of income to avoid the B1 scenario and 2.4 percent of income to avoid the A2 scenario.

Chapter 3: Do Discrete Choice and Hedonic Models Yield Different Results? A Comparison of Approaches in the Context of Urban Amenities

I examine differences between the two principal approaches used to estimate the value of urban amenities: the hedonic model, in which amenities are capitalized into wages and housing prices, and the discrete model of household location choices, which is derived from a random utility framework. Several empirical studies have noted that the discrete choice approach can yield much larger estimates of amenity values than the hedonic approach. Using 2000 PUMS census data, I investigate these differences and their possible causes by estimating how U.S. households value various aspects of climate. I estimate both hedonic and discrete choice models, allowing for heterogeneity in tastes for mean winter and summer temperature. In line with the previous literature, I find that discrete choice models consistently yield mean marginal willingness to pay estimates for climate amenities that significantly exceed those implied by hedonic estimates. Additionally, I find that the household sorting patterns implied by the two models are very different. For example, the discrete choice model suggests that households with the greatest preference for warmer winter temperature tend to locate in cities with the mildest winters, while the hedonic models do not. I show that explanations for these differences advanced by the previous literature, such as differences in mobility assumptions between the two approaches, cannot fully explain my findings, and I suggest an alternative theory that deserve further investigation.

TWO ESSAYS ON
VALUING CLIMATE AMENITIES

by

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Dissertation submitted to the Faculty of the Graduate School of the
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Foreword

Chapter 2 of this dissertation contains material jointly authored with Maureen Cropper and Paramita Sinha. A shortened version of this work has been submitted for publication with the Journal of Environmental Economics and Management. I contributed substantially to this research and have followed all university guidelines with respect to the inclusion of jointly authored material in my dissertation.

Dedication

For Brian and Tucker,

who put everything in perspective

and bring immeasurable joy to my life.

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Finally, I would like to thank the many friends and family who have supported me throughout this journey, notably among them Landon, Felicia, Mark, Karen, Stacey, Ben, and Little Ben. I am especially grateful to my husband, Brian, and to my parents, Mike and Pam Caulkins. Your unconditional love, constant encouragement, and unwavering faith in me has made all the difference. Thank you for everything.

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Chapter 1: Introduction

Climate change associated with the accumulation of greenhouse gases in the atmosphere is projected to have serious impacts on human and natural ecosystems, and it will necessitate significant adaptation and mitigation through climate policy to allay its effects (IPCC Synthesis Report, 2014). Determining the benefit of potential climate policies requires an estimate of the damages associated with climate change, one component of which is the amenity value of climate – for example, a household's willingness-to-pay (WTP) to experience warmer winters or cooler summers. Despite this, climate damage assessments do not typically incorporate amenity values, and with the exception of Fan. et. al. (2016) and Albouy et. al. (2016), recent estimates for the value of climate amenities in the United States are sparse. Measuring these amenity values poses an econometric challenge because, unlike goods traded in formal markets, there is no explicit price defining WTP for climate amenities. Consequently, implicit prices must be estimated by the researcher. While there are two generally accepted revealed preference approaches to valuing amenities that vary spatially – the continuous hedonic and discrete choice random utility models – the literature has paid relatively little attention to whether these models produce similar empirical results. This dissertation attempts to address these gaps in the literature through two studies aimed at estimating the value of climate amenities and exploring its dependence on modelling approach.

In the second chapter of this dissertation, I estimate a discrete choice model of household location decisions, recovering the WTP for mean winter and summer temperatures and using those values to estimate the associated welfare impacts of projected climate change scenarios to U.S. households. In my model, a household chooses the location that maximizes utility, with utility a function of climate amenities, as well as earnings, housing costs, psychological costs from living away from birthplace, and other location-specific attributes. Variation along these dimensions identifies the parameters of household utility functions, which then constitute the value placed on local amenities: the marginal rate of substitution between amenities and income is equivalent to a household's marginal willingness-to-pay (MWTP). Hypothesizing that households have significant taste variation over average seasonal temperatures, I estimate a mixed (or random parameters) logit model, allowing the coefficients on winter and summer temperature to be random and correlated. Indeed, I find that while on average, households favor warmer winters and cooler summers, MWTP varies greatly across households. Furthermore, preferences for winter and summer temperature are negatively correlated, so that households with the strongest preference for mild winters also tend to have the strongest preference for mild summers. I compute MWTP for winter and summer temperature for each household by conditioning on the information inherent in their location decision and then use these conditional (household-specific) MWTP figures to value future climate scenarios. Specifically, I compute each household's expected compensating variation for the temperature changes projected by the B1 and A2 climate scenarios from the IPCC's (Intergovernmental Panel on Climate Change) 2000 Special Report on Emissions Scenarios.

I find that households in the South Atlantic and Pacific states have the highest MWTP for warmer winters and cooler summers, while households in the Midwest have relatively weaker preferences for temperature. Failure to account for this preference heterogeneity and associated geographic sorting impacts welfare measures of the projected climate change scenarios. To illustrate, cities in the New England and Middle Atlantic states will experience larger increases in winter temperature than in summer temperature with the B1 scenario, although the reverse is true for the East South Central and West South Central census divisions. 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 it to households in the Midwest. On net, allowing for taste sorting increases the average household WTP to avoid the B1 scenario by 29 percent compared with a world in which sorting is ignored. While much less pronounced, incorporating sorting actually decreases the WTP to avoid the A2 scenario.

Taking sorting into account, I find that households in are willing to pay 1 to 2 percent of income to avoid the 1° to 2° increases in average winter and summer temperatures associated with the B1 and A2 projections, respectively. Estimates for the United States of market-based damages associated with climate change have typically been in the range of 1 percent of gross domestic product for an increase in mean temperature of 2°C (NRC 2010). My results suggest that the amenity value of climate could significantly increase estimates of climate damages, even for moderate temperature increases.

While Chapter 2 employs a discrete choice model to value climate amenities, the Roback (1982) hedonic model provides an alternative approach, and studies interested in valuing urban amenities like climate typically follow one of these two methodologies.

Unlike the discrete choice approach which recovers MWTP by estimating the parameters of household utility functions, the hedonic model assumes that amenities are capitalized into local wages and property values via the equilibrium sorting of households across locations. This approach involves modelling local wages and property values as a function of local amenities, where the weighted sum of these hedonic regression coefficients yields the implicit amenity prices, or MWTP. Previous research has noted the hedonic and discrete choice approaches to amenity valuation may yield different MWTP estimates, though no careful comparison of the two methodologies exists in the current literature. Furthermore, there has been no systematic attempt to investigate or characterize the root cause of these differences. In the third chapter of this dissertation, I delve into the question of how amenity value estimates depend on the modelling approach used, carefully comparing the estimates produced by hedonic and discrete choice models that have been applied to a common dataset and an identical research question. Given the important role of amenity valuation to comprehensive policy cost-benefit analysis, this provides a relevant and critical step towards obtaining accurate estimates of the demand for local amenities.

In Chapter 3, I examine differences between the continuous hedonic and discrete choice approaches in the context of valuing climate amenities. Specifically, I use the 2000 census Public Use Microdata Sample (PUMS) to estimate hedonic and discrete choice models that value winter and summer temperature. My hedonic models regress the weighted sum of wage and housing price indices on mean winter and summer temperature, other climate amenities, and various city characteristics using metropolitan statistical areas (MSAs) as the geographic unit. Wage and housing price indices are estimated from national labor and housing markets and their weighted sum is constructed according to two sets of weights, one following the adjustments developed by Albouy (2012) and the other following the previous hedonic literature (Roback, 1982; Blomquist, Berger and Hoehn, 1988). I allow the marginal price of winter and summer temperature to vary by city using local linear regressions and find substantial variation across metropolitan areas. My discrete choice model mimics that of the one described in Chapter 2, though I focus on a different sample of households, namely prime-aged households between the ages of 25 and 55, to provide cleaner comparison with the hedonic models.

I find that the discrete choice and hedonic approaches produce very different estimates for the value of local amenities. Specifically, the continuous hedonic approach yields much lower values than the discrete choice approach for both marginal increases in winter temperature and marginal decreases in summer temperature. I also find that the two approaches imply very different patterns of taste-based sorting across metropolitan areas, which is especially pertinent in this context given the expectations for varying geographic impacts of climate change. One possible reason for these differences centers on mobility assumptions: the hedonic model assumes perfect mobility, whereas the discrete choice model can directly incorporate frictions through household utility functions and psychological moving costs. However, while moving costs are an important component of my discrete choice model (both for identification and the value of MWTP figures), eliminating them from the model does not align discrete choice and hedonic estimates. Thus, though likely a factor, the theoretical assumptions regarding mobility cannot fully explain differences in empirical results.

Another, perhaps more telling, difference involves the way each model handles population shares. The hedonic model relies on the geographic price variation that makes households indifferent between locations of different amenity profiles, allowing for labor and housing markets to clear. City populations are a consequence of equilibrium in the hedonic model, but are not explicitly modeled or utilized. In extreme contrast, the discrete choice model is identified on population shares: the discrete choice model predicts the probability a city is chosen using variation in prices and amenities across locations (where, when summed over households, the probability a city is chosen is simply the population share). The results implied by a simple share model, where I regress log population shares on wage and housing price indices in addition to local amenities, support this hypothesis regarding population shares. The share model is essentially a simplified version of the discrete choice model, yet it strips away discrepancies with the hedonic model related to mobility assumptions and how labor and housing markets are defined – the major difference that remains is the use of population shares. I find marginal amenity values from the share model generally agree with those from the discrete choice model and remain much larger than hedonic estimates. This could suggest that differences regarding the treatment of population shares is driving the wedge between MWTP estimates from hedonic and discrete choice models of urban amenity valuation.

Chapter 2: Household Location Decisions and the Value of Climate Amenities

2.1 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 Fan et. al. (2016) and Albouy et al. (2016), 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. I 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. (2016), 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 et al., 2009; Cragg and Kahn, 1997; Fan, Klaiber and Fisher-Vanden, 2016, 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 household utility functions.

The discrete choice approach, which I 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

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[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).

[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.

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. I also incorporate moving costs from birthplace in my model of location choice and demonstrate that their omission significantly understates the value consumers place on temperature and precipitation.

The discrete choice approach more readily incorporates heterogeneity in consumer preferences than the hedonic approach. This can be done by interacting household characteristics with amenities (Fan, Klaiber and Fisher-Vanden, 2016) or by estimating a random coefficients logit model. In the case of climate, the distribution of winter and summer temperature coefficients from a random coefficients logit model can be used to examine how MWTP for winter and summer temperature varies with residential location.

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

2.1.1 My Approach

In this paper, I value climate amenities by estimating a model of residential location choice among metropolitan statistical areas (MSAs) for U.S. households in 2000. I 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. I compute the means of these coefficients for each household, conditional on choice of MSA, and then examine how the average conditional mean MWTP for climate amenities varies across MSAs to describe taste sorting.

I value future changes in temperature in two ways. I use the conditional mean MWTPs to 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. (2016) based on local linear estimates of the hedonic price function. I 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.

My 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] I extend their work, following Bayer et al. (2009), by including moving costs and modeling choices across MSAs. Unlike Bayer et al., however, I cannot use multiple cross sections to difference out unobserved amenities within cities. Historical data indicate that climate changes slowly, forcing me to rely on a single cross section of data rather than data over consecutive decades.[4] I attempt to allay concerns about omitted variable bias by controlling for a wide variety of location-

[3] Cragg and Kahn (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 Ricardian literature that examines the impact of climate on agriculture (e.g., Schlenker, Hanemann, and Fisher, 2006).

specific amenities other than temperature, especially those that are correlated with temperature.

2.1.2 My Findings

My 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. I 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 for households who live in the South than for those in the Midwest. At the level of census regions, households who live in the Midwest and Northeast are less climate sensitive – they have lower MWTPs to increase winter and reduce summer temperatures than households who live in the South and West.

I use these estimates to value changes in mean summer and winter temperatures over the period 2020 to 2050 for 284 U.S. cities that contained over 80 percent of the U.S. 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 by 29 percent 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 value 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 percent of income; it is about 2.4 percent of income for avoiding the A2 scenario. I note that the latter value is within the range reported by

[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. I use projections from a climate-friendly scenario (B1) and a more extreme scenario (A2).

Albouy et al. (2016) for a much more drastic climate scenario in the period 2070-2099.[6] One possible reason for the difference in estimates is that I base my estimates on all households, whereas Albouy et al. (2016) focus on prime-aged households. My results suggest that the value attached to climate amenities varies with the age of the household head: on average, households with heads over the 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, I focus on results based on all households.

The paper is organized as follows. Section 2.2 presents the household's location decision and the econometric models I estimate. Section 2.3 describes the data used in my analysis. Estimation results are presented in Section 2.4. Section 2.5 uses these results to evaluate the value of temperature changes projected by the B1 and A2 SRES scenarios, and Section 2.6 concludes the paper.

2.2 Household Residential Location Model

I model household location in 2000 assuming that each household selected its preferred MSA from the set of MSAs in the United States in 2000.[7] Household utility depends on income less the cost of housing, location-specific amenities, and moving costs

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[6] Albouy et al. (2016) focus on the A2 scenario in the period 2070-2099, when it is expected to raise mean temperature in the United States by 7.3˚F compared with the 1970-1999 period.

[7] Because I focus on the choice of MSA, I am estimating the climate preferences of people who live in urban areas.

from the birthplace of the household head. Specifically, I assume 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 a household residing in a location different from the head of household's birthplace. Put another way, MC_{ij} captures the cost of moving to MSA *j* from the household head's birthplace, and going forward, I refer to these as "moving costs." $\boldsymbol{A}_j$ is a vector of location-specific amenities. Equation (1) assumes that household utility is linear in the Hicksian bundle (i.e., $Y_{ij} - P_{ij}$). I relax this assumption below; however, linearity in the Hicksian bundle simplifies the computation of welfare measures.

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, I estimate hedonic wage and housing price equations for each MSA, as described below.

I allow the coefficients on temperature amenities to vary across households. I hypothesize that households vary in their tastes for climate, and sort across MSAs based on taste differences. In my base case, summer and winter temperature enter the utility function linearly: I assume a constant marginal utility of temperature and estimate a household's willingness to pay for small changes in temperature at their chosen location. As a sensitivity analysis, I allow utility to vary non-linearly with temperature. Specifically, I add the squares of winter and summer temperature to the utility function, restricting their coefficients to be identical across households.[8]

I choose to estimate a random coefficients model rather than using household characteristics to explain heterogeneous preferences across households. Estimating a random coefficients model allows me to compute the distribution of marginal utility of summer and winter temperature (and hence, marginal willingness to pay), conditional on a household's chosen location. I believe that this is more relevant for evaluating climate policy than computing marginal willingness to pay as a function of household characteristics. While it is true that I could calculate preferences conditional on both location and household characteristics, understanding how preferences for climate vary by (e.g.) education is not the aim of this paper.[9]

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 my sample (see Table 2.1, full sample) live in the census region in which the head was born; 67 percent 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.

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[8] Estimation results for this sensitivity are quite similar to the base model and are presented in the Model 11 of Appendix Table C.1.

[9] Fan, Klaiber and Fisher-Vanden (2016) use a model of location choice to examine how preferences to avoid temperature extremes vary by education and birthplace. They find that the college-educated have higher willingness to pay to avoid extremely hot and extremely cold days than people without a college education.

In my base case, following Bayer et al. (2009), I represent moving costs as a series of dummy variables that reflect whether city j is outside of the state, census division, or census region in which household i's head was born. Formally,

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

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.

I also allow for two alternate specifications of moving costs. In one specification, I replace the dummy variables in equation (2) with the log of the distance from the population-weighted centroid of the household head's birthplace state to the population-weighted centroid of the state, division, and region where the household resides. In the other specification, I allow moving costs to vary with the presence of children (following Hamilton and Phaneuf, 2015) and marital status. This controls for the idea that households may have different moving costs; for example, married households may be constrained by finding a city that can accommodate two workers, and households with children may be resistant to relocate their children while school-aged. Specifically, I interact the geographic dummies in equation (2) with variables indicating whether the household contains any children and whether the household head is married.

2.2.1 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, I 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*:

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

Equation (3) is estimated using data on full-time workers in the Public Use Microdata Sample (PUMS).[10] The coefficients of equation (3) are used to calculate the annual earnings of each worker in the sample used to estimate the discrete choice model, under the assumption that individuals work the same number of hours and weeks in all locations. Summing earnings over all individuals in each household, I obtain predicted annual household wages for household *i* in location *j* ($\widehat{W}_{ij}$). Predicted income in city *j*, $\hat{Y}_{ij}$, equals

[10] 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. I have also estimated equation (3) allowing for non-random sorting (Dahl, 2002). Specifically, I compute the probability of moving from each birthplace to current location (in terms of census divisions) conditional on each education group listed in Table 2.1 by taking the appropriate cell counts in my sample of workers (close to 3 million individuals). Including this probability correction term (in quadratic form) in equation (3) has minimal impact on my wage regression results, possibly due to the inclusion of industry and occupation indicators in the equation. The Dahl correction terms are significantly different from zero in only 26 percent of the 284 MSA wage regressions. Further, very few coefficients are affected by the inclusion of the correction terms – the most affected coefficients are "High School" and "Some College" but these change only by 5-6 percent on average. Because the correction terms are rarely significant and have little qualitative impact, I elect to use equation (3) without Dahl corrections to predict wages for my discrete choice model.

the predicted wage income of household *i* plus its non-wage income, which is assumed not to vary by MSA.

The cost of housing in each location is estimated based on hedonic property value equations for each MSA as given by equation (4) below. P_{ij} is the annual cost of owning

$$\ln P_{ij} = \gamma_j^P + \boldsymbol{X}_{ij}^P \boldsymbol{\Gamma}^P + \nu_{ij}^P \quad \forall\, j = 1, \dots, J \qquad (4)$$

house *i* in city *j*, computed as the sum of the imputed monthly mortgage payment or rent and the cost of utilities, property taxes, and property insurance.[11] $\boldsymbol{X}_{ij}^P$ contains a dummy variable indicating whether the house was owned or rented, as well as a vector of dwelling characteristics, which indicate size, age, and composition of the structure. Utility costs are added both to the costs of owning a home and to rents because heating and cooling requirements vary with climate. I wish to separate these costs from climate amenities. Equation (4) is estimated separately for each MSA in my dataset.

I 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. This is clearly a strong assumption. To test its validity, I examine the mean value of key housing characteristics (number of bedrooms and number of rooms) and their standard deviation across MSAs, for different household groups, characterized by income group and household size. The coefficient of variation for number of bedrooms and number

[11] The monthly mortgage payment for each house represents the opportunity cost of owning the house. It is imputed, based on the owner-assessed value of the house and average mortgage interest rates in 2000. It does not represent the actual payment made by the owner of the house.

of rooms within income and household size groups averages only 0.07-0.08, suggesting that households of similar size and income tend to live in dwellings of similar characteristics, thus supporting my methodology for predicting housing expenditures.[12,13]

The results of estimating the individual MSA hedonic wage and housing market equations for my base case are summarized in the last two columns of Table A.1 and Table A.2 of Appendix A. I 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.

I 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) according to Equation (5). I assume that the temperature coefficients ($\beta_i^{WT}, \beta_i^{ST}$) are jointly normally

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

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[12] Table A.3 in Appendix A summarizes the variation of key dwelling characteristics across MSAs. Variation across number of rooms and number of bedrooms is very small. Variation in the age of structure and number of units is somewhat larger, though given that these variables specify ranges for age and units, households are still likely to fall within the same range and have the same values for these indicator variables in the hedonic housing regressions. Home ownership is the variable with the most variation, and I suspect that for households in the two lowest income quintiles (where the proportion of ownership is roughly 50%), I may be incorrectly predicting ownership status to remain unchanged across alternative MSAs. Ownership is higher for households in the three highest income quintiles, and the coefficient of variation across MSAs averages only 10%.

[13] As a sensitivity analysis I estimate a location choice model that uses a housing price index, following Bayer et al. (2009), rather than predicting housing expenditures in each MSA. In Bayer et al. (2009), utility is assumed to be of the Cobb Douglas form, implying that indirect utility is a function of a housing price index that varies across cities, not households. The housing price index for each MSA is the estimated MSA fixed effect in a national hedonic housing price equation. (See Appendix D for further details.)

distributed, with mean vector $\boldsymbol{\mu}$ and variance-covariance matrix $\boldsymbol{\Sigma}$. The elements of $\boldsymbol{\Sigma}$ are estimated in the first stage. Following Murdock (2006), in estimating equation (5), the means of β_i^{WT} and β_i^{ST} are effectively constrained to be zero. Since the MSA fixed effects encompass all local attributes that do not vary across households, the mean vector $\boldsymbol{\mu}$ is contained in $\delta_{j,}$ and thus, is estimated in the second stage. The MSA fixed effects will also capture cost of living differences across locations that are common among households, whereas Y_{ij} and P_{ij} account for household-specific price differences across locations. The error term in the household's utility function 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. The parameters of equation (5) are estimated via simulated maximum likelihood, using a choice set equal to the household's chosen alternative and a random sample of 59 alternatives from the full set of 284 MSAs.[14]

[14] 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. Guevara and Ben-Akiva (2013) prove that the sampling of alternatives in the mixed logit model produces consistent parameter estimates as the number of alternatives sampled approaches the universal choice set. Given the computational trade-offs I face between 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, I must use a sub-sample of the universal choice set. Experiments with the size of the sampled choice set indicated that increasing the size of the choice set beyond 60 MSAs did not significantly alter parameter estimates. This is supported by simulation results from Nerella and Bhat (2004), which finds small sample bias when 50 or more alternatives are sampled from a choice set of 200. While beyond the scope of this paper, another option is to pursue a latent class model as suggested in von Haefen and Domanski (2016).

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 the other location-specific amenities according to equation (6) below. The ratio of the second

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

stage amenity coefficient over the Hicksian bundle coefficient from the first stage yields the marginal rate of substitution between the amenity and income, thus defining MWTP for that local amenity. Because this is a static model, where households are implicitly re-optimizing each period, MWTP values should be interpreted as the annual amount (here, year 2000) that households are willing to pay for local amenities.[15]

2.3 Data

The data used to estimate my location model and hedonic wage and housing equations come from the 5 percent PUMS of the 2000 U.S. census as well as other publicly available data sources.

2.3.1 Sample Households

To select the sample used to estimate my location choice models, I focus on households residing in one of the 284 MSAs for which I have complete amenity data. These

[15] To reiterate, MWTP values in this paper should not be interpreted as the present discounted value of forward-looking agents for local amenities resulting from a dynamic model of household location decisions like the one presented in Bayer, McMillan, Murphy, and Timmins (2016).

MSAs contained 80 percent of the total U.S. 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. I exclude households with heads in the military or in certain occupations (e.g., logging, mining) that would restrict locational choices. I 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.[16]

Table 2.1 describes the characteristics of my sample households and of subsets of these households. I estimate the discrete choice model for the full sample of households and also for two subsamples described in Table 2.1: households with prime-aged heads (i.e., heads between 25 and 55) and households with heads over age 55. I also estimate the discrete choice model on a sample of households that have moved MSAs between 1995 and 2000 ("movers") following some examples in the previous literature (Cragg and Kahn, 1997; Sinha and Cropper, 2013). 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: 98 percent of households with prime-aged heads have some labor income, and on average, 93 percent of the income of these households comes from wages. Forty-seven percent of older households have no wage income.

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

A striking fact in Table 2.1 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 percent in the same census division, and 73 percent in the same census region. This foreshadows the importance of moving costs (from birthplace location) in explaining residential location choice.

2.3.2 Climate Variables

The climate variables in my model are summarized in Table 2.2. All variables are climate normals: the arithmetic mean of a climate variable computed for a 30-year period.[17]

I 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.[18] 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., 2016). The advantage of mean winter and summer temperatures is that they capture seasonality, which annual heating and

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[17] 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.

[18] 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 does Albouy (2012).

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 my models.

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 my 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 Southeast 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 percent (s.d. = 7 percent) and is not highly correlated with either winter temperature (r = 0.06) or summer temperature (r = 0.14).

Following the literature, I 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.

2.3.3 Non-climate Amenities

The non-climate amenity variables used in the second stage of the model are also summarized in Table 2.2. 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. My desire is to be as inclusive as possible. Because climate changes slowly, I cannot use panel data to value climate amenities. I therefore strive to avoid problems of omitted variable bias by including a variety of location-specific amenities in my 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). I therefore do not include population as an amenity, but I do include population density, which may proxy amenities the higher population density supports but which are not adequately captured by other amenities (better public transportation, restaurants, and live sporting events). I also estimate models with population density omitted.

Cragg and Kahn (1997), in estimating a model of choice of state to live in, include the number of cities within each state as a measure of the number of location choices available to residents. I follow their lead by including the number of counties in each MSA. I also estimate models in which population density is replaced by land area, after Bartik (1985), who uses land area as a proxy for abundance of location choices. Other amenities and disamenities for which I control include air pollution (fine particulate matter, or PM2.5), 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. I 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.

2.4 Estimation Results

2.4.1 Discrete Location Choice Models

Table 2.3 describes my base model (Model 1) results for all households, prime-aged households, households with heads older than 55, and movers. 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 the first 18 attributes in Table 2.2, as well as the Hicksian bundle and the moving costs as specified in equation (2). Coefficients on the climate variables have been converted to MWTP by dividing by the coefficient on the Hicksian bundle. For winter and summer temperatures, I report the mean and standard deviation of the distribution of MWTP, as well as the correlation coefficient between the winter and summer temperature coefficients.[19]

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).[20] At the same time,

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[19] Table 2.3 through Table 2.5 report MWTP only for climate variables. MWTPs for all base model coefficients are reported in Appendix Table B.1 and Table B.2. Although I focus on the impacts of summer and winter temperatures, I note that all other amenities except particulate matter and sunshine have expected signs and are statistically significant.

[20] 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.

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 percent 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.[21]

The last model in Table 2.3 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, as do Sinha and Cropper (2013) with 2000 PUMS data. Table 2.3 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 percent higher than the mean MWTP of households in the full sample and 90 percent higher than prime-aged

[21] The negative correlation implies that there are some people who are very sensitive to outdoor temperature – if someone values warmer winters more than the average person then they also value milder summers more than the average person – and those people who are not very sensitive: they are willing to pay less for warm winters and also don't mind hotter summers.

households, who more closely resemble movers in terms of demographic characteristics.[22] Calculating the benefits of policies to avoid climate change should be based on the location decisions of all households. I therefore focus on the full sample of households for the remainder of the paper.

Table 2.4 shows the sensitivity of results for the full sample to the specification of moving costs. It is variation in moving costs across households (as well as variation in wages and housing expenditures) that allows me to identify the parameters of my model; hence, it is important to see how my results vary with changes in moving costs. In Model 2, where moving costs are modeled as the log of distance between birthplace and residence, MWTP is qualitatively the same, though there are some small differences in magnitude. For example, weighting moving costs by log(distance) increases the amenity value of winter temperature from $709 to $790 and lowers the amenity value of summer precipitation from $376 to $254. Interacting the moving cost terms with dummy variables for the presence of children and marital status (Model 3) has little impact on results – MWTP for climate amenities change by less than $10.

I note that if moving costs are removed from the model entirely (Model 4), the marginal value of climate amenities falls and households no longer appear to differ in their preferences for winter temperature; that is, the standard deviation on winter temperature becomes statistically insignificant. As discussed more fully below, it is moving costs that help me to identify taste sorting; omitting them leads to spurious estimates of sorting

[22] The MWTP of movers for a 1° decrease in summer temperature is 27 percent higher than in the full sample and 77 percent higher than in the prime-aged sample.

patterns. Omitting moving costs also reduces (in absolute value) MWTP for winter temperature and for summer temperature, especially, as well as for precipitation, snowfall, and humidity. These results support Bayer et al.'s (2009) assertion that ignoring moving costs may significantly alter WTP for location-specific amenities.[23]

Table 2.5 shows the impact on the coefficients for winter and summer temperatures of alternate specifications of amenities for the full sample: dropping population density (Model 5); replacing population density with land area (Model 6); adding the number of counties in the MSA to the model (Model 7); and removing other climate variables (Model 8). As noted in Section 2.3, 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 that are 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 1 and \$748 and -\$849 in Model 5. Similarly, replacing population density with land area has little impact on the base model: MWTP for winter temperature and summer temperature are \$725 and -\$890, respectively, in Model 6. Adding the number of counties to the base specification affects MWTP estimates a bit more, but results remain

[23] The power of this model for predictive purposes is also significantly impacted by the removal of moving costs. The base model correctly predicts a household's chosen location at a rate over 40% (as compared with choosing at random, which given 284 alternatives, would pick the chosen location less than 1% of the time). In contrast, the model without moving costs obtains correct predictions in about 10% of cases.

qualitatively the same. Specifically, MWTP for winter temperature increases to $815 while summer temperature falls to -$848. Model 8 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 percent (to $1,237), while mean MWTP for summer temperature falls slightly (to -$820).[24] Further sensitivity analyses suggest that when snowfall is omitted, winter temperature picks up its effects, whereas summer temperature is sensitive to July humidity.[25]

Appendix Table C.1 shows the impact of alternate specifications of the Hicksian bundle. In Model 9, I include a quadratic term for the Hicksian bundle in the first stage of the model. When evaluated at the mean Hicksian bundle, MWTPs for all climate amenities fall in absolute value, by about 15 percent for winter and summer temperature and by about 20 percent for the other climate variables. In contrast, I obtain larger MWTP estimates in Model 10, where I follow the Bayer et. al. (2009) housing price index approach (described in detail in Appendix D). Here, the log of total income replaces the Hicksian bundle in the first stage, while the second stage dependent variable is now the MSA fixed effect from the first stage adjusted by the city-level housing price index. MWTPs for all climate

[24] I also considered a model where summer temperature is interacted with July humidity; however, given that climate change scenarios do not produce information on humidity projections, this would greatly complicate the computation of welfare estimates. I do not estimate the interacted model for these reasons, but I do allow the preferences for humidity to be random and correlated with the preferences for summer temperature in a sensitivity. While I do find a strong and significant negative correlation between the preferences for summer temperature and humidity (i.e., households who don’t mind hot summers have a strong preference for less humidity), I find that both the mean and conditional MWTP results for winter and summer temperature are quantitatively and qualitatively unchanged. These results are summarized in Table C.2 of Appendix C.

[25] These sensitivity analyses are available upon request from the author.

variables are higher in this sensitivity analysis – about 20 percent higher for the temperature terms and approximately 50 percent higher for the other climate variables. Specifically, MWTP for winter temperature rises from $709 in the base case to $885 in Model 10, while the MWTP for avoiding summer temperature increases in magnitude from -$873 to -$1,004.

2.4.2 Taste-Based Sorting

To examine how households sort across locations in relation to their taste for winter and summer temperature, I use Model 1 to calculate the joint distributions of the coefficients of winter and summer temperature 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 Figure 2.1 and Figure 2.2.[26]

To compute conditional household-level parameters, I follow the procedure of Revelt and Train (1999), who uses Bayes' Rule to derive the conditional distribution of the temperature coefficients (i.e., conditional on chosen location, $choice_i$; observable household attributes, Z_i, which include the Hicksian bundle and moving costs; and the

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[26] 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 winter temperature and MSA mean MWTP for winter temperature and 0.97 between summer temperature and mean MWTP for summer temperature. It appears (incorrectly) that households in warmer cities place higher values on both summer and winter temperatures.

overall distribution of temperature parameters, $f(\beta|\mu,\Sigma)$). This conditional distribution is described by equation (7) below, and taking its expectation reveals an expression for

$$h(\beta|choice_i, Z_i, \mu, \Sigma) = \frac{\Pr(choice_i|Z_i, \beta)\, f(\beta|\mu, \Sigma)}{\Pr(choice_i|Z_i, \mu, \Sigma)} \tag{7}$$

household-level parameters, or the mean taste parameters, μ_i, of households of type Z_i, according to equation (8). These household-level parameters are estimated via simulation.

$$\mu_i = E(\beta_i|choice_i, Z_i, \mu, \Sigma) = \int \beta_i\, h(\beta|choice_i, Z_i, \mu, \Sigma) d\beta \tag{8}$$

Taking the average over all households in each MSA and dividing by the coefficient on the Hicksian bundle yields average MWTP for all households in a given MSA. Formally, the MWTP for winter temperature in MSA *j* is given by equation (9), where N_j is the number of households in MSA *j*.

$$MWTP_j^{WT} = \frac{1}{N_j}\sum\nolimits_i \mathbf{1}\left[i \text{ resides in } MSA_j\right] (\beta_i^{WT}/\alpha) \tag{9}$$

As seen in Figure 2.1, 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. Specifically, households with higher than average MWTP for winter temperature have located in warmer cities, and households with lower than average MWTP for winter temperature have located in colder cities. 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 2.1 and Panel B of Figure 2.4, and as confirmed by Table 2.6, which shows mean MWTP averaged across the MSAs in each census division, weighted by MSA population.[27] 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

[27] The average MWTP for winter temperature and summer temperature in Table 2.6 ($819 for winter and -$940 for summer temperature), conditional on location, differ from the unconditional values in Table 2.3 ($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 2.3.

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 2.2) 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 South Atlantic divisions have the greatest MWTP to reduce mean summer temperature by 1°.[28] The disamenity value of a 1° increase in mean summer temperature is greatest in absolute value in Palm Beach and Naples, Florida (-$2,194). This result may at first be mis-interpreted. The higher MWTP for cooler summers in Florida as compared to North Dakota does not reflect the fact that summer temperature is higher in Florida than North Dakota: MWTP is the value of a small change in temperature from current temperature levels. The higher MWTP to reduce summer temperature reflects the fact that people living in Florida are in the tails of the taste distribution for both winter and summer temperature – they have a higher than average MWTP to increase winter temperature and a higher MWTP than average to reduce summer temperature – they are climate-sensitive. People living in North Dakota, in contrast, are not very climate-sensitive and have small MWTP for both winter and summer temperatures.

[28] The correlation between mean summer temperature and MWTP for summer temperature in Figure 2.2 is -0.38. If I restrict preferences over winter and summer temperatures to be uncorrelated, I find a strong positive correlation between MWTP for summer temperature and the temperature of the city in which the household lives – see footnote 26.

I note that the sorting patterns displayed in Figure 2.1 and Figure 2.2 are identified by virtue of including moving costs from birthplace in the model. When moving costs are excluded, MWTP for winter temperature does not vary significantly across households, while MWTP for summer temperature increases with the temperature of the city in which the household lives, as pictured in Figure 2.3 and in contrast to Figure 2.2, where moving costs are included. When moving costs are dropped, it appears that people in warmer areas actually like the heat – i.e., that people who live in Florida and Texas have a lower than average MWTP to reduce summer temperature. The fact is that approximately 80% of the people who lived in the South Atlantic and West South Central census divisions in 2000 were born there. But, part of the reason that they live there is that the costs of moving from their birthplace are high. When I ignore moving costs it appears that people in the South actually like warmer summers.

Figure 2.1, Figure 2.2, and Panel A of Table 2.6 suggest that, holding temperature constant, MWTP for winter and summer temperatures varies by geographic region: households in the East North 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 more 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. My base model, however, controls for summer humidity, precipitation, snowfall, and sunshine. Indeed, Model 8 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 percent.

I have also performed several sensitivity analyses to ensure that the random coefficients for winter and summer temperature are not picking up preference heterogeneity for other amenities. In Model 12, I allow the Hicksian bundle parameter to be random, but uncorrelated with the temperature variables. Likewise, Model 13 allows for randomness in the dummy variable indicating whether the household lives in a different census division from the one in which the household head was born. I also allow for the coefficients on humidity and snowfall to be random and correlated with the temperature terms in Models 14 and 15, respectively. Unlike seasonal temperatures, there is very little taste variation across households for humidity and snowfall. Throughout all these models, the spread and correlation coefficients for winter and summer temperature are remarkably similar, and consequently, the associated sorting patterns mimic the base model. The estimation results for Models 12-15 are reported in Appendix Table C.2, with the associated sorting plots in Figure C.1 to Figure C.4.

In summary, although there is considerable variation within census regions, households who have located in the Midwest and the Northeast appear less sensitive to changes in temperature than households who live 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.

2.5 Willingness to Pay for Future Projected Temperature Changes

I 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, I use the results of the Hadley III model to project mean winter and summer temperatures over the 2020 to 2050 period in my 284 MSAs under the B1 and A2 SRES scenarios.[29,30] I estimate WTP for these temperature changes, compared with climate averages over the period 1970 to 2000. I 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. I also compute expected compensating variation for temperature changes using the distribution of (β^{WT}, β^{ST}) for each household, conditional on its location choice.[31]

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

[30] While the SRES projections have been superseded by the RPCs (Representative Concentration Pathways) adopted by the IPCC in 2014, the SRES projections are grounded in climate science and are used here as illustrative temperature changes.

[31] In these scenarios, I ignore the possibility that utility costs may change with climate change scenarios. Households may need to spend less to heat their homes in the winter and more to cool their homes in the summer, though technology and adaptation may also change the nature of utility costs. I avoid modeling this and hold housing expenditures constant when considering the temperature changes.

2.5.1 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.[32] 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.[33] Projections of increases in summer temperature 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. Figure 2.5 and Panel B of Table 2.6 show the population-weighted average winter and summer temperature changes for each scenario by census division. Panel B of Table 2.7 shows temperature changes by census region. 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

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[32] Other authors have focused on the damages associated with climate change at the end of this century, rather than midcentury (Albouy et al. 2016; Deschenes and Greenstone 2011). I focus on smaller, midcentury temperature changes for two reasons. First, changes of the magnitude examined by Albouy et al. (2016) would call for general equilibrium responses that I cannot model. They would result in major changes in wages and housing prices across cities. Second, my model is designed to value marginal temperature changes, rather than non-marginal changes.

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

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.

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.

2.5.2 WTP Conditional on Current Location

Table 2.6 and Figure 2.6 display household WTP for each SRES scenario, conditional on the household's current location. For each scenario, I 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 Figure 2.1 and Figure 2.2). WTP is averaged across MSAs within each census division (weighted by MSA population) and is also computed (population-weighted) for all 284 MSAs. Table 2.7 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, I 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 percent of average household income; under the A2 scenario, it is also negative and is equal to about 2.4 percent of income; however, the distribution of WTP differs greatly across regions. Households in the Middle Atlantic and South Atlantic states are willing to pay a positive amount for the B1 scenario; households in the New England 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 percent 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 percent.[34]

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 percent) primarily

[34] 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.

because ignoring sorting overstates the damages of the A2 scenario in the South Atlantic states.

2.5.3 Exact Welfare Calculations

The WTP estimates in Table 2.6, Table 2.7, and Figure 2.6 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. I would not, a priori, expect these adjustments to be large, given that I am evaluating small temperature changes and given the importance of moving costs in the discrete choice model. I 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 equation (10). I compute the expected

$$\begin{aligned}&\max_j \left[\alpha(\hat{Y}_{ij} - \hat{P}_{ij}) + {WT_j}^0\beta_i^{WT} + {ST_j}^0\beta_i^{ST} + MC_{ij} + \delta_j + \varepsilon_{ij}\right] \\ &\quad = \max_j \left[\alpha\left(\hat{Y}_{ij} - \hat{P}_{ij} - CV_i\right) + {WT_j}^1\beta_i^{WT} + {ST_j}^1\beta_i^{ST} + MC_{ij} + \delta_j + \varepsilon_{ij}\right]\end{aligned} \tag{10}$$

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 (von Haefen 2003). The expected value of CV_i is given by equation (11), and is simulated

$$E(CV_i|k\ chosen) = \int CV_i f(\beta_i, \varepsilon_i|k\ chosen)\, d\beta_i\, d\varepsilon_i \tag{11}$$

following von Haefen (2003). Specifically, I take a draw from the conditional distributions of random coefficients and the vector of error terms ε_{ij} and compute CV_i using equation (10) for each draw. I average these values across 100 draws to compute the household's expected compensating variation.

Table 2.8 and Figure 2.7 display $E(CV_i)$ for the B1 and A2 scenarios by census division. As in Table 2.6, 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 2.6, which are computed assuming that each household cannot change location, are presented for comparison. In all cases, $E(CV)$ is less than WTP:[35] households, on average, require less compensation to endure an adverse climate scenario or – as is 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.

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 percent and the value of avoiding the A2 scenario by about 3 percent compared with Table 2.6. Averaged across all households, the value of avoiding the climate scenarios using exact welfare measures is $574 for the B1 scenario (0.91 percent of average household income) and $1,492 for the A2 scenario (2.36 percent of average household income).

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

2.5.4 WTP Comparison with the Literature

As do Cragg and Kahn (1997), Fan, Klaiber and Fisher-Vanden (2016) and Sinha and Cropper (2013), I find that households value warmer winters, cooler summers, and less humidity. Cragg and Kahn (1997) model the choice of state in which to reside, while Fan et al. (2016) and Sinha and Cropper (2013) model location choice at the MSA level. Fan et al. (2016) focus on willingness to pay to reduce temperature extremes rather than mean winter and summer temperature. In agreement with Cragg and Kahn (1997), I find that MWTP for warmer winters and cooler summers increases with age. My population mean estimate of willingness to pay to reduce July humidity ($764) agrees closely with Fan et al.'s ($729). Overall, the results of my models agree qualitatively with previous studies using the discrete choice approach to valuing climate amenities.

In contrast, my estimates of the welfare losses associated with climate change are larger than those reported by Albouy et al. (2016) using a hedonic approach. Albouy et al. (2016) 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 avoid excess heat than to avoid excess cold 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 2070 to 2099 – changes that average 7.3°F – welfare losses are 2.28 percent of household income assuming homogeneous preferences and 2.79 percent allowing for heterogeneous preferences. I find comparable values for much milder temperature changes, on the order of 3.5°F.

There are several possible reasons for the difference in magnitude of my results. The hedonic approach uses the capitalization of amenities into wages and housing prices to value amenities. This may be appropriate 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, which identifies the parameters of household utility functions in the discrete choice approach. My 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 I were to base my estimates of the value of avoiding the B1 and A2 scenarios solely on prime-aged households, my estimates would fall by over 37 percent in the case of the B1 scenario and 34 percent 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 into wages and housing prices. Whether the capitalization of an amenity into wages and housing prices over- or understates MWTP is an empirical question. I note that removing moving costs from my 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 my model causes the value of reducing summer temperature to fall by almost 50 percent.

2.6 Conclusions

The discrete location choice model that I have estimated 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, I estimate the value of avoiding two climate scenarios in the near term (2020-2050). I find that, aggregated over the entire United States, WTP to avoid the more climate-friendly B1 scenario is approximately 1 percent of household income, while it is approximately 2.4 percent of household income for the A2 scenario. The A2 scenario I 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 percent of gross domestic product for an increase in mean temperature of 2°C (NRC, 2010). My results suggest that the amenity value of climate could significantly increase estimates of climate damages, even for moderate temperature increases.

Figure 2.1 Taste-Sorting for Winter Temperature by Metropolitan Area
(Base Discrete Choice Model: Model 1)

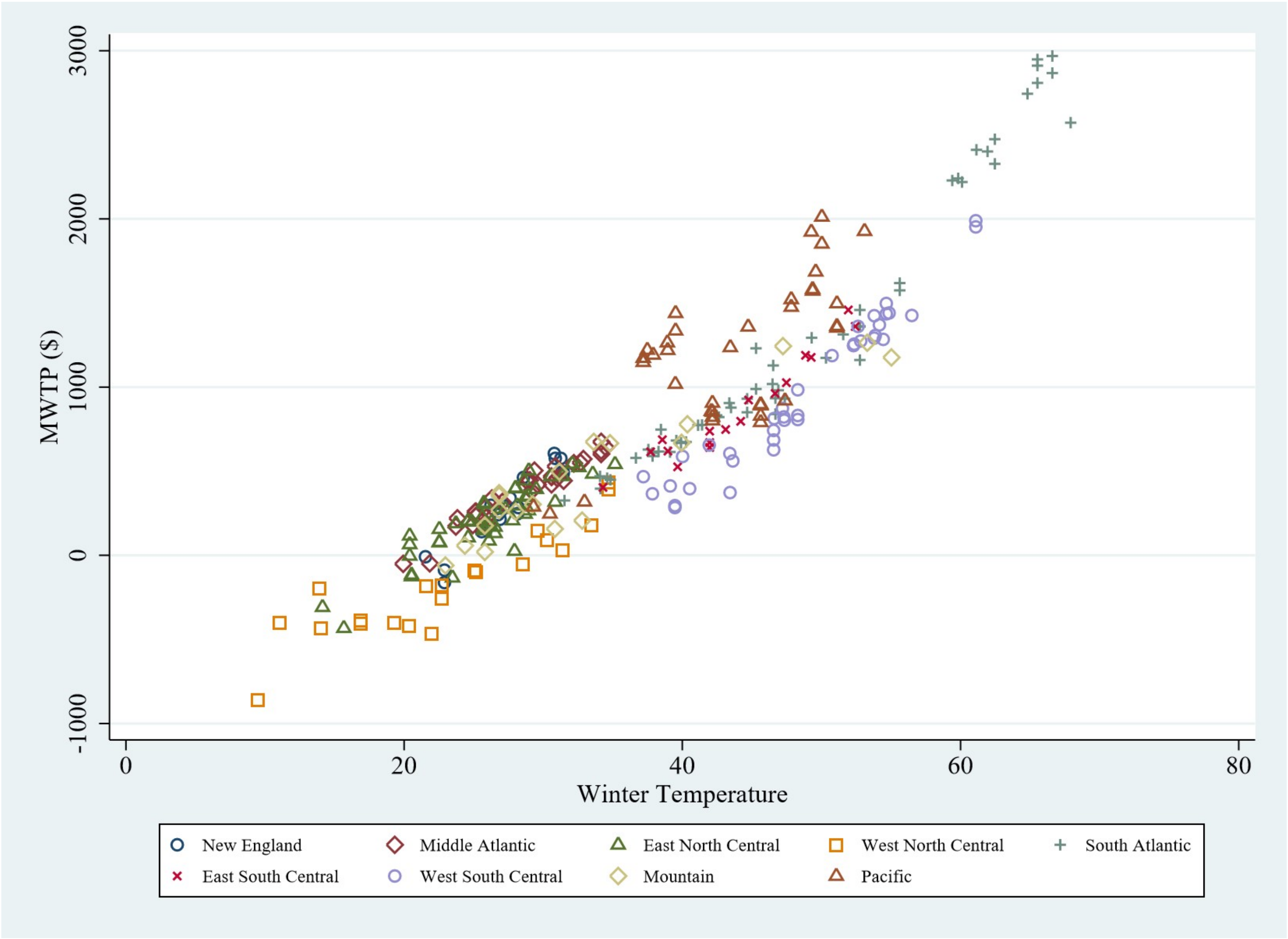


Figure 2.2 Taste-Sorting for Summer Temperature by Metropolitan Area
(Base Discrete Choice Model: Model 1)

Figure 2.3 Taste-Sorting for Summer Temperature by Metropolitan Area (Discrete Choice Model, Moving Costs Omitted: Model 4)

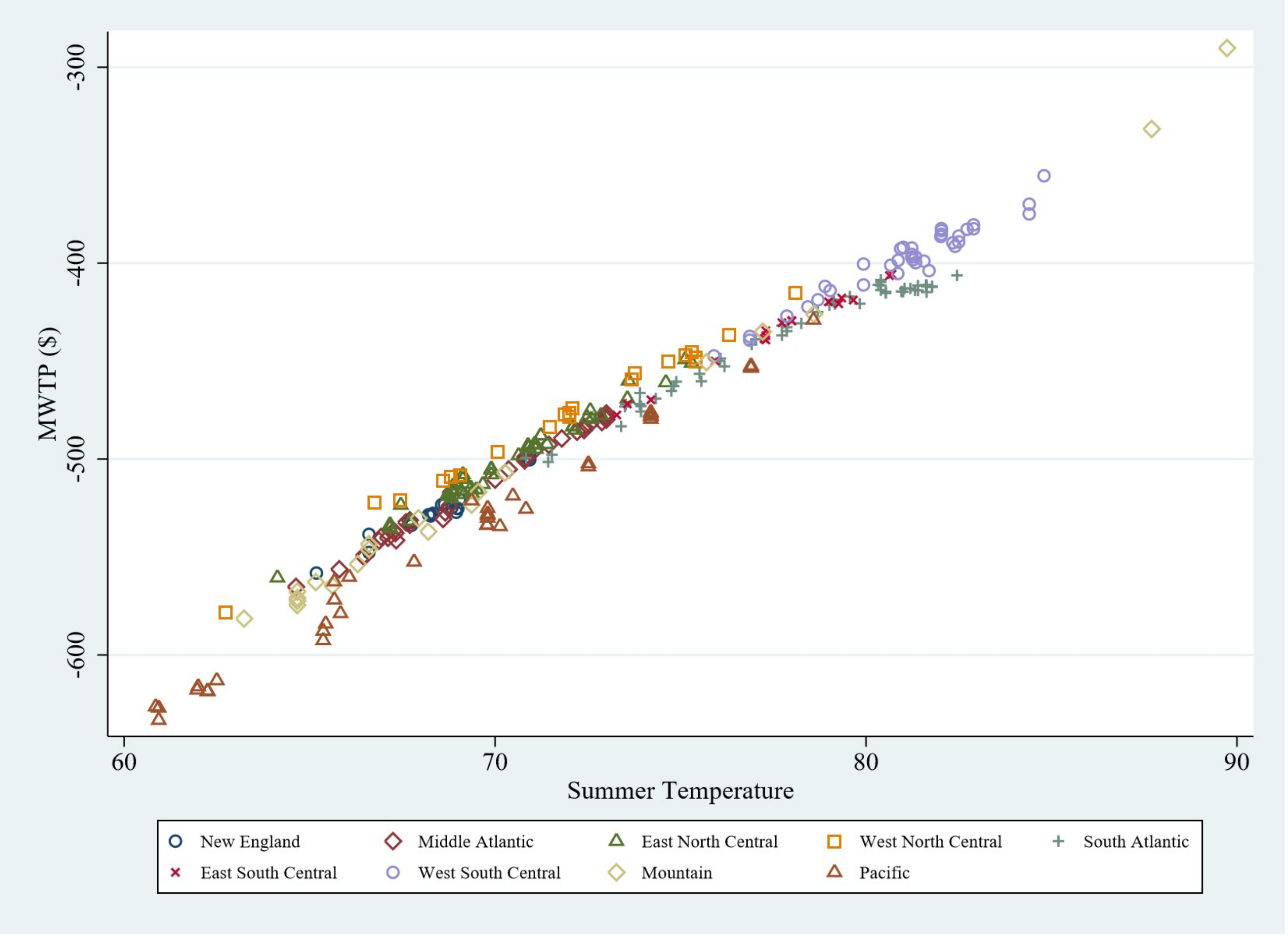
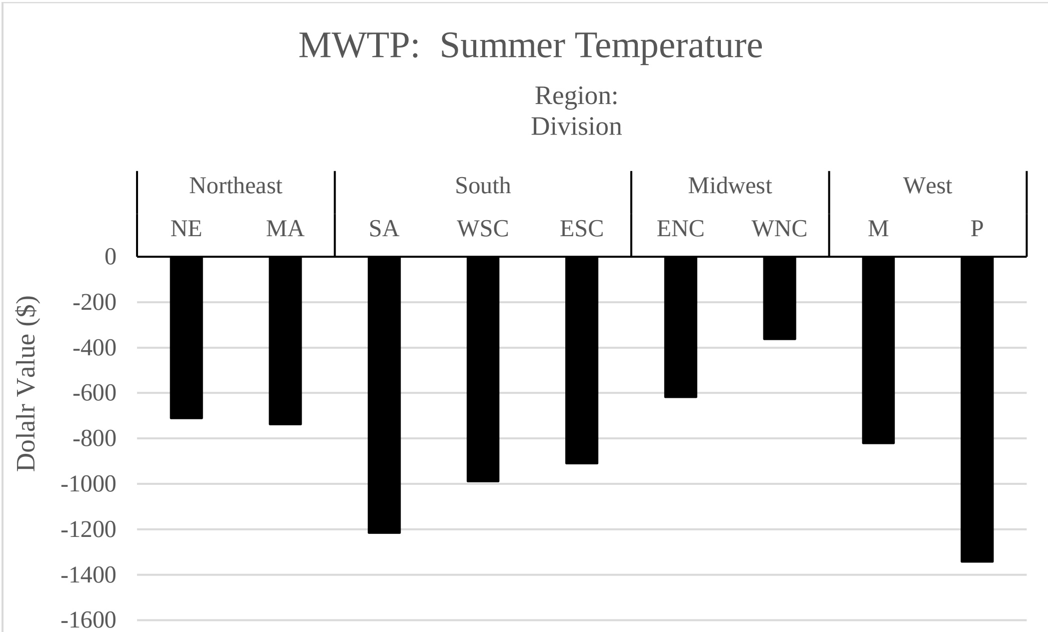


Figure 2.4 Marginal Willingness to Pay Conditional on Current Location, by Census Division

Panel A



Panel B

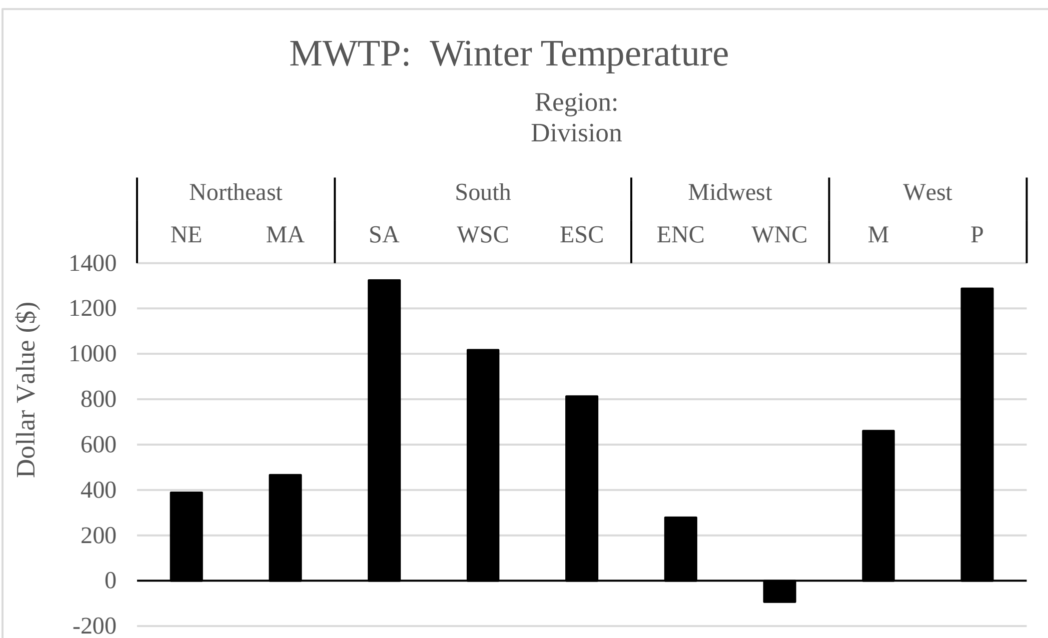
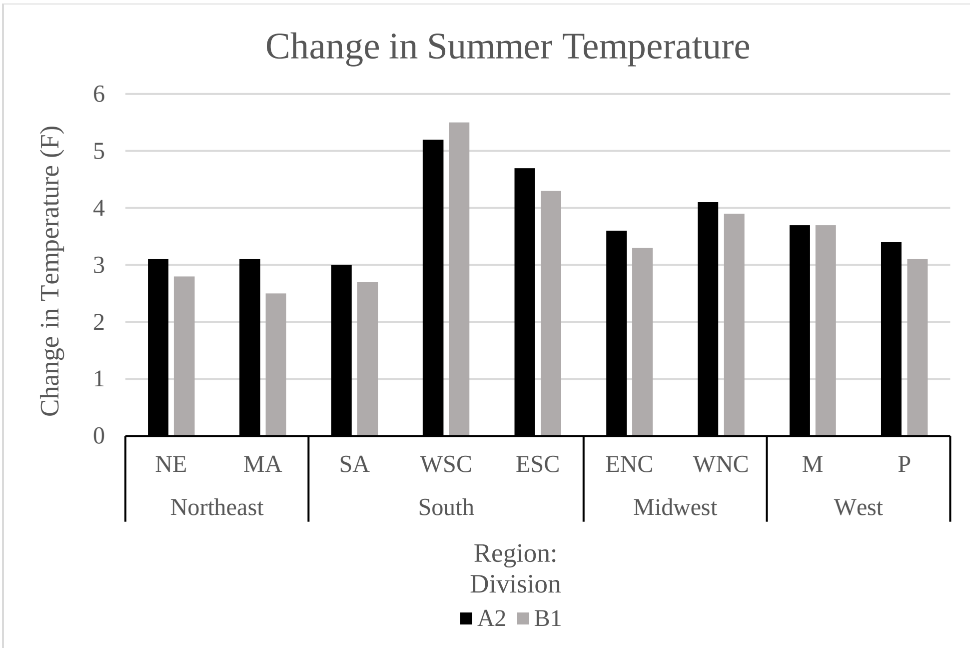


Figure 2.5 Projected Temperature Changes by Census Division, for SRES Scenarios (2020 to 2050)

Panel A



Panel B

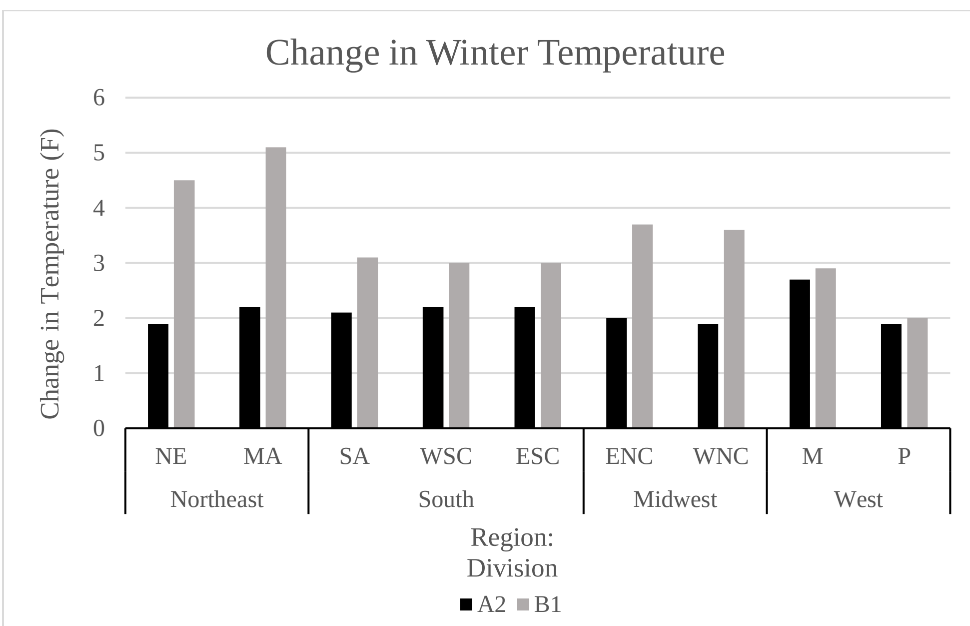
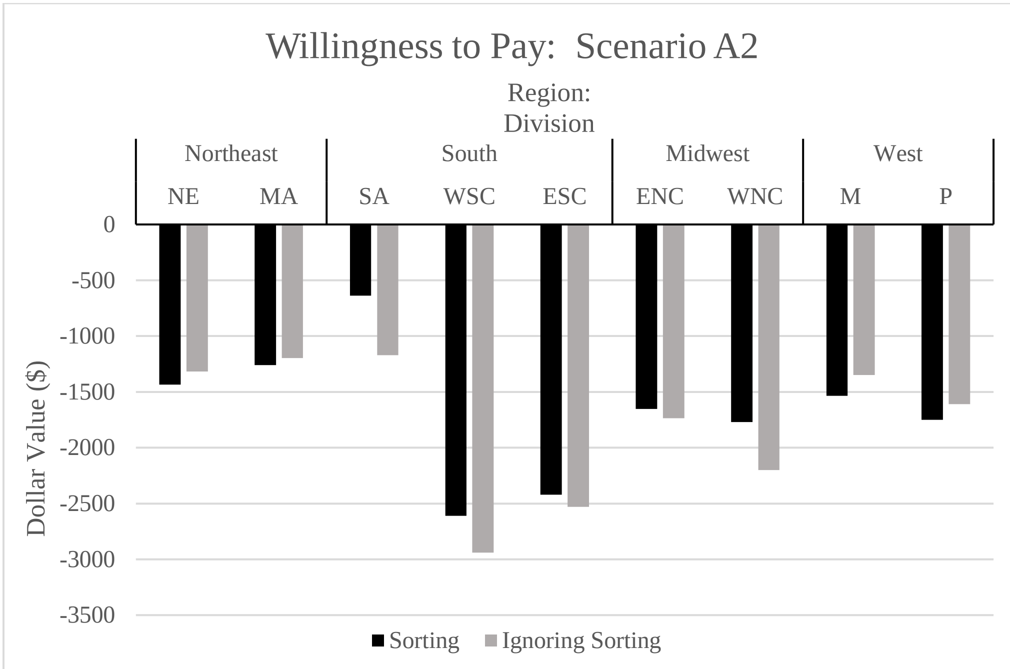


Figure 2.6 Willingness to Pay Conditional on Current Location by Census Division, for Scenarios A2 and B1

Panel A



Panel B

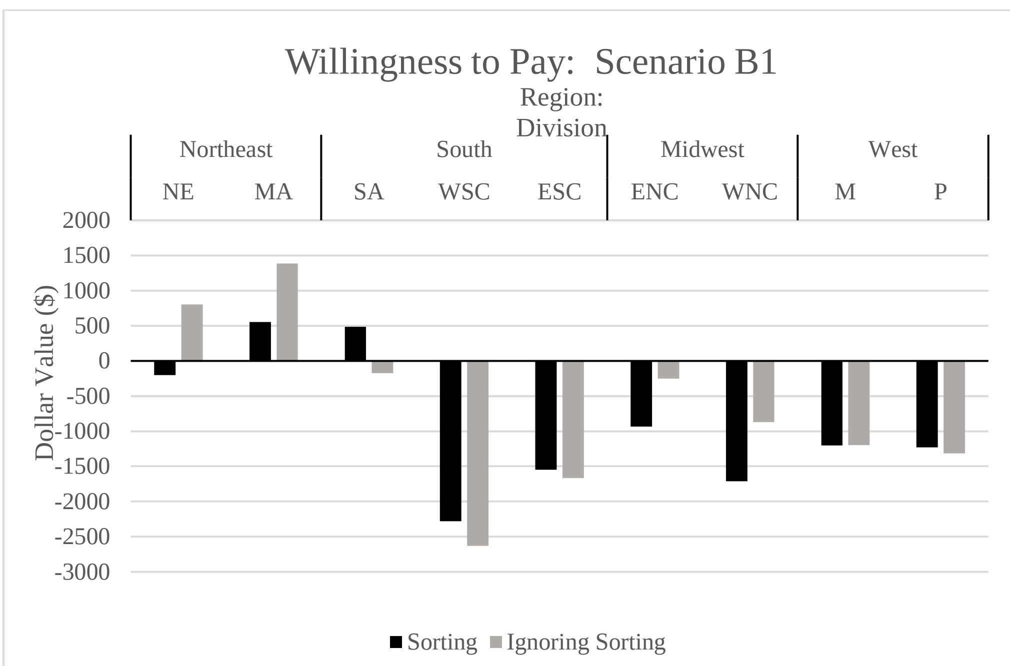
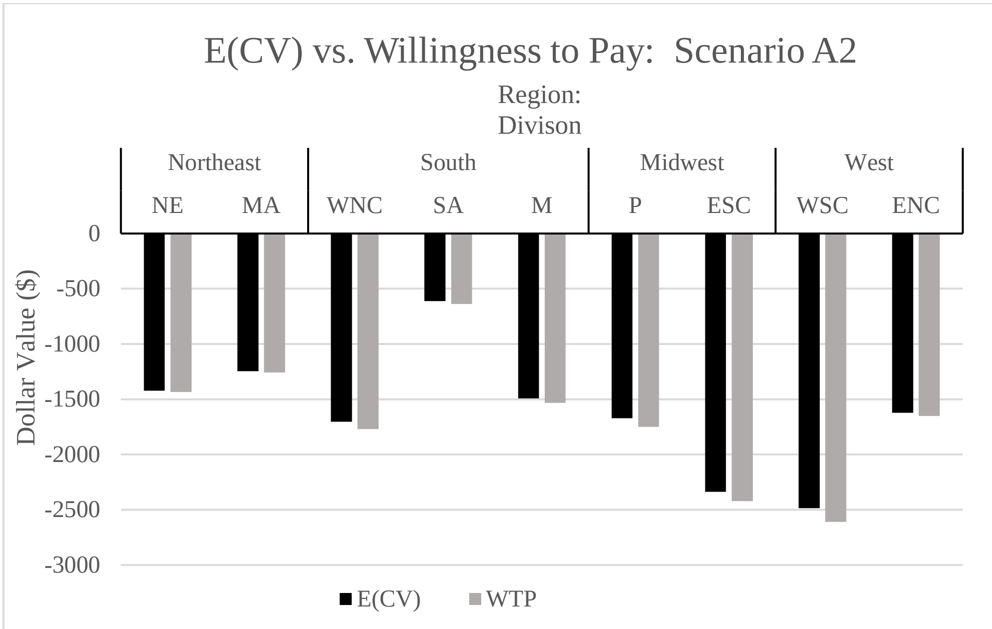


Figure 2.7 Expected Compensating Variation and Willingness to Pay, Holding Location Constant, for Scenarios A2 and B1

Panel A



Panel B

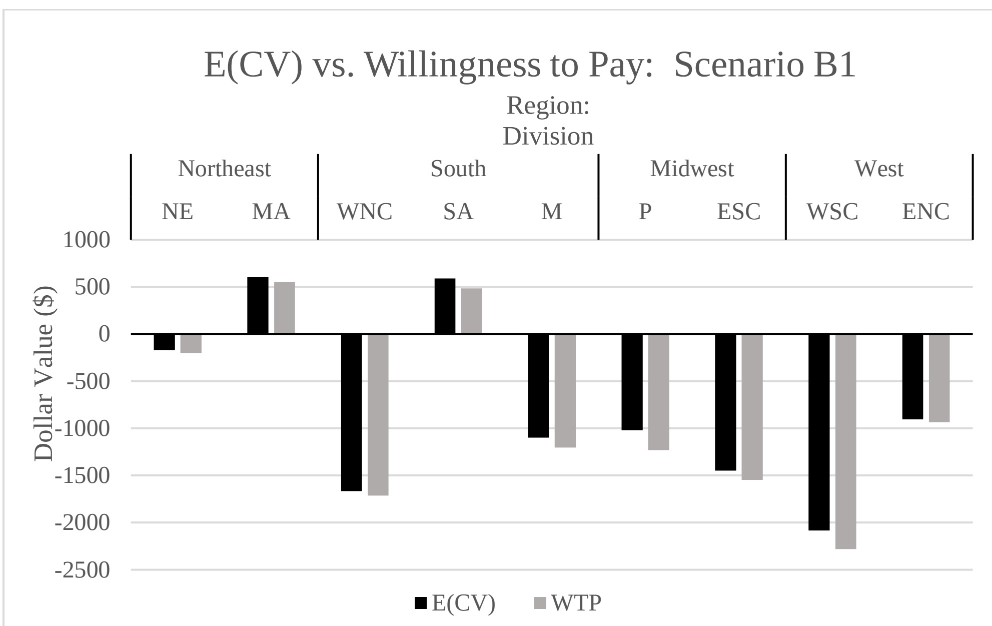


Table 2.1 Descriptive Statistics for Household Characteristics

		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 2.2 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	20.360	21.366	0.000	84.050	18.050
Summer Precipitation (inches)	284	10.966	5.057	0.440	23.300	11.932
July Relative Humidity (%)	284	66.246	10.891	22.500	78.000	70.500
Annual Sunshine (% of possible sunshine in 24 hours)	284	60.764	8.323	43.000	78.000	58.000
Avg Elevation (miles)	284	0.197	0.273	0.000	1.620	0.130
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	5.000	85.500	45.500
Mean PM2.5 (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	5.400	13,043.600	259.050
Violent Crime Rate (number of violent crimes per 1000 persons)	284	4.560	2.214	0.069	12.330	4.349
Park Area (square miles)	284	192.908	584.303	0.000	5,477.564	24.893
Transportation Score	284	50.370	29.181	0.000	100.000	50.280
Education Score	284	51.230	29.322	0.000	100.000	51.130
Arts Score	284	51.137	29.055	0.000	100.000	51.140
Healthcare Score	284	49.201	28.657	0.000	98.300	49.430
Recreation Score	284	53.342	28.386	0.000	100.000	54.245
Land Area (square miles)	284	2,277.136	3,406.116	46.688	39,377.380	1,559.118
Number of Counties	284	2.845	2.906	1.000	25.000	2.000

Table 2.3 Marginal Willingness to Pay for Climate Amenities (Base Discrete Choice Models)

Sample	Model 1 (Full) All Ages (Base Model)		Model 1 (Prime) Prime-Aged		Model 1 (>55) Over 55 Years		Model 1 (Movers) Changed MSA between 1995 and 2000	
PANEL A: 1st Stage Estimates								
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	
	(0.0731)		(0.0827)		(0.1077)		(0.0686)	
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 non-linearly, amenity variables are evaluated at population-weighted means in order to compute MWTP. Non-linear covariates are the following: population density, summer precipitation, and elevation enter in log form while distance to the coast enters the model quadratically.

Table 2.4 Marginal Willingness to Pay for Climate Amenities (Sensitivity to Moving Costs)

Sensitivity	Model 1 Base Model		Model 2 Moving Costs: Ln(Distance)		Model 3 Moving Costs: Married and Children Interactions		Model 4 Moving Costs: Omitted	
PANEL A: 1st Stage Estimates								
Variable	Coef (Std Err)		Coef (Std Err)		Coef (Std Err)		Coef (Std Err)	
Std. Dev: Avg Winter Temperature	0.0666		0.0758		0.0664		0.0022	
	(0.0020)		(0.0020)		(0.0020)		(0.0148)	
Std. Dev: Avg Summer Temperature	0.0522		0.0717		0.0525		0.0210	
	(0.0060)		(0.0049)		(0.0059)		(0.0278)	
Correlation Coefficient	-0.8332		-0.8263		-0.8295		-0.9975	
	(0.0731)		(0.0416)		(0.0726)		(0.0621)	
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	0.0278	$790	0.0248	$704	0.0232	$659
	(0.0056)	($160)	(0.0056)	($162)	(0.0056)	($159)	(0.0054)	($154)
Mean: Avg Summer Temperature	-0.0307	-$873	-0.0319	-$907	-0.0308	-$872	-0.0169	-$478
	(0.0091)	($260)	(0.0095)	($269)	(0.0091)	($259)	(0.0090)	($255)
July Humidity	-0.0269	-$764	-0.0285	-$809	-0.0268	-$758	-0.0189	-$535
	(0.0049)	($142)	(0.0050)	($145)	(0.0049)	($141)	(0.0044)	($125)
Annual Snowfall	-0.0166	-$471	-0.0165	-$468	-0.0165	-$467	-0.0038	-$109
	(0.0024)	($70)	(0.0024)	($70)	(0.0024)	($69)	(0.0023)	($66)
Ln(Summer Precipitation)	0.1408	$376	0.0953	$254	0.1426	$379	0.0922	$245
	(0.0720)	($192)	(0.0739)	($197)	(0.0720)	($192)	(0.0666)	($177)
Annual Sunshine	-0.0155	-$441	-0.0170	-$482	-0.0153	-$434	-0.0100	-$284
	(0.0057)	($162)	(0.0059)	($168)	(0.0057)	($162)	(0.0057)	($161)

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

Table 2.5 Marginal Willingness to Pay for Climate Amenities (Sensitivity to Second Stage Specifications)

	Model 1		Model 5		Model 6		Model 7		Model 8	
Sensitivity	Base Model		Omit Ln(Population Density)		Ln(land area) replaces Ln(population density)		Include number of counties		Omit Other Climate Variables	
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)	Coef (Std Err)	MWTP (Std Err)
Mean: Avg Winter Temperature	0.0249	$709	0.0263	$748	0.0255	$725	0.0287	$815	0.0435	$1,237
	(0.0056)	($160)	(0.0059)	($169)	(0.0060)	($171)	(0.0050)	($142)	(0.0047)	($139)
Mean: Avg Summer Temperature	-0.0307	-$873	-0.0299	-$849	-0.0313	-$890	-0.0298	-$848	-0.0288	-$820
	(0.0091)	($260)	(0.0100)	($285)	(0.0103)	($293)	(0.0091)	($259)	(0.0110)	($313)
July Humidity	-0.0269	-$764	-0.0247	-$702	-0.0219	-$623	-0.0246	-$700		
	(0.0049)	($142)	(0.0055)	($157)	(0.0058)	($166)	(0.0047)	($135)		
Annual Snowfall	-0.0166	-$471	-0.0152	-$434	-0.0142	-$404	-0.0134	-$381		
	(0.0024)	($70)	(0.0026)	($75)	(0.0027)	($77)	(0.0023)	($65)		
Ln(Summer Precipitation)	0.1408	$376	0.0969	$258	0.0925	$247	0.0751	$200		
	(0.0720)	($192)	(0.0769)	($205)	(0.0792)	($211)	(0.0710)	($189)		
Annual Sunshine	-0.0155	-$441	-0.0190	-$540	-0.0184	-$524	-0.0147	-$417		
	(0.0057)	($162)	(0.0059)	($168)	(0.0060)	($170)	(0.0057)	($163)		

Notes:

(1) As these sensitivities only involve changing 2nd stage variables, only estimates from stage 2 are reported.

(2) When entering the regressions non-linearly, amenity variables are evaluated at population-weighted means in order to compute MWTP. Non-linear covariates are the following: population density, summer precipitation, and elevation enter in log form while distance to the coast enters the model quadratically.

Table 2.6 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 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 2.7 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 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 2.8 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 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

Chapter 3: Do Discrete Choice and Hedonic Models Yield Different Results? A Comparison in the Context of Urban Amenities

3.1 Introduction

Estimates of the value of urban amenities have typically followed one of two approaches: they have either used hedonic models of wages and housing prices to value marginal amenity changes (Roback, 1982; Blomquist, Berger and Hoehn, 1988; Albouy et al., 2016) or they have used discrete models of location choice (Cragg and Kahn, 1997; Bayer, Keohane and Timmins, 2009). The former approach infers marginal willingness to pay by estimating hedonic price functions for wages and housing costs as a function of location-specific attributes; the latter, by estimating the probability that consumers choose a location in which to live as a function of wages, housing prices and location-specific attributes.

Cragg and Kahn (1997), Bayer, Keohane and Timmins (2009), and Sinha and Cropper (2013) note that the discrete choice approach typically produces estimates of amenity values that are much larger than estimates implied by the continuous hedonic approach. In a discrete choice model where households choose in which U.S. state to reside, Cragg and Kahn (1997) find the MWTP for July and February temperature exceeds the marginal prices implied by hedonic price functions. Bayer, Keohane and Timmins

(2009) estimate marginal willingness to pay (MWTP) to reduce air pollution using a discrete choice approach and find these figures are three times greater than values capitalized into per capita incomes and property values. Sinha and Cropper's (2013) discrete choice model estimates higher damages associated with predicted changes to climate in U.S. cities than comparable estimates from Albouy et al.'s (2016) hedonic model.

While previous research has noted the two approaches to amenity valuation may yield different MWTP estimates, with the exception of Klaiber and Phaneuf (2009), few careful comparisons of the two methodologies exists in the current literature.[36] Furthermore, there has been no systematic attempt to investigate or characterize the root cause of these differences. Given the important role of amenity valuation to comprehensive policy cost-benefit analysis, this paper provides a relevant and critical step towards obtaining accurate estimates of the demand for local amenities.

In this paper, I examine differences between the continuous hedonic and discrete choice approaches in the context of valuing climate amenities. Specifically, I use the 2000 census Public Use Microdata Sample (PUMS) to estimate hedonic and discrete choice models that value winter and summer temperature. My hedonic models regress the weighted sum of wage and housing price indices on mean winter and summer temperature,

[36] Klaiber and Phaneuf (2009) estimate the MWTP for open space using both a discrete choice random utility model and the traditional hedonic approach. They too find that the MWTP implied by the discrete choice model is generally greater than MWTP estimates from the hedonic model. Their study examines residential housing decisions across neighborhoods within the Minneapolis-St. Paul metropolitan area, whereas my analysis focuses on the choice over metropolitan areas across the United States and implicitly incorporates both labor and housing market decisions.

other climate amenities, and various city characteristics using metropolitan statistical areas (MSAs) as the geographic unit. Wage and housing price indices are estimated following the methodology of Albouy (2012), assuming national labor and housing markets: I construct a weighted sum of wage and housing price indices for each MSA using the same weights as in Albouy (2012) and, alternately, using a traditional set of weights in line with previous hedonic literature (Roback, 1982; Blomquist, Berger and Hoehn, 1988). I allow the marginal price of winter and summer temperature to vary by city using local linear regressions (Bajari and Benkard, 2005; Bajari and Kahn, 2005) and find substantial variation across MSAs.

In my discrete location choice model, consumers choose among MSAs based on predicted wages and housing costs, moving costs from birthplace, and the same set of location-specific amenities as are used in the hedonic models. These discrete choice models are estimated for a sample of all households in the 2000 PUMS and for samples of households with prime-aged heads (25-55 years old), older heads (over 55 years old), and movers (households who have moved MSAs between 1995 and 2000). I estimate a random parameter logit model to capture heterogeneity in preferences for winter and summer temperature. The distributions of MWTP for winter and summer temperature differ significantly by location. Households with higher MWTP for winter temperature tend to locate in cities with warmer winters. I find, however, that preferences for summer and winter temperature are negatively correlated. On average, households with preferences for warmer winters also prefer milder summers.

How do estimates of MWTP for winter and summer temperature from the discrete choice model compare with estimates based on the hedonic model? The answer depends on the weights placed on wage and housing price indices in the hedonic approach and on the households whose preferences are being measured. Mean MWTP estimates from the hedonic and discrete choice approaches (not conditional on location) are closest when I compare the hedonic estimates to the preferences of prime-aged households estimated using the discrete choice model. When the discrete choice model is estimated using prime-aged households the mean MWTP for a one degree increase in winter temperature is $518, while it is $627 for a one degree decrease in summer temperature. When traditional weights are used, the hedonic approach yields mean MWTP for winter and summer temperature of approximately $210 and $230, respectively. The comparable numbers when Albouy weights are used is about $100 and $350. For other samples of households (older heads, movers) the results further diverge.

The pattern of MWTP conditional on household location differs, as well, between the two approaches. The hedonic estimates do not show the positive correlation between winter temperature and MWTP for winter temperature that is indicated by the discrete choice model. Patterns for summer temperature preferences by MSA also differ, but less systematically.

Why should estimates using the two approaches differ from each other? First, the hedonic and discrete choice models differ in their underlying assumptions about market integration and consumer mobility. The hedonic model assumes national labor and housing markets, while discrete choice models, beginning with Cragg and Kahn (1997), do not. The hedonic approach also assumes perfect mobility, whereas moving costs are more easily incorporated in discrete models of location choice. Bayer, Keohane, and Timmins (2009) argue that if psychological (or informational) moving costs prevent people from moving to what is their most preferred location, the gradients of the hedonic wage and price functions may understate consumers' true marginal amenity values. They attribute the differences they observe between their discrete choice and hedonic estimates to this concept but do not test this hypothesis directly. Second, the two models use fundamentally different econometric approaches to capture heterogeneity in tastes. Third, the hedonic approach uses price functions to infer the marginal value placed on amenities, whereas the discrete choice approach, which estimates the probability that consumers purchase commodity bundles, directly accounts for both price variation and quantities purchased.

The question of mobility assumptions can be tested directly in the discrete choice model. When I estimate the discrete choice model without moving costs, the value of cooler summers falls significantly, and the positive correlation between higher MWTP for warmer winters and the temperature of the chosen city is substantially reduced. However, mean MWTP for warmer winters is mostly unaffected, and even the reduced value placed on cooler summers is not enough to bring results in line with the hedonic estimates. Thus, moving costs do not completely explain differences in mean preferences or taste sorting patterns implied by the two sets of models.

More telling is the examination of a simple share model, which emphasizes the important role populations (i.e., quantities purchased) play in location sorting models. To elaborate, first note that the discrete choice model seeks to predict the proportion of the population residing in each location. When this model is simplified to include only variables that differ across MSAs, the discrete choice model reduces to a simple share model where MSA population shares are regressed on city level prices and amenities. This highlights how differently hedonic models treat population shares: specifically, hedonic models regress city level prices on local amenities and don't explicitly account for population shares anywhere. In this paper, I estimate a simple share model and find marginal amenity values that generally agree with those from the discrete choice model. Because the share model avoids discrepancies related to mobility costs and how labor and housing markets are defined, these results suggest that how population shares are incorporated in these models may have important implications for the different results produced by the hedonic and discrete choice approaches to amenity valuation.

The paper is organized as follows. Section 3.2 describes the hedonic model of amenity valuation as originally developed by Roback (1982) and modified by Albouy (2012). I present the discrete location choice model in Section 3.3 and describe the data in Section 3.4. Section 3.5 presents the results of both modeling approaches and provides comparison. This includes estimates of mean MWTP for winter and summer temperature and the implications of both models for taste-based locational sorting. Section 3.6 concludes.

3.2 Hedonic Models of Amenity Valuation

The hedonic approach to valuing location-specific amenities dates from Jennifer Roback's (1982) seminal article "Wages, Rents and the Quality of Life," which built on the model of product differentiation and implicit prices introduced by Rosen (1974). Roback posited that, in a world of perfectly mobile individuals, wages and land prices would adjust to equalize utility in all locations. Differentiation of her equilibrium condition yields an expression for the MWTP for locational amenities, given by equation (1) and

$$\frac{MWTP_a}{W} \equiv \frac{V_a}{V_W}\frac{1}{W} = s_H \frac{d \log r}{da} - \frac{d \log W}{da} \tag{1}$$

where a is a local amenity, W is income, V is the consumer's indirect utility, s_H is the share of income spent on housing, and r is the rental price of housing.[37]

The literature following Roback (1982) has inferred MWTP for local amenities by estimating hedonic wage and property value equations. For example, Blomquist et al. (1988) use census data on individuals residing in different counties to estimate hourly wage (w) and housing expenditure (P) equations like those described in equations (2) and (3) below. The hourly wage earned by worker *m* in location *j* is denoted by w_{mj}, $\boldsymbol{X}_{mj}^{w}$ is a

$$w_{mj} = \gamma^0 + \boldsymbol{X}_{mj}^{w}\boldsymbol{\Gamma}^{X,0} + \boldsymbol{A}_j \Gamma^{A,0} + \nu_{mj}^0 \tag{2}$$

$$P_{ij} = \delta^0 + \boldsymbol{X}_{ij}^{P}\boldsymbol{\Delta}^{X,0} + \boldsymbol{A}_j \boldsymbol{\Delta}^{A,0} + \omega_{mj}^0 \tag{3}$$

vector measuring the education, experience, demographic characteristics, and industry and occupation of worker *m*, P_{ij} is housing expenditure by household *i* in location *j*, $\boldsymbol{X}_{ij}^{P}$ is a vector of dwelling characteristics, and $\boldsymbol{A_j}$ is a vector of attributes characterizing location *j*. In using equations (2) and (3) to infer the value of location-specific amenities, Blomquist et al. (1988) multiply the hourly wage differential by the average number of workers per household, the average number of hours worked per week, and the number of weeks

[37] Roback's model deals with land, not housing. In the subsequent literature, *r* is treated as the rental rate on housing.

worked per year and subtract this from the monthly housing differential multiplied by 12. Implicitly, wage differentials across counties are weighted approximately 3.6 times as much as housing price differentials.

3.2.1 The Albouy Hedonic Model

Albouy (2012) makes significant modifications to Roback's approach. First, he argues that the weight placed on the cost of non-traded goods is too low relative to wage income in the Roback model. Non-traded goods, as Albouy points out, include more than housing, and hence occupy a larger fraction of the household's budget. At the same time, it is after-tax income that matters; this further raises the weight placed on non-traded goods (proxied by housing) relative to wages. Second, Albouy suggests an alternate two-stage approach to estimating the value of local amenities: he first estimates wage and housing price indices for each geographic area and combines them into a quality of life (QOL) index using his adjusted weights; next, his QOL index is regressed on location-specific amenities to estimate marginal amenity values.

To see how this yields MWTP for an amenity, consider the utility maximization problem faced by households where indirect utility depends on income (both wage and non-wage), the prices of non-traded goods, taxes, and the quality of life (Q) in each location. Assume that Q is some function of location-specific amenities. Then by applying Roback's equilibrium condition, differentiating, and making various substitutions and rearrangements, the MWTP for Q as a percentage of average total income ($\bar{m}$) can be shown to be equal to the QOL index described by equation (4), and where s_H is the share

$$QOL_j \equiv \frac{MWTP_Q}{\bar{m}} = (s_H + \gamma s_O)\frac{dp_{j,H}}{\bar{p}} - (1-\tau)s_w\frac{dw_j}{\bar{w}} \tag{4}$$

of income spent on housing, s_O is the share of income spent on other non-traded goods, s_w is the share of income that comes from wages, and τ is the marginal tax rate. The expressions $dp_{j,H}/\bar{p}$ and $dw_j/\bar{w}$ represent the ceteris paribus impact of city *j* on housing prices and wages in city *j*. Finally, γ is the ratio of the housing price to the price of non-traded goods.[38] The QOL index can be viewed as the consumption a household is willing to forgo to live in city *j* as compared to living in the average city – it measures how high cost of living is relative to wages in city *j* as compared to the average city. Recalling that Q is a function of location-specific attributes, differentiation of QOL_j with respect to each amenity will yield the MWTP for that amenity. To see how this is related to Roback's MWTP formulation, differentiate equation (4) with respect to amenity *a* as follows and assume that housing is the only local non-traded good ($s_O = 0$), that all income comes from

$$\frac{MWTP_a}{\bar{m}} \equiv \frac{\partial QOL_j}{\partial a} = (s_H + \gamma s_O)\frac{d\ln(p_{j,H})}{da} - (1-\tau)s_w\frac{d\ln(w_j)}{da} \tag{5}$$

wages ($s_w = 1$), and that there are no income taxes ($\tau = 0$). Under these assumptions, equation (5) just reduces to Roback's MWTP expression in equation (1).

Albouy's approach implicitly estimates equations (2) and (3) in two stages. Including location-specific fixed effects in the hourly wage and housing rent equations in

[38] Albouy uses ACCRA cost-of-living index data to estimate γ.

the first stage yields wage and housing price indices, λ_j^w and λ_j^P.[39,40] These indices are then used to construct the QOL index using equation (4), where λ_j^w and λ_j^P from equations (2′)

$$\ln w_{mj} = \boldsymbol{X}_{mj}^{w} \boldsymbol{\Gamma}^{X,1} + \lambda_j^w + \nu_{mj}^1 \qquad (2')$$

$$\ln P_{ij} = \boldsymbol{X}_{ij}^{P} \boldsymbol{\Delta}^{X,1} + \lambda_j^P + \omega_{mj}^1 \qquad (3')$$

and (3′) replace $dp_{j,H}/\bar{p}$ and $dw_j/\bar{w}$. Using the weights computed by Albouy (2012) yields the QOL index in equation (6), which is then regressed on location-specific amenities.

$$QOL_j \equiv 0.33\lambda_j^P - 0.51\lambda_j^w = \boldsymbol{A_j}\boldsymbol{\theta} + \xi_j \qquad (6)$$

Albouy and co-authors (2016) apply this approach to PUMA-level data from the 2000 census to estimate the value of changes in temperature in the United States. They use flexible functional forms to relate binned temperature data to the QOL index while also controlling for other amenities. To allow for taste sorting, they apply a variant of Bajari and Benkard's (2005) local linear regression to estimate separate temperature coefficients for each PUMA.

To motivate taste sorting in the hedonic model, consider the case where households have heterogeneous preferences over a local amenity k. Households sort across locations

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[39] This is similar to the approach followed by Bieri et al. (2013), who argue that estimation in two stages ensures that the implicit price of the amenity is not conflated with the implicit price of unobserved worker and housing attributes.

[40] Coefficients for the individual and dwelling characteristics controlled for in equations (2′) and (3′) are reported in the first columns of Appendix Table A.1 and Table A.2.

according to these heterogeneous preferences, and locational equilibrium implies that each household's MWTP for amenity *k* is equal to the implicit price of amenity *k*, which is just the slope of the hedonic price function with respect to *k*. If the true hedonic price function is non-linear, the slope will vary with the level of amenity *k*, which reflects the fact that households who live in different locations have different underlying MWTPs. As Roback (1982) pointed out, MWTP estimates from the hedonic model (as traditionally estimated) will be an average of the true MWTP across the different households. Estimating a local linear model like that in Bajari and Benkard (2005) provides a way of recovering the gradient of the hedonic price function for each level of amenity *k*. This yields location-specific MWTP for amenity *k*, which reflects a kind of mean MWTP over the households that have sorted into that location.

3.2.2 Estimation of the Hedonic Models

I estimate two sets of hedonic models – one using traditional weights on the wage and housing price indices generated by equations (2') and (3') (i.e., the weights from equation (1)) and the other applying the weights proposed by Albouy (2012) to the same wage and housing price indices (i.e., the adjusted weights in equation (6)). The national wage and property value equations are estimated using the same set of explanatory variables that are used for predicting wages and housing expenditures (for each household in each alternative MSA) in the discrete choice model.[41] These equations also use the same

[41] See the first column of Appendix Table A.1 and Table A.2 for estimation results from the national wage and housing expenditure regressions.

samples of workers and housing units and are described in more detail in the following section.

I regress each set of QOL indices (traditional- and Albouy-weighted) on the same set of amenity variables used in estimating the discrete choice model. The estimates of equations (2') and (3') yield price indices for 284 MSAs; hence, I have 284 observations for the second stage QOL regressions.[42] The results of the second stage regressions yield mean MWTP for local amenities according to the hedonic model.

To allow the coefficients on temperature variables to vary by MSA, I use a modified local linear regression in the spirit of Bajari and Benkard (2005) and Bajari and Kahn (2005). Specifically, I regress the QOL index on all amenities except for winter and summer temperature and then use the residuals ($\hat{e}_j$) from this equation in a kernel-weighted least squares regression for each location *j*. Locations with similar temperature profiles to location *j* are weighted more heavily, which follows intuitively from the idea of taste-sorting on temperature: households sort geographically according to heterogeneous temperature preferences, with households residing in similar climates having likewise similar MWTP. This local linear approach allows me to recover a different hedonic price function gradient for each MSA (i.e., each possible bundle of winter and summer temperatures).

[42] I estimate these models using OLS and compute robust standard errors. Albouy et al. (2016) indicate that they weight observations by population in their QOL models. I have also estimated Albouy QOL models using population weights. The results are not significantly different from the unweighted results reported here.

This approach is described in equation (7) below, which is estimated for each MSA and where $\hat{\boldsymbol{e}} = [\hat{e}_j]$, $\boldsymbol{T} = [[wt_j]\ [st_j]]$, and $\boldsymbol{W} = [diag(K_h(\boldsymbol{T}_j - \boldsymbol{T}_{j^*}))]$. Kernel weights

$$\boldsymbol{\Phi}_{j^*} = \underset{\boldsymbol{\Phi}}{\operatorname{argmin}}(\hat{\boldsymbol{e}} - \boldsymbol{T\Phi})'\boldsymbol{W}(\hat{\boldsymbol{e}} - \boldsymbol{T\Phi}) \tag{7}$$

are described by $K(Z) = \prod_{z=wt,st} N\big((z_j - z_{j^*})/\hat{\sigma}_z\big)$ with $K_h(Z) = K(Z/h)/h$ and where $N(\,)$ denotes the normal distribution, h is bandwidth, and $\hat{\sigma}_z$ is the sample standard deviation of characteristic z. This approach yields coefficients for each MSA for summer and winter temperature, where the notation j^* in equation (7) emphasizes this.

3.3 A Discrete Choice Approach to Valuing Climate Amenities

The discrete choice approach to amenity valuation assumes that households choose among geographic locations based on the utility they receive from each location, where that utility depends on wages, housing costs and location-specific amenities. Variation in wages, housing costs, and amenities across locations permits identification of the parameters of the household’s indirect utility function.

One advantage of the discrete choice approach is that it allows the researcher to more easily incorporate market frictions, including the psychological and informational costs of moving. 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 MWTP for an amenity (equation (1)). Bayer, Keohane and Timmins (2009) demonstrate that this equality fails to hold in the presence of moving costs. In their empirical model they incorporate the psychological and informational costs of leaving one's birthplace into an equilibrium model of household location choice. Barriers to mobility also 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 (Cragg and Kahn, 1997).

3.3.1 The Discrete Choice Model

My discrete choice model builds on the work of Bayer, Keohane and Timmins (2009) and Cragg and Kahn (1997). I model household location for the year 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, I assume that the utility that household *i* receives from city *j* is given by equation (8), where

$$U_{ij} = \alpha\left(Y_{ij} - P_{ij}\right) + MC_{ij} + WT_j\beta_i^{WT} + ST_j\beta_i^{ST} + \boldsymbol{A}_j'\Gamma \tag{8}$$

Y_{ij} is household i's income and P_{ij} its housing expenditure in city j. I refer to this after-housing consumption $\left(Y_{ij} - P_{ij}\right)$ as the "Hicksian bundle."[43] MC_{ij} represents the costs – psychological and other – of moving from the head of household's birthplace to city j. WT_j and ST_j are mean winter and summer temperatures in city *j*, and $\boldsymbol{A}_j'$ is a vector of all the location-specific amenities of my model, excluding winter and summer temperature.

[43] In the specifications presented in this paper, I allow income to enter the utility function linearly which facilitates computation of MWTP for temperature changes. Estimates of mean MWTP for climate amenities are similar when the Hicksian bundle enters the utility function in log and quadratic forms.

Household income, Y_{ij}, is the sum of the wages of all workers in the household, W_{ij} , plus any non-wage income which is assumed not to vary by residential location. Housing costs, P_{ij}, are the annual expenditures on housing, including mortgage payments or rent, as well as utilities and taxes. Because household income and housing expenditures are observed only at the chosen location, they are predicted using MSA-specific hedonic wage and housing price equations. These are described in more detail below.

Moving costs capture the psychological, search, and out-of-pocket costs of leaving a household's place of origin. Seventy-four percent of households in my sample (see Table 3.1, full sample) live in the census region in which the head was born; 67% live in same the 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 temperature.

Following Bayer et al. (2009), I model 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,

$$MC_{ij} = \pi_0 d_{ij}^{state} + \pi_1 d_{ij}^{division} + \pi_2 d_{ij}^{region} \tag{9}$$

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 the head of household *i* was born, $d_{ij}^{division} = 1$ if location *j* is outside of the census division in which the household head was born, and $d_{ij}^{region} = 1$ if location j lies outside of the census region in which the household head was born.[44]

The i subscripts on the coefficients for winter and summer temperature denote the fact that this model allows for heterogeneity in taste for seasonal temperature across households, though in principle, this model could allow all utility parameters to vary across households.[45] I assume that $(\beta^{WT}, \beta^{ST}) \sim N(\boldsymbol{\mu}, \boldsymbol{\Sigma})$, where $\boldsymbol{\Sigma}$ may have non-diagonal elements, allowing for correlation in the preferences for seasonal temperatures.

MWTP in this model is given by the marginal rate of substitution between income and any given amenity. Thus, MWTP is a function of the parameters of utility such that the MWTP for a one degree increase in winter temperature, for example, is given by the ratio of the income and winter temperature coefficients:

$$MWTP_{WT} \equiv \frac{\partial V / \partial WT}{\partial V / \partial Y} = \frac{\beta^{WT}}{\alpha} \tag{10}$$

3.3.2 Estimation of the Discrete Choice Model

Estimating the location choice model requires information on the wages that a household would earn in each MSA as well as the housing costs incurred. Because wages

[44] Other specifications for moving costs have been analyzed with little change to estimation results. See Chapter 2.

[45] I have relaxed this assumption in previous work and find the temperature parameters to be robust to several sensitivity specifications where I allow other arguments of household utility (Hicksian bundle, moving costs, humidity, and snowfall) to be random in addition to winter and summer temperature. See Chapter 2 and Appendix C for details.

and housing expenditures are observed only in the household's chosen location, these must be estimated for all other possible locations.

In order to predict W_{ij} for all alternate MSAs, I estimate a hedonic wage equation for each MSA. The hedonic wage equation for MSA j, given by equation (11) 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, industry, and occupation, among

$$\ln w_{mj} = \gamma_j^2 + \boldsymbol{X}_{mj}^{w}\boldsymbol{\Gamma}^{X,2} + \nu_{mj}^2 \quad \forall\, j = 1, \dots, J \tag{11}$$

others – of worker *m*. Equation (11) is estimated using data on full-time workers in the PUMS.[46] The coefficients of (11) are used to predict the annual earnings of each worker in any household included in the sample used to estimate the discrete choice model. A key assumption here is that individuals work the same number of hours and weeks in all locations. Summing earnings over all individuals in each household, I obtain predicted household wages ($\widehat{W}_{ij}$) for household *i* in location j.[47]

In a similar fashion, the cost of housing in each location is estimated based on hedonic property value equations for each MSA according to equation (12), where P_{ij} is

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[46] 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 same data are used to estimate Equation (2′).

[47] Household income is composed of the predicted household wages that vary across MSAs as well as an MSA-independent non-wage income. I model household income gross of income taxes, which makes my MWTP results more comparable with the hedonic MWTP estimates: while Albouy's hedonic model does incorporate an income tax when forming the quality-of-life indices, amenity value estimates represent MWTP as a percentage of gross income, and the hedonic coefficient estimates are multiplied by gross income to obtain dollar amounts.

the annual housing expenditure for household 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

$$\ln P_{ij} = \delta_j^2 + \boldsymbol{X}_{ij}^{P}\boldsymbol{\Delta}^{X,2} + \omega_{mj}^2 \quad \forall\, j = 1, \dots, J \tag{12}$$

rented, as well as dwelling characteristics like age of structure and number of rooms. Utility costs are added to both the costs of owning a home and to rents because heating and cooling requirements vary with climate, and I wish to separate these costs from climate amenities. Equation (12) is estimated separately for each of the MSAs in my dataset. I predict housing expenditures for household i in city j assuming that the household purchases the same bundle of housing characteristics in city j as it purchases in its chosen city.[48]

The results of estimating the hedonic wage and housing market equations for each city separately are summarized in the last two columns of Appendix Table A.1 and Table A.2. I 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.

[48] This is clearly a strong assumption. In previous work, I tested its validity by examining the mean value of key housing characteristics (number of bedrooms and number of rooms) and their standard deviation across MSAs, for different household groups, characterized by income group and household size. The coefficient of variation across these attributes is small suggesting households of similar size and income tend to live in dwellings of similar characteristics. Furthermore, I have performed a sensitivity analysis where a housing price index enters the second stage as in Bayer, Keohane, and Timmins, 2009, preempting the need to predict housing costs, and find results similar to those reported below. See Chapter 2 for details.

Given predicted wages and housing expenditures for each household in all possible locations, estimation of the discrete location choice model follows in two stages. The first stage models indirect utility, portrayed in equation (13) below, as a function of all components of utility that vary by household – the Hicksian bundle, moving costs, and unobserved heterogeneity in the preferences for winter and summer temperature – as well as an MSA fixed effect (δ_j), which captures the mean effect of all the attributes that vary

$$V_{ij} = \delta_j + \alpha\left(\hat{Y}_{ij} - \hat{P}_{ij}\right) + MC_{ij} + \beta_i^{WT} WT_j + \beta_i^{ST} ST_j + \varepsilon_{ij} \qquad (13)$$

by location.[49] In this first stage, I constrain the mean vector of the distribution of winter and summer temperature coefficients to be zero according to $(\beta^{WT}, \beta^{ST}) \sim N(\mathbf{0}, \boldsymbol{\Sigma})$ so that only the components of $\boldsymbol{\Sigma}$ are estimated in the first stage. The mean vector $\boldsymbol{\mu}$ is contained in the fixed effects component of utility, δ_j, and will be estimated in the second stage along with the parameters for all other location-specific attributes.

The household's utility function is known to the researcher only up to an error term ε_{ij}; i.e., $V_{ij} = U_{ij} + \varepsilon_{ij}$. 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

[49] The MSA fixed effects, δ_j, will capture cost of living differences across locations that are common among households, whereas Y_{ij} and P_{ij} account for household-specific price differences across locations.

logit formulation in equation (14). The parameters of equation (14) are estimated via

$$P(i\ selects\ j) \quad = \int_{-\infty}^{\infty} \frac{exp(V_{ij}(\delta_j, \alpha, \boldsymbol{\beta}_i, \boldsymbol{\pi}))}{\sum_k exp(V_{ik}(\delta_k, \alpha, \boldsymbol{\beta}_i, \boldsymbol{\pi}))} f(\boldsymbol{\beta}|\boldsymbol{\mu}, \boldsymbol{\Sigma}) d\beta \qquad (14)$$

simulated maximum likelihood, using a choice set equal to the household's chosen alternative and a sample of 59 alternatives from the full set of 284 MSAs.[50]

Equation (15) describes the second stage of my model where the estimated city-specific fixed effects are regressed on the vector of amenities that do not vary across

$$\hat{\delta}_j = \mu^{WT} WT_j + \mu^{ST} ST_j + \boldsymbol{A}_j' \Gamma + u_{\boldsymbol{j}} \qquad (15)$$

households. The results of this second stage estimation yield the mean utility parameters associated with winter and summer temperature, as well as the fixed (non-random) utility parameters for all other location-specific attributes.

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[50] 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. Guevara and Ben-Akiva (2013) prove that the sampling of alternatives in the mixed logit model produces consistent parameter estimates as the number of alternatives sampled approaches the universal choice set. Given the computational trade-offs I face between 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, I must use a sub-sample of the universal choice set. Experiments with the size of the sampled choice set indicated that increasing the size of the choice set beyond 60 MSAs did not significantly alter parameter estimates. This is supported by simulation result from Nerella and Bhat (2004), which finds small sample bias when 50 or more alternatives are sampled from a choice set of 200. While beyond the scope of this paper, another option is to pursue a latent class model as suggested in von Haefen and Domanski (2016).

3.3.3 MWTP Conditional on Location

In order to examine how taste heterogeneity affects where people choose to locate, I compute household-level temperature parameters. By conditioning on where a household has chosen to locate, it is possible to pin down where their particular preferences fit into the larger population distribution. I follow a procedure by Revelt and Train (1999) which uses Bayes' Rule to show that the conditional distribution of the temperature parameters (i.e., conditional on chosen location, household attributes, and the overall distribution of temperature parameters) is given by equation (16). As shown in equation (17), taking the

$$h(\beta|choice_i, X_i, \boldsymbol{\mu}, \boldsymbol{\Sigma}) = \frac{\Pr(choice_i|X_i, \beta)\, f(\beta|\boldsymbol{\mu}, \boldsymbol{\Sigma})}{\Pr(choice_i|X_i, \boldsymbol{\mu}, \boldsymbol{\Sigma})} \quad (16)$$

expectation of this conditional distribution reveals an expression for household-level parameters, or the mean taste parameters, $\boldsymbol{\mu_i}$, of households of type X_i. A similar method

$$\mu_i = E(\beta_i|choice_i, X_i, \boldsymbol{\mu}, \boldsymbol{\Sigma}) = \int \beta_i\, h(\beta|choice_i, X_i, \boldsymbol{\mu}, \boldsymbol{\Sigma}) d\beta \quad (17)$$

can be used to derive the conditional variance-covariance matrix $\boldsymbol{\Sigma_i}$. These household level parameters are estimated via simulation. I then average the conditional mean coefficients over all households living in each MSA. The ratio of these MSA-level coefficients over the coefficient on the Hicksian bundle yields mean MWTP for temperature in each MSA. I plot the MSA-level MWTPs against MSA average temperatures to examine patterns of taste sorting.

3.4 Data

The data used to estimate both the discrete choice and hedonic models come from the 5% PUMS of the 2000 census, as well as other publicly available data sources containing information on location-specific attributes. The census PUMS data provides information at the household-level (for example, property values and rent payments, migration information, and physical dwelling characteristics) as well as individual-level data for all household members, such as age, sex, race, education, and earnings.

3.4.1 Households Used to Estimate the Discrete Choice Model

The 2000 PUMS contains information on more than 5.6 million households. In estimating the discrete choice model, I focus on households residing in one of the 284 MSAs for which I have complete amenity data. These MSAs contained 80% of the total U.S. population in 2000. In order to be included in my sample, a household must be headed by a person 16 years of age or older who was born in the continental US. I exclude households whose heads are in the military, or who are in certain occupations (e.g., logging, mining) which would restrict locational choices. I also eliminate households whose members are self-employed due to difficulty in predicting the wages of the self-employed, and I drop households with negative Hicksian bundles at their chosen locations.[51] This leaves over 2 million households. A 2.5% sample of these households yields the 54,008

[51] These households may have substantial accumulated wealth (e.g., in real property) which I cannot measure.

households described in Table 2.1.[52] I also examine a sample of "movers," or households who changed MSAs between 1995 and 2000. As there are fewer of these households, I obtain all the movers from a 10% sample of all the PUMS households that fit my criteria yielding almost 23,000 households.

I have estimated the discrete choice model for the full sample of households and also for the three sub-samples described in Table 2.1: households with prime-aged heads (i.e., heads between 25 and 55), households with heads over age 55, and movers (households with heads who have moved MSAs between 1995 and 2000). The results presented in this paper focus on households with prime-aged heads. As Table 2.1 indicates, 98% of these households have some labor income, and, on average, 93% of the income of these households comes from wages. The hedonic approach, which uses wage and housing cost differentials to value amenities, is most appropriately applied to prime-aged households given their strong labor force attachment.[53] My results also suggest that preferences for winter and summer temperature differ significantly between prime-aged households and households with older heads; hence, focusing on a single demographic group makes for a cleaner comparison with the hedonic approach. Furthermore, the sample of prime-aged households is closely aligned to the sample used by Albouy (2012) and Albouy et. al. (2016) in their hedonic computations.

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[52] Computational difficulties lead me to use such a small sample of households. However, I have estimated the mixed logit model on larger samples and find the results to be stable.

[53] Hedonic wage equations in Albouy et al. (2016) are based on prime-aged workers.

3.4.2 Households Used to Estimate the Hedonic Model

The first stage of the hedonic model involves estimating MSA fixed effects from wage and housing expenditure regressions based on individual and household-level data from the 2000 census 5% PUMS. Wage regressions are estimated with individuals working full-time (30-60 hours per week, at least 40 weeks per year), and excludes those who are self-employed or in farming, fishing, forestry, military, or mining industries. This yields just under 3 million individuals for the wage regressions. Housing expenditure regressions are estimated using household-level data and exclude households residing on farms or in mobile homes or boats. About 3.3 million households are included in the property value regressions.

3.4.3 Location-Specific Attributes

I control for a variety of location-specific attributes in my models. In presenting results, I focus on variables related to climate, which feature more variation across MSAs than within. The climate variables that I control for are mean winter (December – February) and mean summer (June – August) temperature, July humidity, annual snowfall, mean summer precipitation, and annual sunshine. All variables are climate normals, the arithmetic mean computed for a 30-year period, sourced from the NOAA.[54] I refer the reader to Section 2.3.2 of Chapter 2 for a more complete description of the climate variables used in this analysis. Descriptive statistics are presented in Table 2.2.

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

Table 2.2 also summarizes the non-climate amenities included in the second stage regressions. In an effort to mitigate omitted variable bias, I control for amenities that may be correlated with climate, such as elevation, visibility, and measures of parks and recreation opportunities. I also control for population density, hoping to capture amenities associated with bigger cities that may not be adequately captured by other variables. Other (dis)amenities I control for include air pollution (U.S. EPA measure for fine particulate matter) and an index of violent crime from the FBI's Uniform Crime Reporting Program. Also included are several 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. Section 2.3.3 of Chapter 2 contains a more comprehensive discussion of these non-climate variables.

3.5 Estimation Results

In the spirit of Cragg and Kahn (1997) and Bayer, Keohane and Timmins (2009) I compare estimates of mean MWTP from the discrete choice and hedonic models to see whether the discrete choice approach indeed yields larger estimates of amenity values.[55] I am, however, also interested in taste sorting. From the perspective of valuing climate, it matters how MWTP for temperature changes varies geographically – are households living

[55] Both the discrete choice and hedonic models estimated in this paper are static models, which assumes that households are not forward looking and that they re-optimize their location decisions every period. Consequently, MWTP should be interpreted as annual values. See Bayer, McMillan, Murphy, and Timmins (2016) and Bishop and Murphy (2011) for examples of dynamic location choice models emerging in the discrete choice and hedonic literatures.

in areas where temperatures are likely to increase under future climate scenarios willing to pay more (or less) than the mean for warmer winters or cooler summers? I approach this by measuring MWTP for temperature changes conditional a household's current location.

3.5.1 Discrete Choice Results

As noted above, I estimate discrete location choice models for various population groups – households headed by persons between 25 and 55 (prime-aged households), households whose heads are over 55, households headed by persons 16 years of age and older (full sample), and movers (households who have moved MSAs between 1995 and 2000). In comparing the discrete choice and continuous hedonic approaches, I focus on prime-aged households because of their strong labor-force attachment (see Table 2.1). It is, however, important to note that prime-aged households have different preferences for climate amenities than households headed by persons over age 55 and different preferences from the full sample of households. I am also interested in comparing the sample of movers with the hedonic results. Intrinsically, hedonic models capture the preferences of the marginal consumer, so to the extent that movers may better embody the set of marginal households, it is useful to see if their preferences better align with those implied by hedonic estimates.

Table 3.1 describes the results of my base model for four samples: all households, prime-aged households, households with heads older than 55, and movers. The base model is a mixed logit model that allows the coefficients on winter and summer temperature to be jointly normally distributed and controls for the first 18 attributes in Table 2.2, as well as the Hicksian bundle and moving costs.[56] Amenity coefficients have been converted to MWTP by dividing by the coefficient on the Hicksian bundle. For winter and summer temperature, I report the mean and standard deviation of the distribution of MWTP, as well as the correlation coefficient between the winter and summer temperature coefficients.[57] Standard errors are reported for all MWTP estimates.[58]

The most striking result in Table 3.1 is that the mean MWTP for winter and summer temperature differs significantly across samples. While all groups, on average, view higher winter temperature as an amenity and higher summer temperature as a disamenity, the magnitudes of MWTP are much greater for older households than for prime aged households. Mean MWTP for winter temperature is about twice as high for older households as for prime-aged households ($1,035 v. $518). Similarly, older households are, on average, willing to pay much more to decrease summer temperature than prime-aged households ($1,424 v. $627). This suggests the importance of considering all households when evaluating climate impacts for policy purposes.

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[56] The second stage regressions for both the discrete choice and hedonic models use estimated dependent variables, which introduces heteroskedasticity into the second stage error. My base results are reported with robust standard errors, which Lewis and Linzer (2005) suggest may work well compared with the standard weighted least squares (WLS) approach, which likely underestimates standard errors. As a sensitivity, I present discrete choice and hedonic second stage results using weighted least squares, as well as two feasible generalized least squares (FGLS) approaches following Lewis and Linzer (2005), which yield consistent and efficient standard error estimates. Second stage coefficients and standard errors are robust across these specifications and are reported in Appendix F.

[57] Table 2.3 through Table 2.5 in the text report MWTP only for climate variables. MWTP for all model coefficients are reported in Appendix B.

[58] MWTP figures are computed using both first and second stage parameter estimates. Standard errors are computed using the delta method, where the covariance terms between first and second stage parameters are assumed to be zero. Due to computational burden from the first stage, bootstrapping standard errors is infeasible.

Households who have moved MSAs between 1995 and 2000 also have different preferences from the population as a whole. Their mean MWTP for winter and summer temperature is $983 and $1,109, respectively – almost double the estimates for the prime-aged households who are similar to movers in most of the demographic characteristics like age, education, and earnings.

I focus henceforth on prime-aged households. Table 3.2 presents estimates of MWTP for winter and summer temperature and other climate amenities based on three mixed logit models. The base model (Model M.1) controls for the first 18 amenities in Table 2.2, as well as moving costs, and allows the coefficients on winter and summer temperature to be jointly normally distributed. Model M.2 is identical, except that I have included a quadratic term for the temperature variables in the second stage, which by construction is restricted to be identical across households (unlike the linear term which is permitted to vary across households). The second stage results from Model M.2 are extremely similar to those of the base model, Model M.1.

Model M.1 suggests that, on average, higher winter temperature is an amenity and warmer summer temperature a disamenity. Mean MWTP to decrease summer temperature by one degree is higher than mean MWTP to increase winter temperature ($627 v. $518). There is, however, considerable variation in tastes as seen by the standard deviation coefficients in Panel A and exhibited in Figure 3.1 and Figure 3.2, which show how households sort across locations in relation to their taste for winter and summer temperature, respectively. In order to produce these plots of taste-based sorting, I calculate the joint distribution of the coefficients of winter and summer temperature for each household conditional on the household's choice of location. The means of these conditional distributions are averaged across all households in each city, divided by the coefficient on the Hicksian bundle, and plotted against city temperature.

As seen in Figure 3.1, households with high MWTP for warmer winters tend to locate in cities with warmer winters. For example, households in the South Atlantic and Pacific census divisions, regions with mild winters, have the highest MWTP for warmer winters, whereas West North Central households have the lowest MWTP for winter temperature and have located in cities with the harshest winters. As supported by the negative correlation coefficient between the parameters on winter and summer temperature, Figure 3.2 shows that households in the South Atlantic and Pacific also have the highest MWTP for cooler summers, while households in the West North Central division have relatively low MWTP to avoid summer heat.

Failure to control for moving costs has a significant impact on the estimated value of climate amenities, as well as on the spatial distribution of MWTP for winter and summer temperature. Model M.3 in Table 3.2 shows the impact of dropping moving costs from the discrete choice model. While the mean of the distribution of MWTP for winter temperature remains positive, its magnitude drops by more than 10%. The mean of the distribution on the coefficient of summer temperature is even more sensitive: its magnitude drops by about 43% when moving costs are omitted. The magnitude of the coefficients on other climate variables is also altered – snowfall becomes less of a disamenity and summer precipitation less of an amenity.

Figure 3.3 shows the impact of removing moving costs on taste sorting. Removing moving costs causes the sorting on winter temperature to all but disappear: the variation is very small, and all MSAs have a mean MWTP within about $20 of each other. Furthermore, the standard deviation coefficient for winter temperature is no longer statistically significant. Figure 3.3 suggests that MWTP for warmer summers is positively associated with summer temperature, but the standard deviation coefficient isn't significant. I present these results to show the importance of controlling for moving costs. Moving costs are highly significant for all the samples of households I examine and clearly belong in the discrete choice model. They also may be crucial to identifying the random parameters.[59]

Finally, while the sample of movers had different mean MWTP from prime-aged households, the sorting patterns of these two sets of households are very similar. The plots in Figure 3.4 are almost identical to those in Figure 3.1 and Figure 3.2 with the obvious exception of scale – the magnitudes of MWTP for the mover households are higher across the board as expected from Table 3.1.

3.5.2 Hedonic Results

The value placed on winter and summer temperature using the hedonic approach varies significantly with the weights used to construct the quality of life (QOL) indices described in Section 3.2. There is no systematic pattern as to which set of hedonic results – traditional (Roback) weights or adjusted (Albouy) weights – lead to results that are closer

[59] Identification of the random parameters comes from the variables that vary across both households and locations, i.e., the Hicksian bundle and moving costs. These variables subtly create multiple markets which is what drives identification in the typical random parameter models of the industrial organization literature.

to estimates produced by the discrete choice model: summer temperature is closer under the Albouy weights, but winter temperature is closer under traditional weights. The taste sorting implied by the two hedonic models is also quite different from the taste sorting implied by the discrete choice model.

Table 3.3 displays MWTP for climate amenities implied by the QOL models using, alternately, adjusted and traditional weights.[60] Each model controls for the first 18 amenities listed in Table 2.2. Models H.1a (adjusted weights) and H1.t (traditionally weights) allow winter and summer temperature to enter linearly, while Models H.2a and H.2t include the temperature terms in quadratic form. In each model, MWTP is computed at the mean of each climate variable.[61] Several points are worth noting. All models imply that warmer winter temperature is an amenity and warmer summer temperature a disamenity; however, the models with Albouy weights indicate that when evaluated at temperature means, summer temperature is more of a disamenity than winter temperature is an amenity. Specifically, MWTP to avoid an increase in summer temperature is, on average, over three times as great as MWTP for an increase in winter temperature (approximately $100 for winter temperature and $350 for summer temperature). In

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[60] The results of Table 3.3 are produced by simple OLS models and represent the mean MWTP for local amenities across all households. Figure 3.5 through Figure 3.8, discussed below, portray the results of the local linear regressions that show how households sort on temperature in the hedonic specification.

[61] MWTP in Table 3.3 is calculated by multiplying the relevant coefficient by the mean gross income of prime-aged households.

contrast, the two values are approximately equal in magnitude when traditional weights are used (e.g., about $200 for winter temperature and $230 for summer temperature).[62]

Table 3.3 suggests that the mean MWTP for winter and summer temperature produced by the hedonic and discrete models cannot be reconciled using either set of weights. In relative terms, the hedonic model with traditional weights produces estimates that are closer to the discrete choice model: summer temperature is just slightly more of a disamenity than winter temperature is an amenity. However, the magnitudes are much lower for this model. In the hedonic model with Albouy weights, the magnitude of MWTP for summer temperature is closer to the discrete choice approach; however, the mean MWTP for winter temperature in the hedonic model with Albouy weights is even further away from discrete choice estimates as compared with the estimates when traditional weights are used. It is also important to note that the discrete choice results for the sample of households that moved between 1995 and 2000 also cannot explain differences between the two models: the MWTP for movers is even higher than that of prime-aged households, thus further diverging from the hedonic estimates.[63]

I have also used the QOL indices from the two hedonic models to estimate flexible local linear regressions that allow the coefficients on summer and winter temperature to vary by MSA. Specifically, I regress the QOL index on all amenities except for winter and

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[62] There are other differences in the value attached to climate amenities by the two sets of hedonic models. Snowfall is a disamenity using adjusted weights, but an amenity using traditional weights. Summer precipitation is an amenity when traditional weights are used but a disamenity with adjusted weights.

[63] It may be that households who have recently moved are not a good proxy for the marginal consumer, but this result still suggests the differences between these two models isn't strictly a question of whose preferences are being estimated.

summer temperature and then use the residuals from this equation in a local linear regression with kernel weights described in equation (7). With only 284 observations, results are extremely sensitive to the bandwidth chosen for the kernel weights. In general, the smaller the bandwidth, the greater the range of estimated MWTP values across cities.[64] The marginal hedonic prices for winter and summer temperature are plotted in Figure 3.5 and Figure 3.6 for the Albouy weight models using a bandwidth of 1. The comparable plots for the models estimated using traditional weights are shown in Figure 3.7 and Figure 3.8.[65]

The results of the local linear regressions are interesting, although I believe they should be interpreted with caution given the small number of observations involved. As shown in Figure 3.7 and Figure 3.8, when traditional weights are used, marginal hedonic prices for winter temperature generally decline with winter temperature, while marginal prices for summer temperature generally increase with summer temperature. In contrast, the pattern of marginal hedonic prices using the adjusted weights in Figure 3.5 and Figure 3.6 is quite different: marginal hedonic prices for winter temperature exhibit a U-shape

[64] Choosing too small a bandwidth will essentially result in data interpolation, while choosing too large a bandwidth will over-smooth the data and won't allow for any sorting behavior. I follow the lead of Bajari and Benkard (2005) and Albouy et. al. (2016) in choosing a bandwidth that looks reasonable given my data. Albouy et. al. (2016) computed the optimal bandwidth in their analysis and found it far too small to yield meaningful results, thus I have not pursued the optimal bandwidth in this setting.

[65] I have also estimated each model using bandwidths of 0.5, 2 and 4. For bandwidths of 2 and 4, there is little variation in marginal hedonic prices. To illustrate, marginal prices for winter temperature using Albouy weights vary across cities between $47 and $60 when the bandwidth equals 2, and between $50 and $52 when the bandwidth equals 4. For a bandwidth of 0.5, the data becomes noisy and the spread of MWTP vastly increases. Appendix E contains scatter plots showing these bandwidth sensitivities.

with winter temperature, while the marginal prices for summer temperature decrease with summer temperature.

How do the local linear results compare with the sorting patterns implied by the discrete choice model? Mostly, these two sets of results are very different. For winter temperature, the discrete choice and traditionally-weighted local linear hedonic plots are almost perfectly opposite of one another. The Albouy-weighted hedonic plots are a mixture: while the Albouy-weighted plots do show the South Atlantic households having high MWTP for winter temperature (as is also seen in Figure 3.1 from the discrete choice results), they also show this for West North Central households who have the lowest MWTP for winter temperature in the discrete choice plots. The plots for summer temperature tell a very similar story. The traditionally-weighted hedonic plots are mostly in opposition to those of the discrete choice plots, while the Albouy-weighted plots coincide for some households (households in the South Atlantic have high distaste for summer temperature in both models), but not for others (e.g., Pacific households have strong preferences for cooler summers in the discrete choice model, while they have the weakest preference in the Albouy-weighted hedonic model.)

3.5.3 The Role of Market Share

As previously discussed, the discrete choice and hedonic models have some differences that can make the two models hard to compare. One alternative is to consider a simple share model where a location's market share (i.e., proportion of overall population) is regressed on local prices and local attributes. This closely relates to the discrete choice model which aims to predict market share; specifically, the predicted probabilities of moving to each MSA, summed over all households, yields the market share of that MSA.

To motivate the simple share regression, consider the following model: without loss of generality, suppose households face a decision between two different locations, 1 and 2, where household *i* chooses location 1 if $Z_i'\varphi + u_i > 0$ and chooses location 2 otherwise. Then under the assumption of logit error, the probability household *i* chooses location 1 is given by $P_{i1} = \frac{e^{Z_i'\varphi}}{1+e^{Z_i'\varphi}} \equiv P(Z_i'\varphi)$ and the probability household *i* chooses location 2 is $P_{i2} = 1 - P(Z_i'\varphi)$. The first order condition of the log-likelihood implied by this formula is $\frac{1}{N}\sum_i [s_i - P(Z_i'\varphi)]\, Z_i = 0$ where $s_i = 1$ if household *i* chooses location 1 and is zero otherwise. Now consider the case where Z_i consists only of a constant (implicitly location-specific), so that $P(Z_i'\varphi) = P(\varphi)$ and the first order condition becomes $\frac{1}{N}\sum_i [s_i - P(\varphi)] = 0$. Solving this equation for φ we have $\varphi = \ln\left(\frac{\bar{s}}{1-\bar{s}}\right)$, where $\bar{s} = \frac{1}{N}\sum s_i$ is just the proportion of households choosing location 1. Likewise, $1 - \varphi$ produces the proportion of households choosing location 2.[66]

This simple example shows how dependent the discrete choice model is on MSA populations. At the extreme, when only location specific constants are included in the model, the estimated parameters will exactly reflect the share of households choosing each

[66] Full derivations are omitted for brevity, but are relatively simple and available upon request.

location.[67] In the random utility model framework, these alternative-specific constants can be interpreted as the mean utility provided by each location. Consequently, if one thinks about location-specific constants as a function of local prices and local amenities according to $\varphi_j = \tilde{\varphi}(prices_j, A_j; \tilde{\theta})$, then a regression of log population shares on local wages, housing prices, and amenities will yield their respective contributions to location mean utility levels so that (a function of) $\tilde{\theta}$ will represent the marginal utility of these location attributes. Taking the ratio between the coefficients on the amenities and wages will yield MWTP for the local amenities.

To estimate the share model, I replace the income and housing expenditure components of utility in the discrete choice model with the wage and housing price indices from national labor and housing markets (λ_j^W and λ_j^P, respectively, from the hedonic model) and drop the moving cost variables. Per the derivation above, the discrete choice model reduces to the following share model described by equation (18), where s_j denotes the

$$\ln(s_j) = \tilde{\theta}^P \lambda_j^P + \tilde{\theta}^W \lambda_j^W + \boldsymbol{A_j}\tilde{\boldsymbol{\theta}} + \epsilon_j \tag{18}$$

share of population in city j. From this formulation, it is striking how differently the discrete choice and hedonic methods use the data. Recall the hedonic formulation from equation (6), reproduced below. Here the price indices are on the left-hand side and

$$QOL_j \equiv 0.33\lambda_j^P - 0.51\lambda_j^W = \boldsymbol{A_j}\boldsymbol{\theta} + \xi_j \tag{6}$$

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[67] To be precise, the location specific constants will equal the log odds ratio, $\ln(\bar{s}/(1-\bar{s}))$. For simplicity, I use $\ln(\bar{s})$ as the dependent variable in my share model; however, I have estimated the model with the log odds ratio as the dependent variable and the estimates are almost identical.

quantities (or market shares) do not enter the equation at all.

I estimate equation (18) using the same price indices as used in the hedonic models and compute the implied mean MWTP, which is just mean income multiplied by the ratio of the amenity coefficient over the wage coefficient. Those results are presented in Table 3.4, where for purposes of comparison, I also report the estimates from the base discrete choice and hedonic models. Mean MWTP for winter and summer temperature in the share model is $514 and $518, respectively. These are quite close to the corresponding estimates from the discrete choice model of $518 and $627. In contrast, the hedonic results are much lower in magnitude: $104 to $207 for winter temperature and $228 to $358 for summer.[68]

The results of this share equation may very well be biased – a thorough analysis would attempt to instrument for wage and housing prices which appear on the right-hand side – however, they are still useful in explaining how and why the discrete choice and hedonic models might produce different MWTP estimates. In this comparison between the share equation and the hedonic model, there is no discrepancy in how labor and housing markets are treated (the same price indices are used), nor is there a discrepancy in mobility assumptions as the share model does not incorporate any moving costs. The key difference

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[68] The similarity of results between the discrete choice and share models is suggested by the strong correlation (0.86) between the discrete choice MSA fixed effects and the MSA log populations shares (which are the dependent variables in the local amenity regressions). In contrast, the discrete choice fixed effects are not strongly correlated with the QOL measures, only 0.21 for the Albouy-weighted QOL and -0.25 for QOL with traditional weights. Interestingly, the correlation between the two QOL measures is only 0.20, supporting the very different MWTP implied by each. My findings also support Albouy's (2012) conclusion that hedonic models using traditional weights appear to suggest that big cities have lower quality of life, while his adjusted weights correct this (correlation between log population shares and the traditional-weights QOL is -0.44; for the Albouy-weighted QOL, correlation is just 0.11).

between these models is how market share is incorporated: market share is the dependent variable in the share equation but does not enter the hedonic model explicitly at all.

3.6 Conclusions

The goal of this paper is to compare the continuous hedonic and discrete choice approaches to valuing climate amenities – in particular, summer and winter temperature. Though researchers have observed that the two approaches can yield different willingness-to-pay estimates, no previous studies in amenity valuation have established this in a careful or systematic way, nor have they adequately explored the important question of "Why?" Furthermore, this literature has only noted the differences in mean MWTP (Cragg and Kahn, 1997; Bayer, Keohane and Timmins, 2009), whereas I have expanded the analysis to compare how conditional (on location) MWTP varies across the two approaches. Preferences for temperature represent a classic case of taste sorting, and for the purposes of valuing climate policies, it is essential to measure how MWTP for temperature varies with geographic location.[69] .

Simply put, the pattern of taste sorting produced by the two approaches is quite different. The discrete location choice model suggests that households who place a higher value on warmer winters tend to live in warmer cities, although there is variation across

[69] I interpret both the mean of the coefficient on winter and summer temperature conditional on location (where conditional means are aggregated to the city level in the discrete choice model) and the marginal hedonic prices in the local linear regressions as measuring MWTP for small changes in temperature at a location by people currently living there.

cities in MWTP holding temperature constant. The continuous hedonic approach using traditional weights and local linear regression suggests the opposite: it suggests the MWTP for an increase in winter temperature of people living in North Dakota is higher than it is for those in Florida. The hedonic results with Albouy weights are a U-shaped function of temperature: MWTP is highest for people living in the West North Central (where it is very cold) and in Florida (where winters are mild) and is lowest in locations where mean winter temperature is between 40 and 50 degrees.

In terms of summer temperature, the hedonic local linear regressions with Albouy weights suggest that MWTP to avoid warmer summers is negatively correlated with temperature at current location: people on the Pacific coast and in the mountain states consider warmer summers to be a disamenity, but less so than people living in the South Atlantic, West South Central and East South Central census divisions, who will bear the brunt of climate change under the A2 and B1 SRES scenarios.[70] In contrast, the hedonic local linear regressions with traditional weights suggests that people living in these census divisions are actually willing to pay less to avoid an increase in mean summer temperature than people in other parts of the country. Finally, the discrete choice model estimates that MWTP to avoid warmer summers is highest in the Pacific and South Atlantic census divisions, which only partly agrees with some of the hedonic plots.

[70] 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 Special Report on Emissions Scenarios (SRES). Among these scenarios is a climate-friendly scenario (B1) and a more extreme scenario (A2).

There is also a difference in the mean MWTP across models: MWTP for warmer winters is lower, on average, in both sets of hedonic models than in the discrete choice case: it is approximately $200 in the hedonic model with traditional weights and $100 in the hedonic model with Albouy weights, but over $500 in the discrete choice model. Mean MWTP to avoid warmer summers is also lower in the hedonic models (approximately $230 and $350 for the traditional- and Albouy-weighted models, respectively) than in the discrete choice model, where MWTP is approximately $630.[71]

These findings raise the obvious question: why do results differ across models? Bayer, Keohane and Timmins (2009) suggest that it is the inclusion of moving costs in the discrete choice model that causes their hedonic and discrete choice results to differ. When I omit moving costs from the discrete choice model, I find that mean MWTP for winter and summer temperature drops, but not enough to agree with hedonic estimates. Furthermore, these results don't match in terms of sorting patterns. When moving costs are omitted, the sorting on winter temperature disappears and the sorting on summer temperature becomes positive, but with weak significance at best. This positive correlation between MWTP for summer temperature and summer temperature somewhat resembles the traditionally-weighted local linear hedonic model (though there are regional differences), but is in clear opposition to the Albouy-weighted model. So, while moving costs do appear to be an important contributing factor explaining differences between hedonic and discrete choice model estimates, they are certainly not the only one.

[71] The mean estimates for the hedonic models vary with the functional form of winter and summer temperature in Table 3.3.

Do the results differ because the two approaches are measuring the preferences of different populations? The hedonic model relies on indifference across locations, and thus inherently captures the preferences of marginal households, i.e. households just indifferent between their chosen location and its alternatives. In contrast, the discrete choice model can capture the preferences of marginal and infra-marginal households alike. To test whether this explains the difference in MWTP estimates between the two models, I attempted to identify the preferences of marginal households by estimating the discrete choice model for households who had recently moved cities. The MWTP for the sample of movers is over double that of the regular sample of households from my base discrete choice model, further increasing the gap between discrete choice and hedonic estimates, as opposed to closing it. This may simply suggest that movers do not embody marginal households. However, it could suggest that the distinction between the preferences of marginal and infra-marginal households is not materially significant to why hedonic and discrete choice results diverge.

The hedonic and discrete choice approaches differ in other ways. First, the econometric models underlying the two approaches make different distributional assumptions, and it is difficult to judge the impact of these factors. Second, the construction of hedonic quality of life indices is based on national labor and housing market equations which assume that the returns to human capital and the marginal cost of a bedroom are everywhere equal. The discrete choice approach, in contrast, relies on variation in the returns to human capital across geographic areas and allows the marginal price of dwelling characteristics to vary across cities. Because identification of the discrete choice model's random parameters rests on meaningful household-location specific variation, I must preserve variation in wages and housing costs across alternative locations within a household. Thus, it is not feasible to estimate a random parameters discrete choice model where wages and housing expenditures are estimated based on national labor and housing markets.

Perhaps most importantly, the two models make use of different information: the hedonic model relies strictly on price variation, while the discrete choice model exploits price variation but also incorporates data on quantity purchased, or market share. This market share information is only in the background of the hedonic model through the imposition of market equilibrium, whereas the discrete choice model incorporates it directly. When I estimate the share model, which can be viewed as a simplified aggregate version of the discrete choice model, I find that the implied MWTP estimates are much closer to the discrete choice estimates based on individual household data and are still substantially larger than hedonic estimates. Interestingly, these share model results omit two possible sources of difference between the discrete choice and hedonic models: moving costs are absent in the share model and wages and housing costs are measured identically.

What I have not answered in this paper is the question that is most important to policymakers: which of the approaches yields the most reliable estimates of the value of climate amenities for use in evaluating climate policy? Given how different the estimates are, this is a question that clearly deserves more research.

Table 3.1 Marginal Willingness To Pay for Climate Amenities (Base Discrete Choice Models)

	Model M.1 (Full)	**Model M.1 (Prime)**	**Model M.1 (>55)**	**Model M.1 (Movers)**
Sample	All Ages	Prime-Aged (Base Model)	Over 55 Years	Changed MSA between 1995 and 2000

PANEL A: 1st Stage Estimates

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
	(0.0731)	(0.0416)	(0.0726)	(0.0621)

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 non-linearly, amenity variables are evaluated at population-weighted means in order to compute MWTP. Non-linear covariates are the following: population density, summer precipitation, and elevation enter in log form while distance to the coast enters the model quadratically.

Table 3.2 Marginal Willingness To Pay for Climate Amenities (Discrete Choice Model Sensitivities)

	Model M.1		**Model M.2**		**Model M.3**	
	Base Model		Quadratic Temperature Specification		Omit Moving Costs	

PANEL A: 1st Stage Estimates

Variable	Model M.1 Coef (Std Err)	Model M.2	Model M.3 Coef (Std Err)
Std. Dev: Avg Winter Temperature	0.0588	Same 1st Stage	0.0011
	(0.0026)	Estimates as	(0.0128)
Std. Dev: Avg Summer Temperature	0.0592	Model M.1	0.0352
	(0.0068)		(0.0215)
Correlation Coefficient	-0.6893		0.8614
	(0.0827)		(0.2756)

PANEL B: 2nd Stage Estimates

Variable	M.1 Coef (Std Err)	M.1 MWTP (Std Err)	M.2 Coef (Std Err)	M.2 MWTP (Std Err)	M.3 Coef (Std Err)	M.3 MWTP (Std Err)
Mean: Avg Winter Temperature	0.0209	$518	0.0559	$489	0.0184	$491
	(0.0058)	($144)	(0.0169)	($162)	(0.0055)	($146)
Mean: Avg Summer Temperature	-0.0253	-$627	-0.1547	-$608	-0.0145	-$386
	(0.0100)	($249)	(0.1764)	($258)	(0.0108)	($288)
July Humidity	-0.0208	-$514	-0.0207	-$512	-0.0165	-$440
	(0.0054)	($135)	(0.0055)	($136)	(0.0046)	($124)
Annual Snowfall	-0.0170	-$422	-0.0154	-$380	-0.0047	-$126
	(0.0026)	($66)	(0.0028)	($69)	(0.0025)	($67)
Ln(Summer Precipitation)	0.1708	$403	0.2158	$509	0.0678	$172
	(0.0768)	($181)	(0.0808)	($191)	(0.0732)	($186)
Annual Sunshine	-0.0149	-$368	-0.0075	-$185	-0.0082	-$219
	(0.0060)	($149)	(0.0077)	($192)	(0.0060)	($159)

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

Table 3.3 Marginal Willingness To Pay for Climate Amenities (Base Hedonic Models)

	Ajusted Hedonic Weights				Tradtional Hedonic Weights			
	Model H1.a		Model H2.a		Model H1.t		Model H2.t	
Temperature Specification	Linear (Base Model)		Quadratic		Linear (Base Model)		Quadratic	
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)
Avg Winter Temperature	0.0015	$104	0.0031	$110	0.0030	$207	0.0043	$186
	(0.0005)	($33)	(0.0014)	($41)	(0.0006)	($42)	(0.0019)	($46)
Avg Summer Temperature	-0.0052	-$358	-0.0048	-$355	-0.0033	-$228	-0.0228	-$228
	(0.0009)	($64)	(0.0158)	($65)	(0.0010)	($68)	(0.0131)	($68)
July Humidity	0.0010	$71	0.0010	$71	0.0012	$84	0.0012	$84
	(0.0003)	($24)	(0.0003)	($23)	(0.0005)	($35)	(0.0005)	($35)
Annual Snowfall	-0.0002	-$16	-0.0001	-$10	0.0004	$29	0.0005	$33
	(0.0002)	($11)	(0.0002)	($11)	(0.0002)	($16)	(0.0002)	($16)
Ln(Summer Precipitation)	-0.0031	-$19	-0.0014	-$9	0.0128	$81	0.0157	$99
	(0.0067)	($42)	(0.0069)	($44)	(0.0080)	($50)	(0.0087)	($55)
Annual Sunshine	0.0028	$191	0.0030	$205	0.0019	$129	0.0025	$172
	(0.0005)	($35)	(0.0007)	($45)	(0.0006)	($44)	(0.0008)	($57)
Num. of Obs. (MSAs)	284		284		284		284	
Adjusted R-squared	0.59		0.59		0.50		0.50	

Note: MWTP is computed at mean household income for the prime-aged sample ($69,188). When entering the regressions non-linearly, amenity variables are evaluated at population-weighted means in order to compute MWTP. Non-linear covariates are the following: population density, summer precipitation, and elevation enter in log form while distance to the coast enters the model quadratically.

Table 3.4 Marginal Willingness to Pay Compared Across Base Models and Share Model

	Share	**Discrete Choice**	**Hedonic** Adjusted Weights	**Hedonic** Traditional Weights
		Base Model	Base Model	Base Model
Variable	MWTP (Std Err)	MWTP (Std Err)	MWTP (Std Err)	MWTP (Std Err)
Avg Winter Temperature	$514	$518	$104	$207
	($100)	($144)	($33)	($42)
Avg Summer Temperature	-$518	-$627	-$358	-$228
	($164)	($249)	($64)	($68)
July Humidity	-$300	-$514	$71	$84
	($90)	($135)	($24)	($35)
Annual Snowfall	-$61	-$422	-$16	$29
	($39)	($66)	($11)	($16)
Ln(Summer Precipitation)	$199	$403	-$19	$81
	($96)	($181)	($42)	($50)
Annual Sunshine	-$47	-$368	$191	$129
	($102)	($149)	($35)	($44)

Note: For the share and hedonic models, MWTP is computed at mean household income for the prime-aged sample ($69,188). When entering the regressions non-linearly, amenity variables are evaluated at population-weighted means in order to compute MWTP. Non-linear covariates are the following: population density, summer precipitation, and elevation enter in log form while distance to the coast enters the model quadratically.

Figure 3.1 Taste-Sorting for Winter Temperature by Metropolitan Area
(Base Discrete Choice Model – Model M.1)

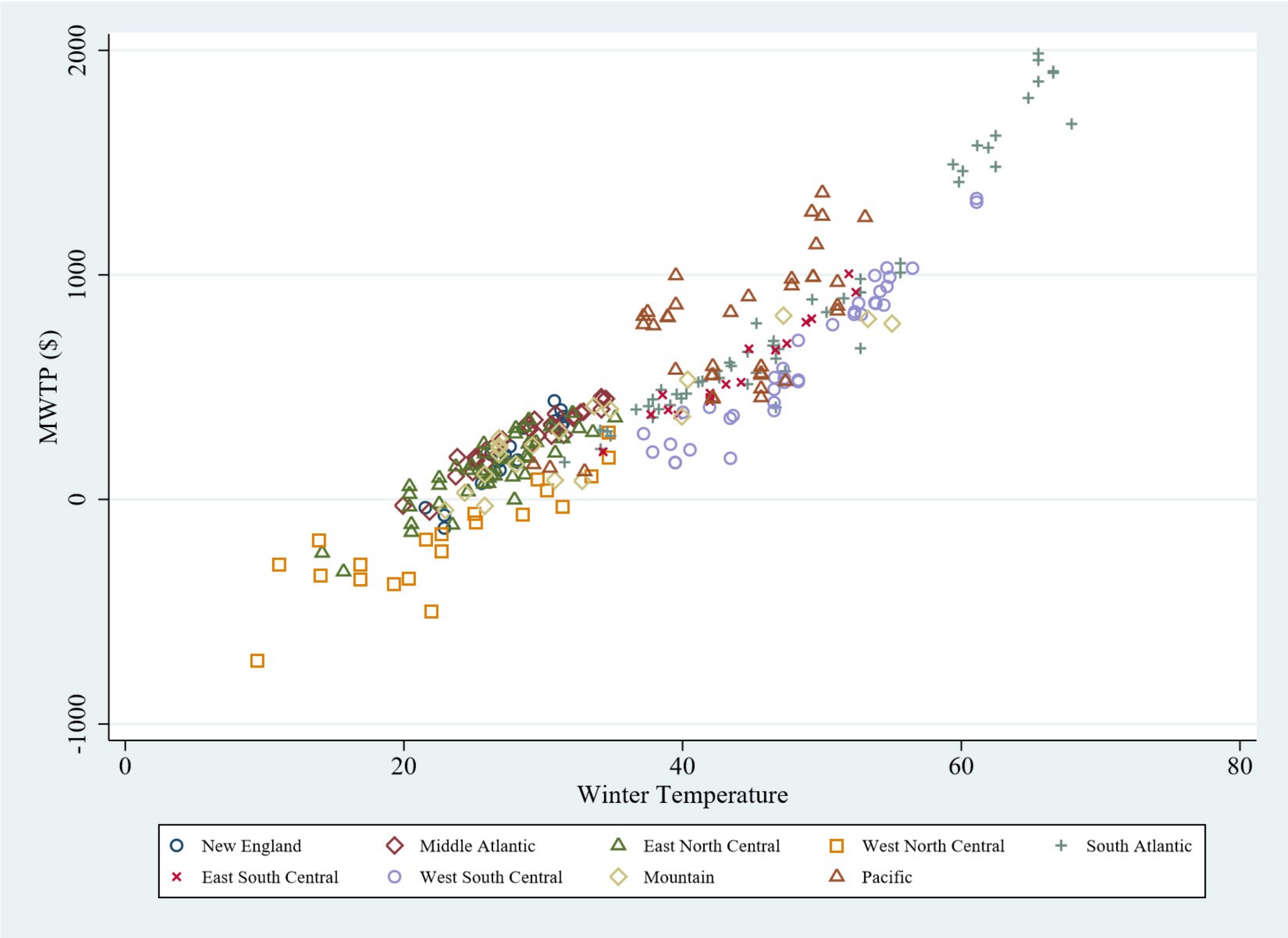


Figure 3.2 Taste-Sorting for Summer Temperature by Metropolitan Area
(Base Discrete Choice Model – Model M.1)

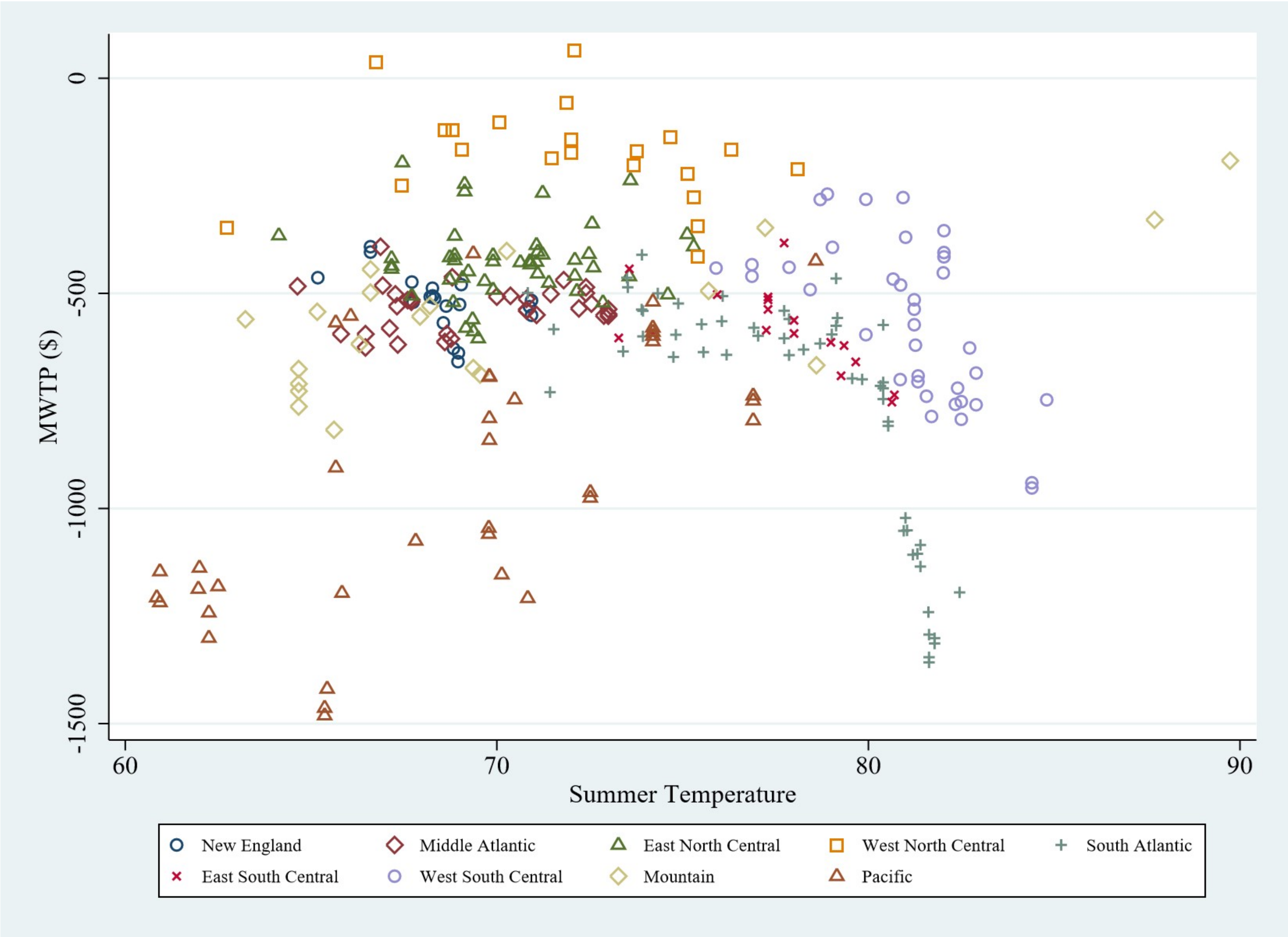


Figure 3.3 Taste-Sorting by Metropolitan Area
(Discrete Choice Model with No Moving Costs – Model M.3)

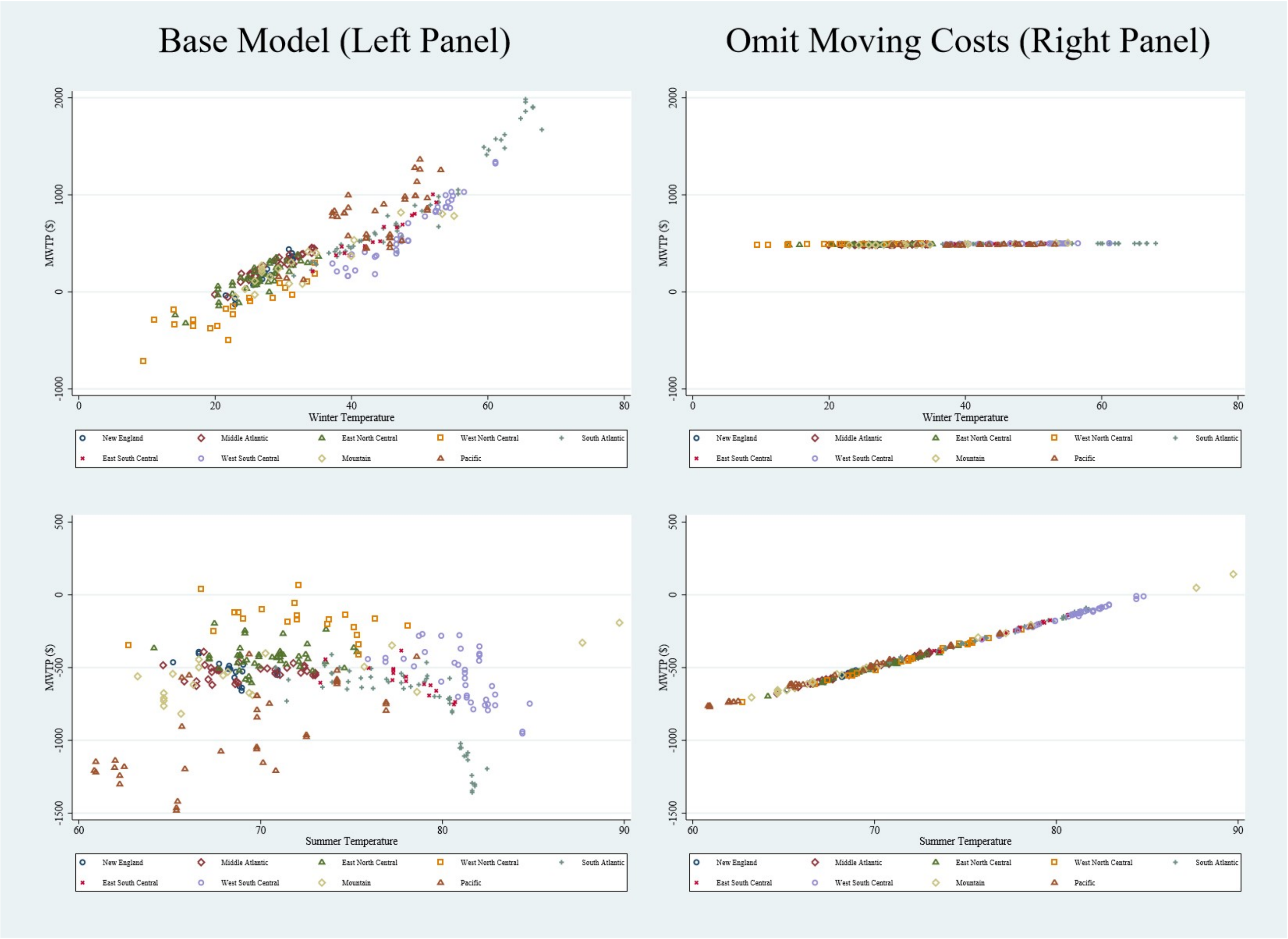


Figure 3.4 Taste-Sorting by Metropolitan Area
(Base Discrete Choice Model for Movers)

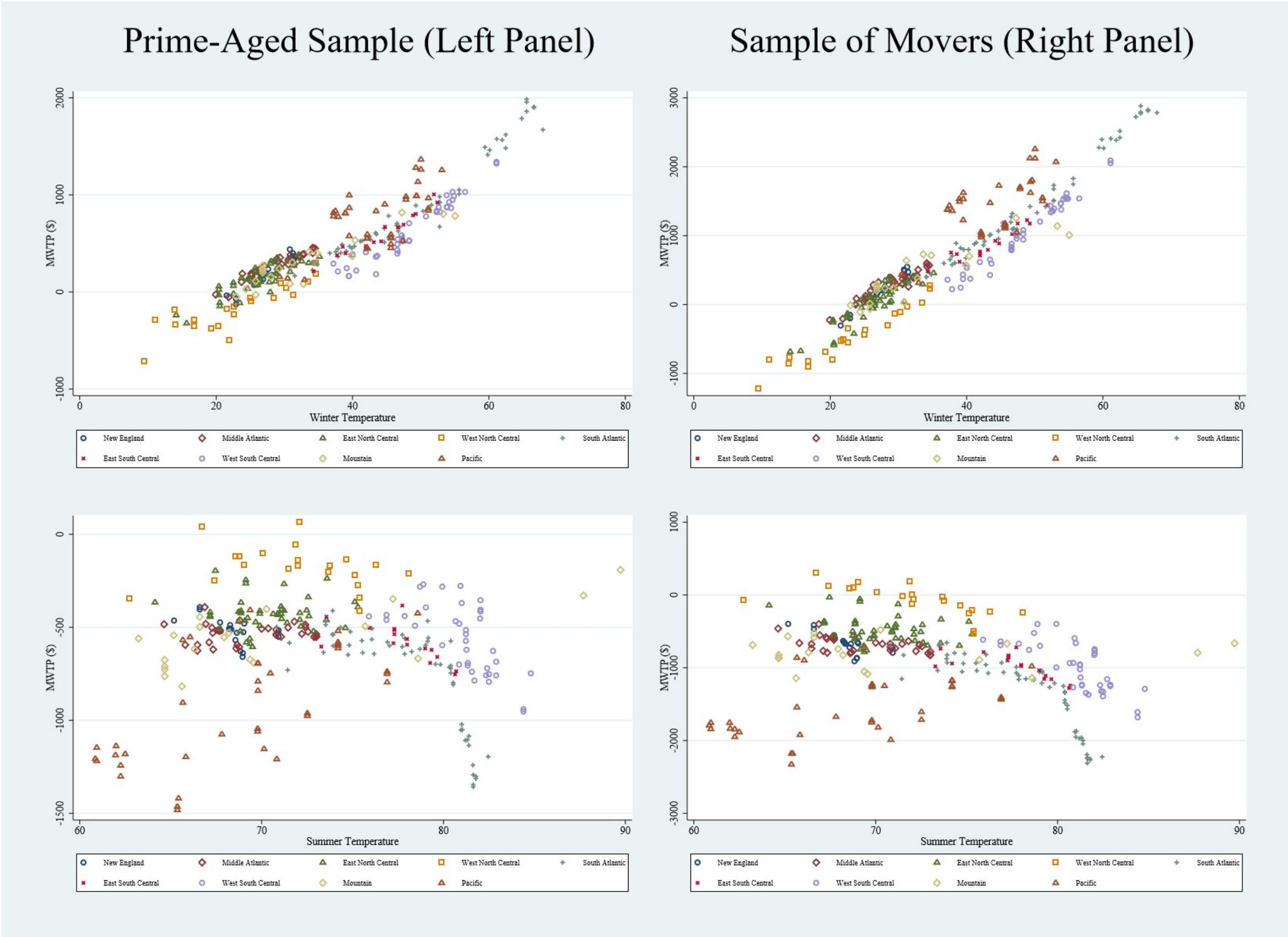


Figure 3.5 Taste-Sorting for Winter Temperature by Metropolitan Area
(Local Linear Hedonic Model, Adjusted Weights, Bandwidth = 1.0)

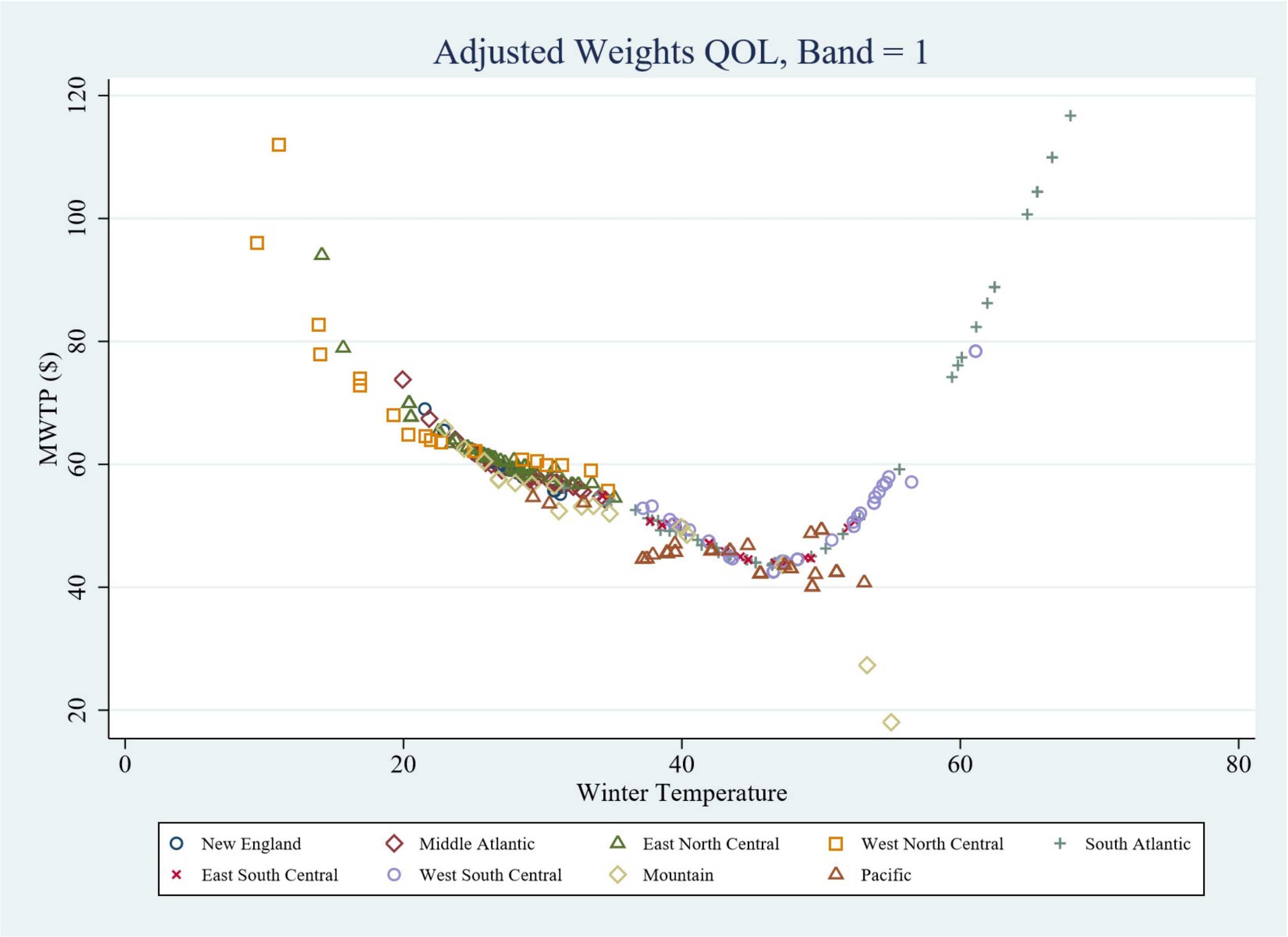


Figure 3.6 Taste-Sorting for Summer Temperature by Metropolitan Area
(Local Linear Hedonic Model, Adjusted Weights, Bandwidth = 1.0)

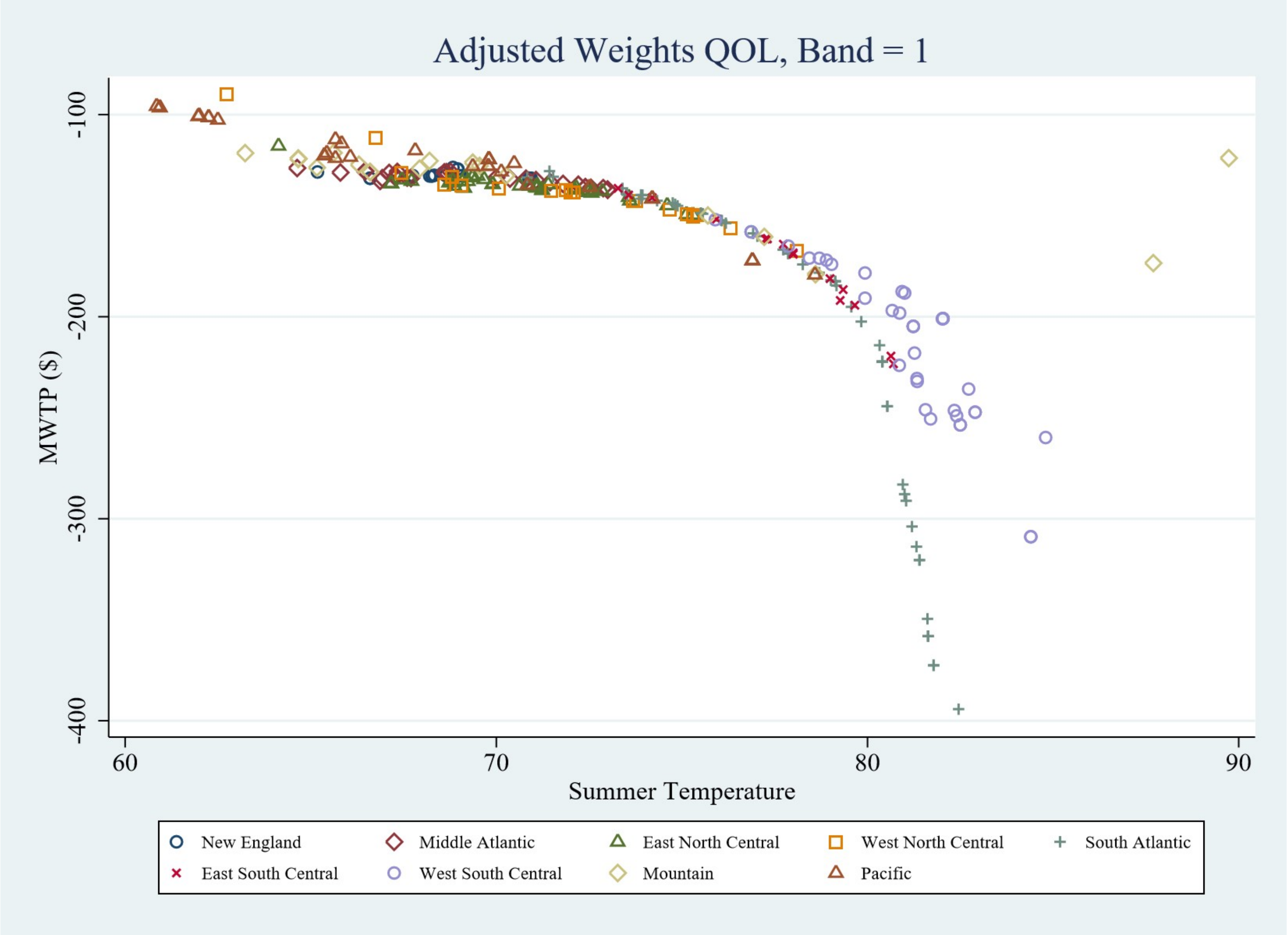


Figure 3.7 Taste-Sorting for Winter Temperature by Metropolitan Area (Local Linear Hedonic Model, Traditional Weights, Bandwidth = 1.0)

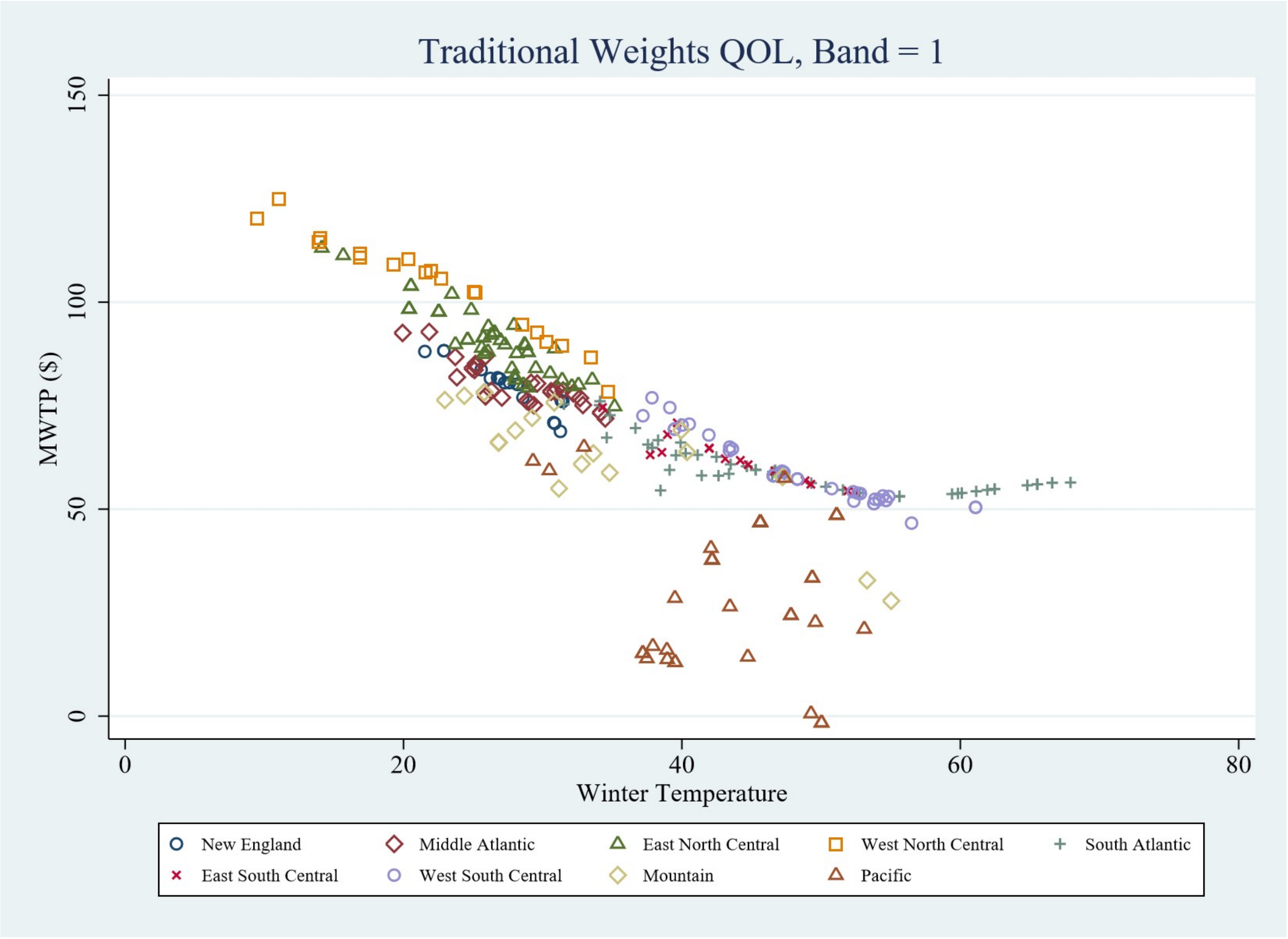
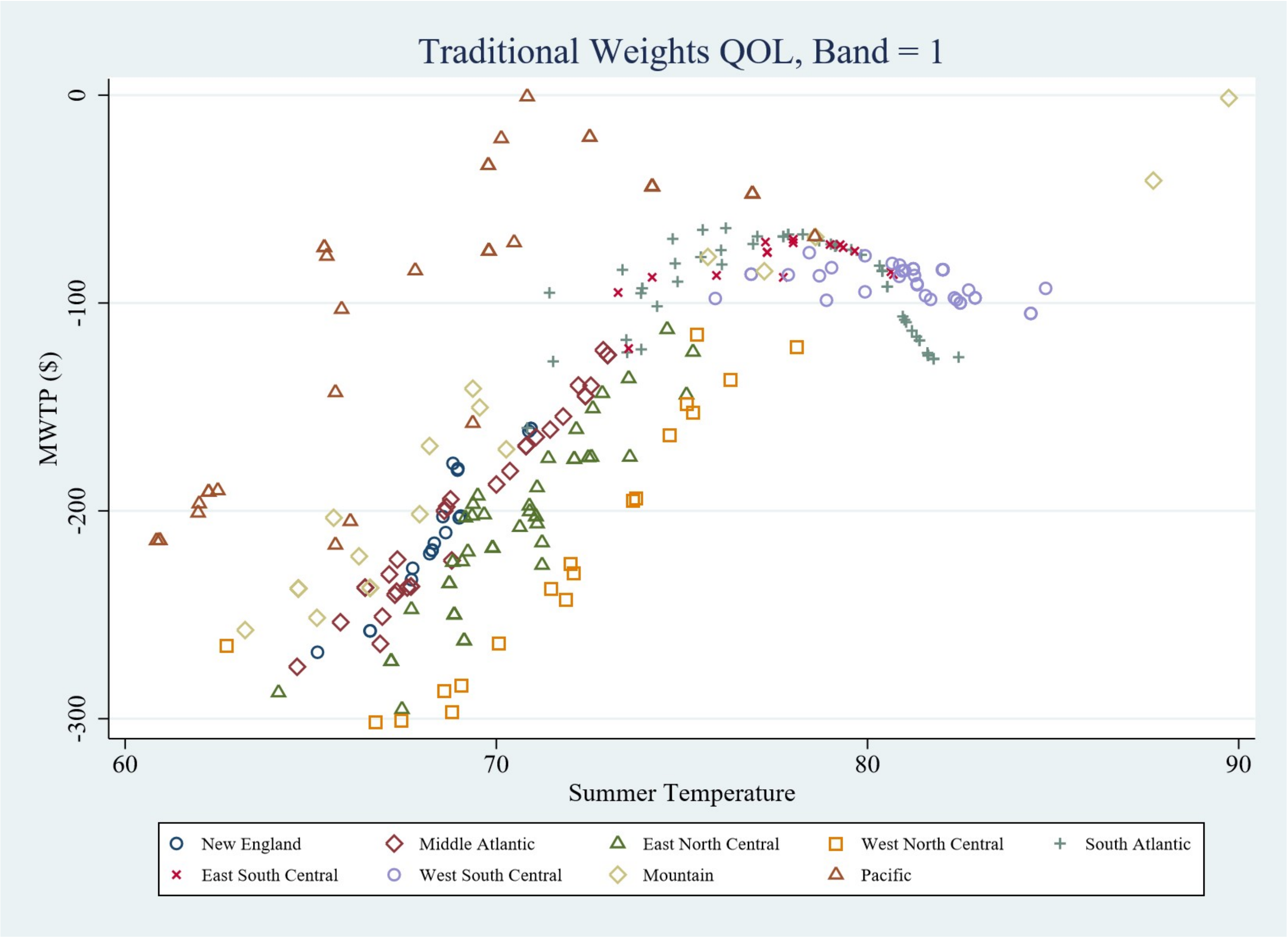


Figure 3.8 Taste-Sorting for Summer Temperature by Metropolitan Area
(Local Linear Hedonic Model, Traditional Weights, Bandwidth = 1.0)



Appendix A – Hedonic Wage and Housing Equations

Table A.1 Summary of Hedonic Wage Coefficients

Variables	National Equation	MSA-Specific Equations (284)	
(Dependent Variable: log(wage rate))	Coef	Mean(Coef)	StdDev(Coef)
High School (left out category is no high school)	0.117	0.098	0.038
Some College	0.212	0.180	0.045
College Graduate	0.418	0.382	0.069
Higher Education	0.577	0.546	0.074
Age	0.049	0.048	0.007
Age squared (divided by 100)	0.000	0.000	0.000
Married	0.093	0.092	0.021
Male	0.197	0.215	0.040
Black (left out category is white)	-0.082	-0.070	0.070
Other Race	-0.086	-0.055	0.054
Speaks English Well	0.213	0.126	0.103
Hispanic	-0.075	-0.057	0.074
Business Operations Occupation	-0.120	-0.122	0.067
(left out category is Management Occupation)			
Financial Specialists Occupation	-0.139	-0.116	0.072
Computer and Math Occupation	0.010	0.004	0.089
Engineering Occupation	-0.088	-0.073	0.083
Life, Physical, & Social Sciences Occupation	-0.206	-0.180	0.100
Social Services Occupation	-0.354	-0.328	0.078
Legal Occupation	-0.023	-0.039	0.127
Teachers Occupation	-0.221	-0.190	0.093
Other Educational Occupation	-0.502	-0.473	0.129
Arts, Sports & Media Occupation	-0.220	-0.243	0.094
Healthcare Practitioners Occupation	0.025	0.062	0.078
Healthcare Support Occupation	-0.351	-0.330	0.078
Protective Services Occupation	-0.257	-0.240	0.106
Food and Serving Occupation	-0.453	-0.428	0.077
Maintenance Occupation	-0.485	-0.472	0.074
Personal Care Service Occupation	-0.435	-0.423	0.114
High Skill Sales Occupation	-0.154	-0.136	0.067
Low Skill Sales Occupation	-0.227	-0.228	0.062
Office Support Occupation	-0.316	-0.298	0.049
Construction Trades & Extraction Workers Occupation	-0.248	-0.246	0.090
Maintenance Workers Occupation	-0.206	-0.192	0.065
Production Occupation	-0.346	-0.317	0.084
Transportation Occupation	-0.375	-0.357	0.075
Construction Industry (left out category is Mining and Utilities)[a]	-0.179	-0.180	0.095
Manufacturing Industry	-0.127	-0.120	0.107
Wholesale Industry	-0.190	-0.185	0.097
Retail Industry	-0.344	-0.339	0.094
Transportation Industry	-0.111	-0.084	0.107
Information & Communications Industry	-0.111	-0.134	0.109
Finance Industry	-0.151	-0.175	0.105
Professional and Scientific Management Services Industry	-0.197	-0.220	0.101
Educational and Health Social Services Industry	-0.280	-0.267	0.092
Recreation and Food Services Industry	-0.352	-0.370	0.110
Other Services Industry	-0.348	-0.343	0.101
Public Administration Industry	-0.123	-0.126	0.095

[a] Since these two industries have a very low number of observations, we bundled them together as the omitted category

Table A.2 Summary of Hedonic Housing Coefficients

	National Equation	MSA-Specific Equations (284)	
(Dependent Variable: log(user costs including insurance and utility costs))	Coef	Mean(Coef)	StdDev(Coef)
House is Owned	0.504	0.464	0.144
3 Bedrooms (left out category is less than three bedrooms)	0.128	0.160	0.061
4 Bedrooms	0.152	0.208	0.082
5 Bedrooms	0.283	0.324	0.110
Greater than 5 Bedrooms	0.485	0.500	0.163
2 Rooms (left out category is less than two rooms)	0.137	0.080	0.133
3 Rooms	0.137	0.053	0.140
4 Rooms	0.166	0.075	0.146
5 Rooms	0.230	0.126	0.154
6 Rooms	0.327	0.218	0.156
Greater than 6 Rooms	0.531	0.413	0.176
Complete Kitchen	-0.033	-0.104	0.261
Complete Plumbing	0.219	0.221	0.212
1 to 10 Acres	0.214	0.246	0.140
0 to 1 years old (left out category is over 61 years old)	0.391	0.428	0.157
2 to 5 years old	0.371	0.404	0.158
6 to 10 years old	0.316	0.358	0.150
11 to 20 years old	0.218	0.247	0.127
21 to 30 years old	0.110	0.150	0.122
31 to 40 years old	0.059	0.093	0.113
41 to 50 years old	0.020	0.039	0.089
51 to 60 years old	-0.026	-0.011	0.075
Number of Units in Structure: Single-Attached (left out category is single family detached)	-0.158	-0.082	0.105
2 Units in Structure	-0.055	-0.089	0.107
3 to 4 Units in Structure	-0.112	-0.135	0.095
5 to 9 Units in Structure	-0.139	-0.167	0.106
10 to 19 Units in Structure	-0.114	-0.132	0.127
20 to 49 Units in Structure	-0.169	-0.154	0.151
Over 50 Units in Structure	-0.152	-0.190	0.207

Table A.3 Variation in Key Dwelling Characteristics, Controlling for Household Size and Income

Income Quintile	Household Size	No. of Bedrooms		No. of Rooms		Owns Home		Age of Structure		No. of Units	
		Mean	Std Dev	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev	Mean	Std Dev
1	1 Person	1.92	0.18	4.13	0.38	0.43	0.09	33.21	5.73	9.02	3.55
	2 Persons	2.26	0.18	4.65	0.39	0.48	0.12	32.43	6.60	5.28	2.99
	3-4 Persons	2.45	0.21	4.77	0.43	0.30	0.09	30.85	7.10	4.74	2.68
	5+ Persons	2.81	0.34	5.17	0.57	0.32	0.12	31.94	7.76	3.35	2.49
2	1 Person	2.15	0.18	4.57	0.35	0.55	0.09	31.05	6.96	6.05	3.02
	2 Persons	2.50	0.16	5.11	0.34	0.66	0.10	31.67	6.95	3.32	2.27
	3-4 Persons	2.64	0.20	5.17	0.43	0.52	0.11	30.59	7.46	3.06	2.20
	5+ Persons	2.96	0.33	5.46	0.57	0.51	0.13	31.70	7.64	2.15	1.97
3	1 Person	2.34	0.21	4.93	0.37	0.65	0.08	28.37	6.95	4.92	2.96
	2 Persons	2.67	0.15	5.44	0.29	0.75	0.08	29.49	7.07	2.40	1.90
	3-4 Persons	2.86	0.16	5.59	0.37	0.71	0.09	28.61	7.39	1.70	1.53
	5+ Persons	3.16	0.28	5.81	0.49	0.69	0.11	29.64	7.48	1.26	1.42
4	1 Person	2.50	0.22	5.19	0.39	0.70	0.09	26.41	6.94	4.50	3.06
	2 Persons	2.86	0.16	5.79	0.30	0.84	0.08	26.54	6.75	1.72	1.76
	3-4 Persons	3.09	0.14	6.01	0.29	0.85	0.07	25.28	7.03	0.87	1.01
	5+ Persons	3.40	0.24	6.16	0.40	0.82	0.08	26.66	7.19	0.66	0.90
5	1 Person	2.64	0.24	5.42	0.38	0.75	0.09	26.90	6.34	5.04	3.70
	2 Persons	3.15	0.17	6.22	0.26	0.91	0.05	23.91	5.91	1.28	1.88
	3-4 Persons	3.41	0.16	6.42	0.21	0.93	0.04	22.12	6.13	0.49	0.79
	5+ Persons	3.72	0.22	6.48	0.29	0.90	0.05	23.08	6.28	0.41	0.56

Note: The breakpoints for the household income quintiles are $20k, $36.4k, $56k, and $86.25k.

Appendix B – Estimation Results for All Covariates

Table B.1 Estimation Results, All Stage 1 Covariates, Discrete Choice Base Models

	Discrete Choice Full (All Ages) Sample Base Model	**Discrete Choice** Prime-Aged Sample Base Model
Variable	Coef (Std Err)	Coef (Std Err)
Hicksian Bundle	0.0352 (0.0009)	0.0404 (0.0011)
Moved from State of Birth	-3.1189 (0.0185)	-3.1080 (0.0237)
Moved from Division of Birth	-0.9162 (0.0240)	-0.8543 (0.0305)
Moved from Region of Birth	-0.4569 (0.0220)	-0.5362 (0.0279)
Std. Dev: Avg Winter Temperature	0.0666 (0.0020)	0.0588 (0.0026)
Std. Dev: Avg Summer Temperature	0.0522 (0.0060)	0.0592 (0.0068)
Correlation Coefficient	-0.8332 (0.0731)	-0.6893 (0.0827)

Table B.2 Estimation Results, All Stage 2 Covariates, Discrete Choice and Hedonic Base Model

	Discrete Choice Full (All Ages) Sample Base Model		**Discrete Choice** Prime-Aged Sample Base Model		**Hedonic** Albouy Weights Base Model		**Hedonic** Traditional Weights Base Model	
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)
Avg Winter Temperature	0.0249	$709	0.0209	$518	0.0015	$104	0.0030	$207
	(0.0056)	($160)	(0.0058)	($144)	(0.0005)	($33)	(0.0006)	($42)
Avg Summer Temperature	-0.0307	-$873	-0.0253	-$627	-0.0052	-$358	-0.0033	-$228
	(0.0091)	($260)	(0.0100)	($249)	(0.0009)	($64)	(0.0010)	($68)
July Humidity	-0.0269	-$764	-0.0208	-$514	0.0010	$71	0.0012	$84
	(0.0049)	($142)	(0.0054)	($135)	(0.0003)	($24)	(0.0005)	($35)
Annual Snowfall	-0.0166	-$471	-0.0170	-$422	-0.0002	-$16	0.0004	$29
	(0.0024)	($70)	(0.0026)	($66)	(0.0002)	($11)	(0.0002)	($16)
Ln(Summer Precipitation)	0.1408	$376	0.1708	$403	-0.0031	-$19	0.0128	$81
	(0.0720)	($192)	(0.0768)	($181)	(0.0067)	($42)	(0.0080)	($50)
Annual Sunshine	-0.0155	-$441	-0.0149	-$368	0.0028	$191	0.0019	$129
	(0.0057)	($162)	(0.0060)	($149)	(0.0005)	($35)	(0.0006)	($44)
Ln(Population Density)	0.2283	$7	0.2094	$6	0.0173	$2	-0.0179	-$3
	(0.0452)	($1)	(0.0494)	($1)	(0.0039)	($1)	(0.0049)	($1)
Mean PM2.5	0.0708	$2,014	0.0572	$1,416	-0.0044	-$303	-0.0056	-$384
	(0.0159)	($455)	(0.0164)	($408)	(0.0011)	($75)	(0.0014)	($95)
Violent Crime Rate	0.0045	$129	0.0006	$15	-0.0042	-$288	-0.0043	-$301
	(0.0136)	($386)	(0.0142)	($352)	(0.0013)	($87)	(0.0017)	($116)
Transportation Score	0.0093	$263	0.0105	$259	-0.0001	-$9	0.0003	$23
	(0.0015)	($42)	(0.0015)	($39)	(0.0001)	($8)	(0.0001)	($10)
Education Score	0.0034	$97	0.0043	$106	0.0000	$1	0.0000	$2
	(0.0015)	($44)	(0.0016)	($41)	(0.0001)	($9)	(0.0001)	($10)
Arts Score	0.0048	$136	0.0043	$106	0.0001	$5	-0.0004	-$26
	(0.0017)	($49)	(0.0018)	($46)	(0.0001)	($9)	(0.0002)	($12)
Healthcare Score	0.0005	$13	0.0002	$4	0.0003	$24	0.0002	$11
	(0.0012)	($33)	(0.0012)	($31)	(0.0001)	($7)	(0.0001)	($8)
Recreation Score	0.0131	$374	0.0124	$307	0.0001	$4	-0.0002	-$17
	(0.0015)	($44)	(0.0016)	($41)	(0.0001)	($9)	(0.0002)	($12)
Park Area	0.0002	$4	0.0001	$4	0.0000	$0	0.0000	-$1
	(0.0001)	($2)	(0.0001)	($1)	(0.0000)	($0)	(0.0000)	($0)
Visibility > 10 Miles	0.0078	$222	0.0073	$180	0.0000	-$1	-0.0010	-$68
	(0.0032)	($92)	(0.0033)	($82)	(0.0002)	($16)	(0.0003)	($21)
Ln(Elevation)	0.0810	$13,069	0.0895	$12,450	0.0021	$740	0.0027	$965
	(0.0441)	($7,126)	(0.0481)	($6,706)	(0.0032)	($1,126)	(0.0043)	($1,531)
Distance to Coast	-0.0025	-$45	-0.0020	-$25	-0.0001	-$3	0.0003	$16
	(0.0007)	($15)	(0.0007)	($14)	(0.0001)	($3)	(0.0001)	($3)

Appendix C – Discrete Choice Model Sensitivities

Table C.1 Marginal Willingness to Pay for Climate Amenities (Hicksian Bundle and Temperature Specifications)

	Model 1 Base Model		**Model 9** Quadratic HB		**Model 10** Log(Wage) in 1st stage with housing price index in 2nd stage		**Model 11** Quadratic Temperature	
PANEL A: 1st Stage Estimates								
Variable	Coef (Std Err)		Coef (Std Err)		Coef (Std Err)			
Std. Dev: Avg Winter Temperature	0.0666 (0.0020)		0.0664 (0.0020)		0.0673 (0.0020)		Same 1st Stage Estimates as Model 1	
Std. Dev: Avg Summer Temperature	0.0522 (0.0060)		0.0536 (0.0059)		0.0527 (0.0059)			
Correlation Coefficient	-0.8332 (0.0731)		-0.8273 (0.0699)		-0.8257 (0.0723)			
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)	0.0253 (0.0055)	$588 ($135)	0.0226 (0.0057)	$885 ($247)	0.0581 (0.0162)	$711 ($174)
Mean: Avg Summer Temperature	-0.0307 (0.0091)	-$873 ($260)	-0.0319 (0.0091)	-$740 ($220)	-0.0256 (0.0093)	-$1,004 ($402)	-0.0856 (0.1449)	-$849 ($246)
July Humidity	-0.0269 (0.0049)	-$764 ($142)	-0.0264 (0.0049)	-$614 ($120)	-0.0296 (0.0050)	-$1,160 ($224)	-0.0268 (0.0050)	-$763 ($142)
Annual Snowfall	-0.0166 (0.0024)	-$471 ($70)	-0.0166 (0.0024)	-$385 ($60)	-0.0169 (0.0024)	-$662 ($110)	-0.0149 (0.0025)	-$425 ($72)
Ln(Summer Precipitation)	0.1408 (0.0720)	$376 ($192)	0.1433 (0.0716)	$312 ($161)	0.1495 (0.0737)	$550 ($297)	0.1784 (0.0768)	$476 ($205)
Annual Sunshine	-0.0155 (0.0057)	-$441 ($162)	-0.0143 (0.0056)	-$331 ($135)	-0.0183 (0.0059)	-$716 ($253)	-0.0101 (0.0074)	-$286 ($210)

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

Table C.2 Marginal Willingness to Pay for Climate Amenities (Random Parameter Sensitivities)

PANEL A: 1st Stage Estimates	**Model 1** [a] (Base Model) RP: WT, ST (WT, ST correlated)	**Model 12** [b] RP: HB, WT, ST (HB uncorrelated)	**Model 13** [c] RP: MC Div, WT, ST (MC uncorrelated)	**Model 14** [d] RP: Humidity, WT, ST (all correlated)	**Model 15** [e] RP: Snowfall, WT, ST (all correlated)
Variable	Coef (Std Err)	Coef (Std Err)	Coef (Std Err)	Coef (Std Err)	Coef (Std Err)
Hicksian Bundle	0.0352		0.0357	0.0351	0.0352
	(0.0009)		(0.0009)	(0.0009)	(0.0009)
Mean: Hicksian Bundle		0.0358			
		(0.0009)			
Std. Dev: Hicksian Bundle		0.0220			
		(0.0025)			
Moved from State of Birth	-3.1189	-3.1260	-3.1910	-3.1159	-3.1189
	(0.0185)	(0.0186)	(0.0202)	(0.0184)	(0.0185)
Moved from Division of Birth	-0.9162	-0.9162		-0.9167	-0.9162
	(0.0240)	(0.0240)		(0.0241)	(0.0240)
Mean: Moved Division			-0.9654		
			(0.0259)		
Std. Dev: Moved Division			0.9716		
			(0.0482)		
Moved from Region of Birth	-0.4569	-0.4589	-0.4551	-0.4513	-0.4564
	(0.0220)	(0.0220)	(0.0219)	(0.0220)	(0.0220)
Std. Dev: Avg Winter Temperature	0.0666	0.0661	0.0620	0.0664	0.0671
	(0.0020)	(0.0020)	(0.0022)	(0.0020)	(0.0028)
Std. Dev: Avg Summer Temperature	0.0522	0.0505	0.0337	0.0463	0.0525
	(0.0060)	(0.0061)	(0.0049)	(0.0061)	(0.0059)
Correlation Coefficient (WT, ST)	-0.8332	-0.8383	-0.9966	-0.9134	-0.8033
	(0.0731)	(0.0773)	(0.0345)	(0.0822)	(0.0745)
Std. Dev: July Humidity				0.0038	
				(0.0051)	
Std. Dev: Annual Snowfall					0.0023
					(0.0055)

Table C.2 Marginal Willingness to Pay for Climate Amenities (Random Parameter Sensitivities) (Cont'd)

	Model 1 [a] (Base Model) RP: WT, ST (WT, ST correlated)		Model 12 [b] RP: HB, WT, ST (HB uncorrelated)		Model 13 [c] RP: MC Div, WT, ST (MC uncorrelated)		Model 14 [d] RP: Humidity, WT, ST (all correlated)		Model 15 [e] RP: Snowfall, WT, ST (all correlated)	
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)	Coef (Std Err)	MWTP (Std Err)
Mean: Avg Winter Temperature	0.0249	$709	0.0251	$703	0.0285	$797	0.0251	$714	0.0249	$709
	(0.0056)	($160)	(0.0056)	($158)	(0.0057)	($160)	(0.0056)	($160)	(0.0056)	($160)
Mean: Avg Summer Temperature	-0.0307	-$873	-0.0311	-$870	-0.0362	-$1,014	-0.0309	-$879	-0.0305	-$867
	(0.0091)	($260)	(0.0092)	($257)	(0.0092)	($260)	(0.0092)	($262)	(0.0091)	($261)
July Humidity (Mean: Model 14)	-0.0269	-$764	-0.0270	-$756	-0.0283	-$792	-0.0266	-$758	-0.0267	-$761
	(0.0049)	($142)	(0.0050)	($141)	(0.0050)	($142)	(0.0050)	($143)	(0.0049)	($142)
Annual Snowfall (Mean: Model 15)	-0.0166	-$471	-0.0166	-$465	-0.0169	-$474	-0.0166	-$473	-0.0164	-$467
	(0.0024)	($70)	(0.0024)	($69)	(0.0025)	($70)	(0.0024)	($70)	(0.0024)	($70)
Ln(Summer Precipitation)	0.1408	$376	0.1408	$369	0.1467	$385	0.1367	$365	0.1384	$369
	(0.0720)	($192)	(0.0725)	($190)	(0.0733)	($193)	(0.0718)	($192)	(0.0721)	($192)
Annual Sunshine	-0.0155	-$441	-0.0157	-$440	-0.0148	-$416	-0.0160	-$455	-0.0155	-$441
	(0.0057)	($162)	(0.0057)	($161)	(0.0058)	($162)	(0.0057)	($162)	(0.0057)	($162)

Notes:

[a] Random parameters: winter and summer temperature; winter and summer temperature correlated

[b] Random parameters: Hicksian bundle, winter, and summer temperature; winter and summer temperature correlated

[c] Random parameters: moving cost (from Census division of birthplace), winter, and summer temperature; winter and summer temperature correlated

[d] Random parameters: relative July humidity, winter temperature, and summer temperature; humidity, winter temperature, and summer temperature all correlated

[e] Random parameters: annual snowfall, winter temperature, and summer temperature; snowfall, winter temperature, and summer temperature all correlated

Figure C.1 Taste-Sorting, Impact of Adding Uncorrelated Hicksian Bundle as a Random Parameter (Model 1 vs. Model 12)

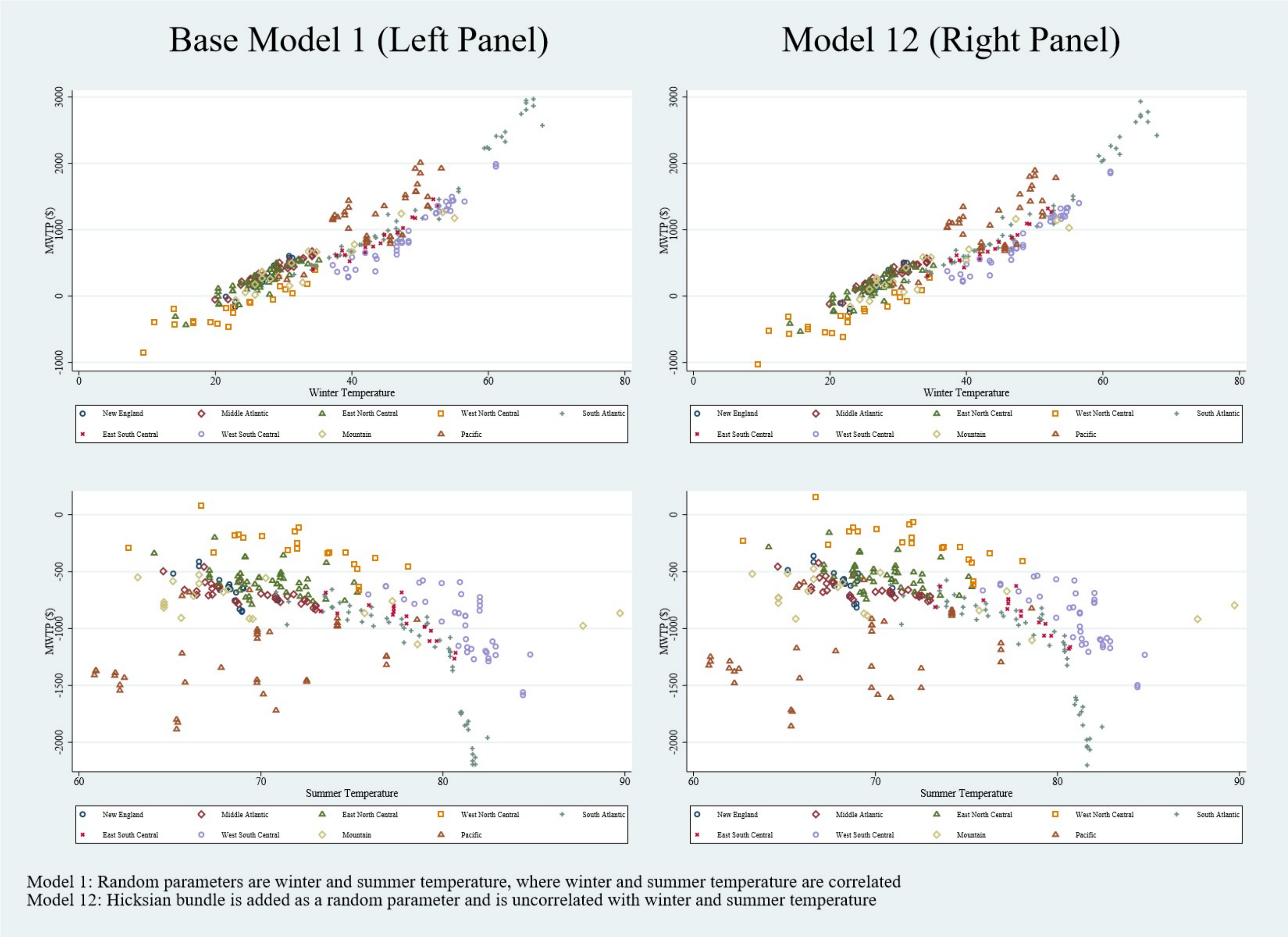


Figure C.2 Taste-Sorting, Impact of Adding Uncorrelated Moving Cost (Division Dummy) as a Random Parameter (Model 1 vs. Model 13)

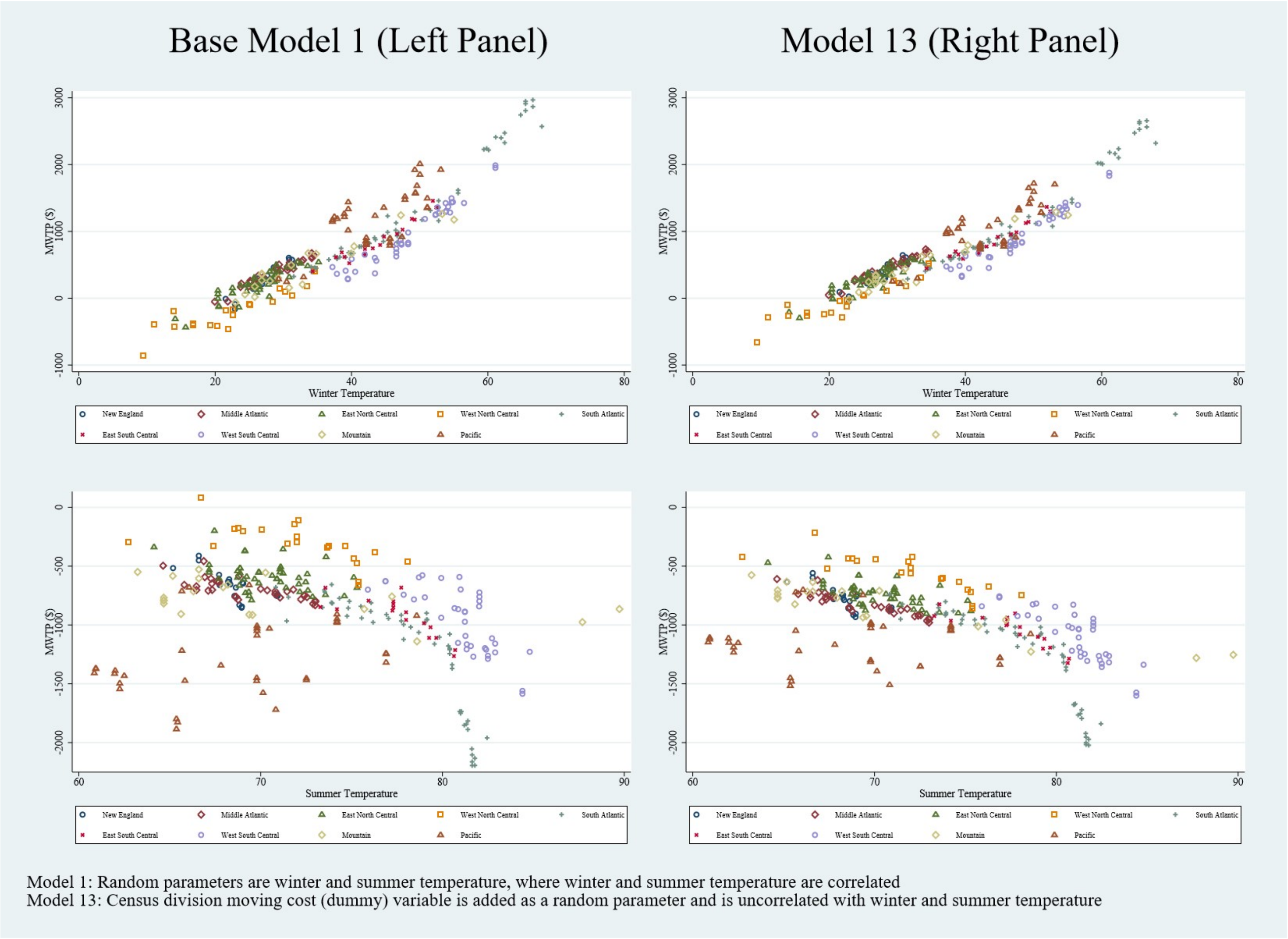
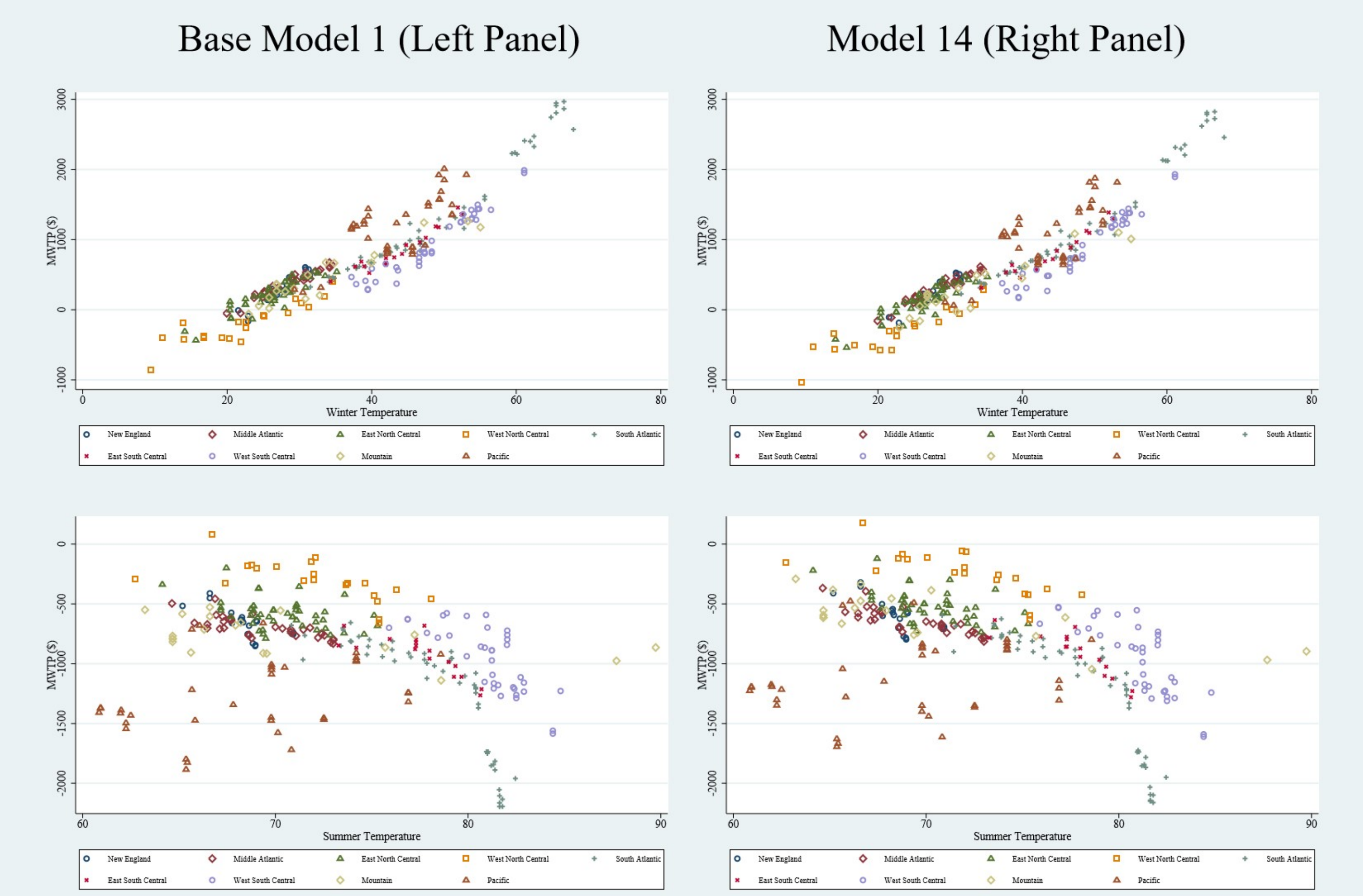
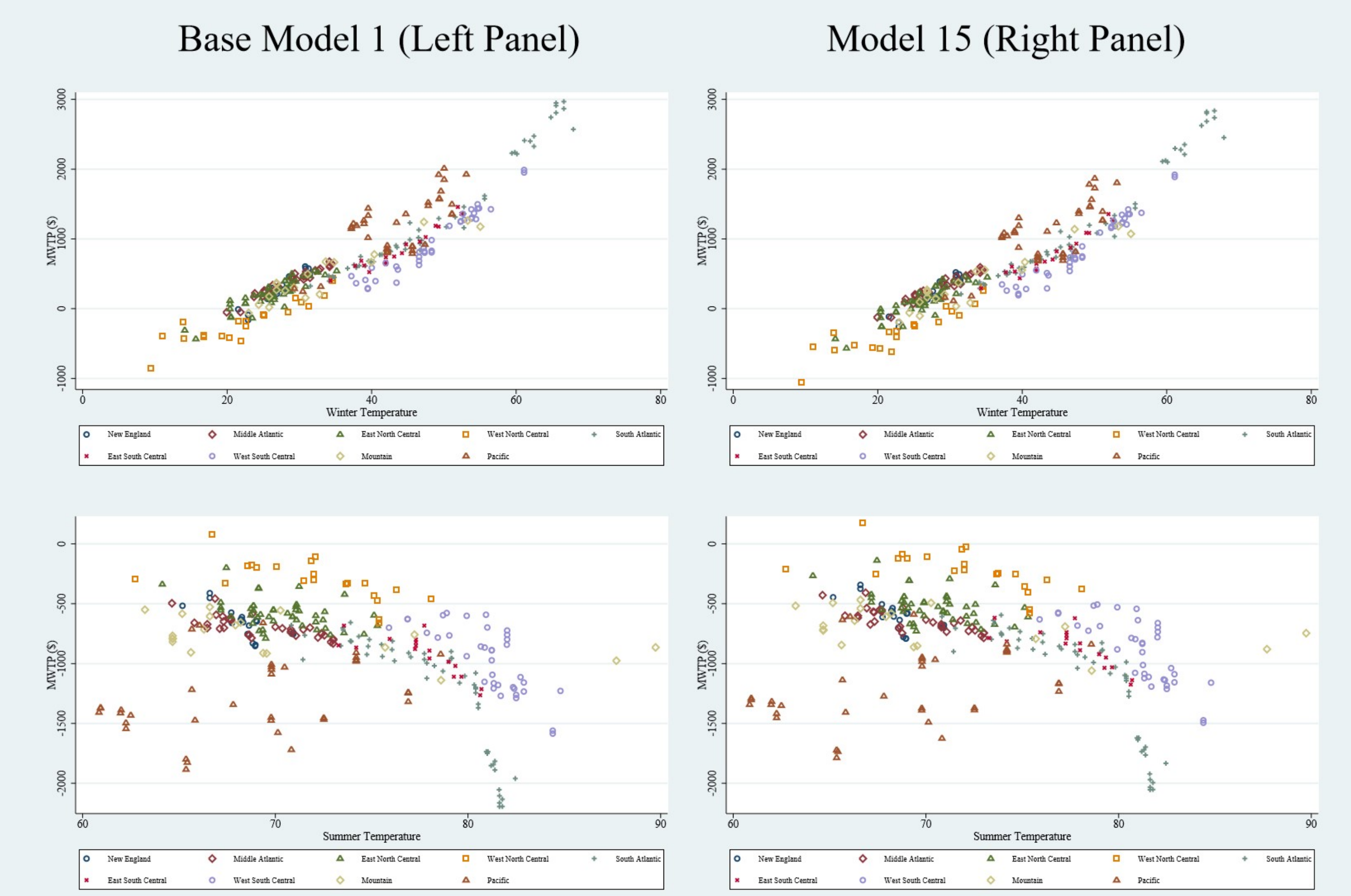


Figure C.3 Taste-Sorting, Impact of Adding Correlated Relative July Humidity as a Random Parameter (Model 1 vs. Model 14)



Model 1: Random parameters are winter and summer temperature, where winter and summer temperature are correlated
Model 14: Relative July humidity is added as a random parameter and is correlated with winter and summer temperature

Figure C.4 Taste-Sorting, Impact of Adding Correlated Annual Snowfall as a Random Parameter (Model 1 vs. Model 15)



Model 1: Random parameters are winter and summer temperature, where winter and summer temperature are correlated
Model 15: Annual snowfall is added as a random parameter and is correlated with winter and summer temperature

Appendix D – Notes on Model 10 (Housing Price Index in Stage 2 Regression)

Suppose household *i* maximizes a Cobb-Douglas utility function subject to a budget

$$U_{ij} = C_{ij}^{\alpha_C} H_{ij}^{\alpha_H} e^{MC_{ij}} e^{\boldsymbol{A}_j \boldsymbol{\beta}_i}$$

constraint $C_{ij} + \rho_j H_{ij} = Y_{ij}$ where C_{ij} is consumption of a composite good in city *j*, H_{ij} is housing, ρ_j is a city-specific housing price index, and all other variables are as previously defined. Substituting optimal values for C_{ij} and H_{ij} and taking logs yields the following specification for indirect utility for household *i* living in city *j*, where $\alpha_Y = \alpha_C + \alpha_H$:[72]

$$\ln V_{ij} = \alpha_0 + \alpha_Y \ln Y_{ij} + MC_{ij} - \alpha_H \ln \rho_j + \boldsymbol{A}_j \boldsymbol{\beta}_i$$

Combining terms that vary only by MSA gives an alternative expression of indirect utility,

$$\ln V_{ij} = \alpha_0 + \alpha_Y \ln Y_{ij} + MC_{ij} + \delta_j'$$

where $\delta_j' = -\alpha_H \ln \rho_j + \boldsymbol{A}_j \boldsymbol{\beta}_i$. First stage estimation proceeds via simulated maximum likelihood as in my base case.

In the second stage, I would like to regress the estimated MSA fixed effects ($\hat{\delta}_j'$) on the housing price index and local amenities according to the following regression:

[72] $\alpha_0 = \alpha_C \left(\frac{\alpha_C}{\alpha_C + \alpha_H}\right) + \alpha_H \left(\frac{\alpha_H}{\alpha_C + \alpha_H}\right)$

$$\hat{\delta}_j' = -\alpha_H \ln\rho_j + \boldsymbol{A}_j\boldsymbol{\beta}_i + \eta_{ij}$$

However, ρ_j is likely to be correlated with the error term η_{ij}. Thus, I rearrange and estimate the equation below, recalling that ρ_j is the estimated fixed effect from a national

$$\hat{\delta}_j' + \alpha_H \ln\rho_j = \boldsymbol{A}_j\boldsymbol{\beta}_i + \eta_{ij}$$

hedonic regression of housing expenditures on housing characteristics and that, by the properties of Cobb-Douglas utility, I have that α_H/α_Y is the proportion of income spent on housing. Thus, multiplying the median share of income spent on housing from my sample of households (0.25) by $\hat{\alpha}_Y$ (estimated in the first stage) gives me an estimate for α_H.

Appendix E – Bandwidth Sensitivities for Local Linear Hedonic Model

Figure E.1 Winter Temperature Bandwidth Sensitivities, Adjusted Weights

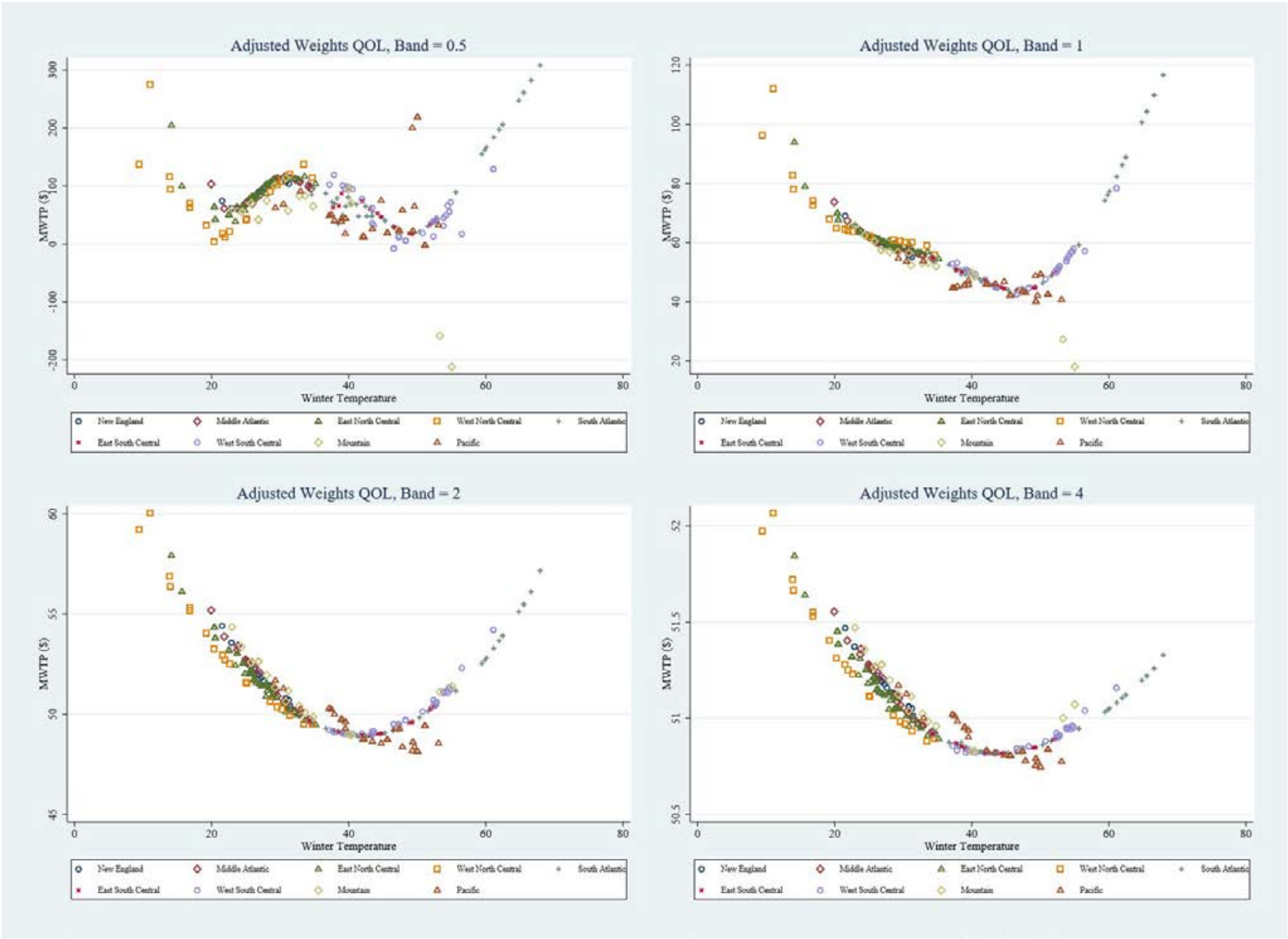


Figure E.2 Summer Temperature Bandwidth Sensitivities, Adjusted Weights

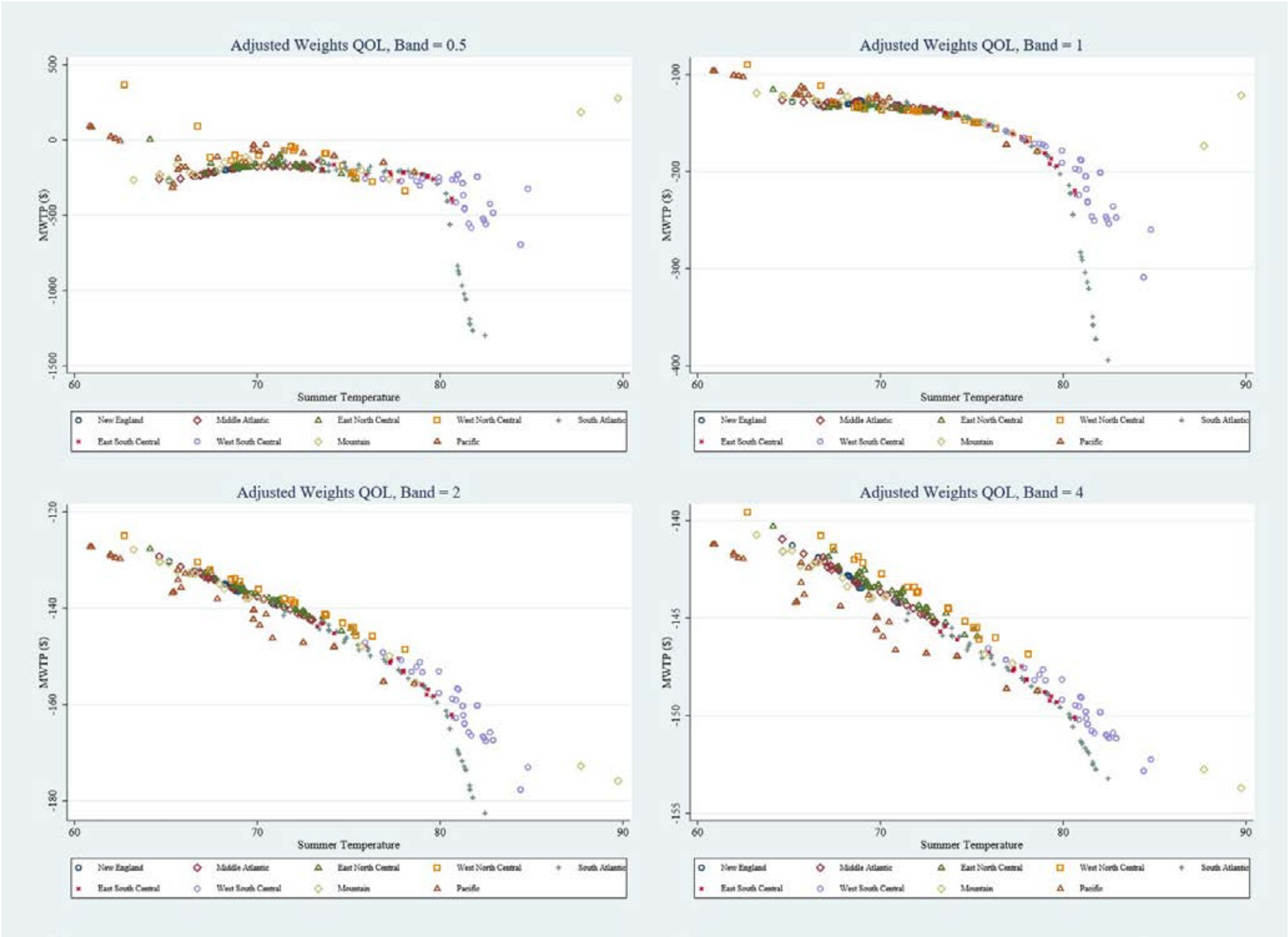


Figure E.3 Winter Temperature Bandwidth Sensitivities, Traditional Weights

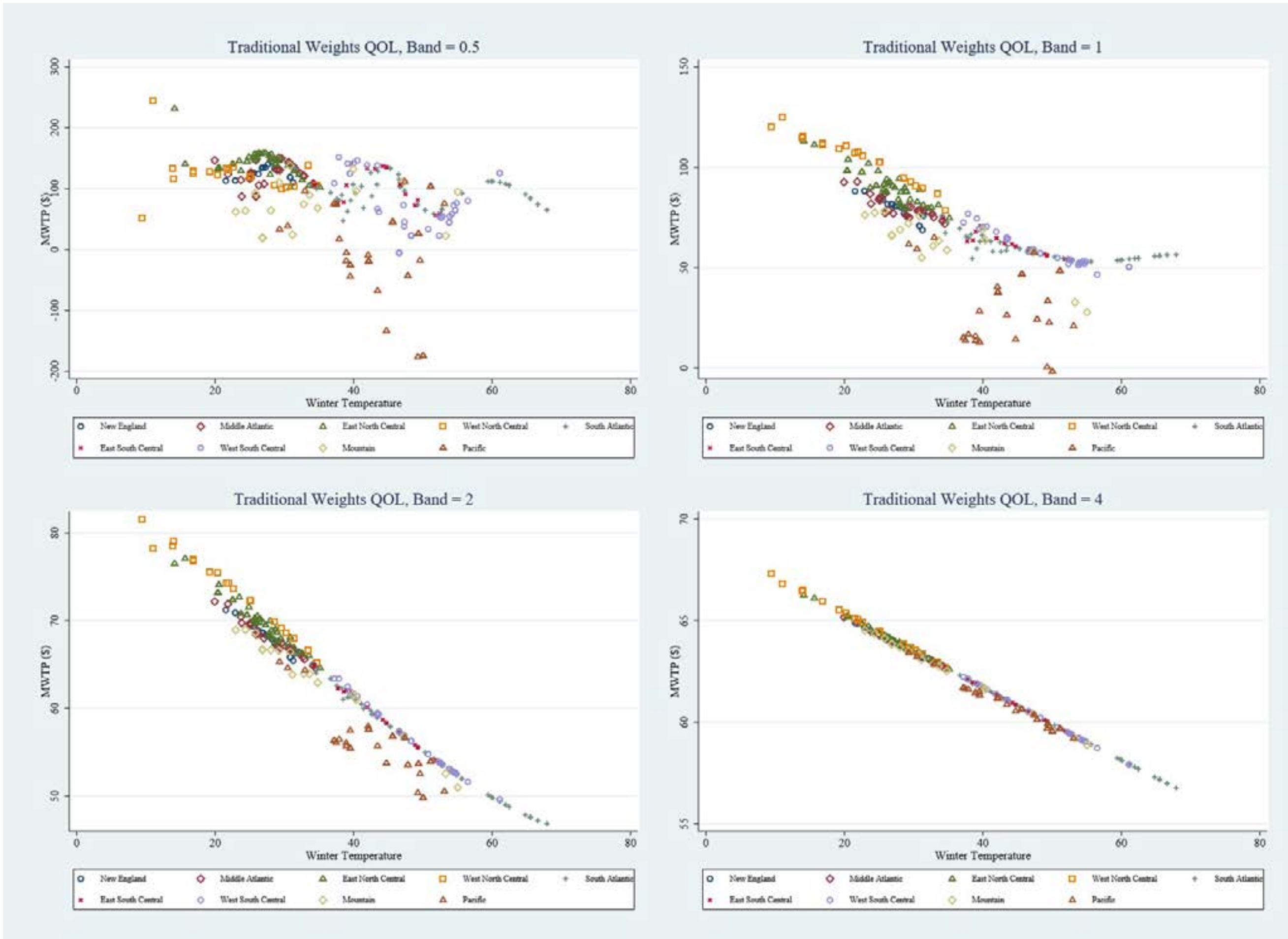
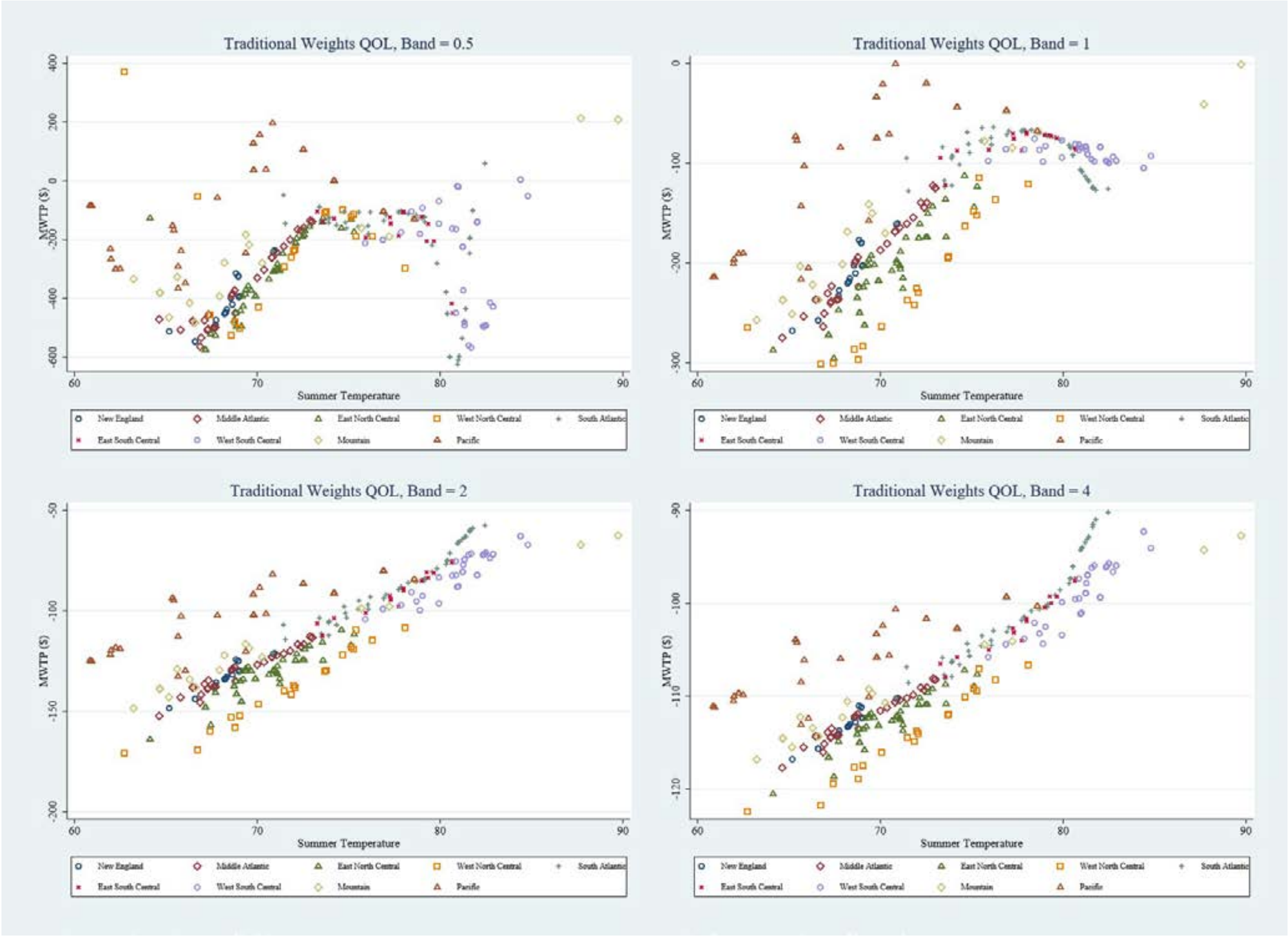


Figure E.4 Summer Temperature Bandwidth Sensitivities, Traditional Weights



Appendix F – Estimated Dependent Variable (EDV) Model and Stage 2 Standard Error Corrections

Table F.1 Standard Error Sensitivities, Stage 2 Regressions, Discrete Choice Model

2nd Stage Estimates	Base Model (OLS, Robust SEs)	WLS[a]	FGLS (Version 1)[b]	FGLS (Version 2)[c]
Variable	Coef (Std Err)	Coef (Std Err)	Coef (Std Err)	Coef (Std Err)
Mean: Avg Winter Temperature	0.0209	0.0196	0.0204	0.0212
	(0.0058)	(0.0059)	(0.0058)	(0.0058)
Mean: Avg Summer Temperature	-0.0253	-0.0225	-0.0240	-0.0257
	(0.0100)	(0.0100)	(0.0100)	(0.0100)
July Humidity	-0.0208	-0.0208	-0.0208	-0.0206
	(0.0054)	(0.0054)	(0.0054)	(0.0054)
Annual Snowfall	-0.0170	-0.0173	-0.0171	-0.0170
	(0.0026)	(0.0027)	(0.0026)	(0.0026)
Ln(Summer Precipitation)	0.1708	0.1562	0.1632	0.1710
	(0.0768)	(0.0751)	(0.0759)	(0.0770)
Annual Sunshine	-0.0149	-0.0151	-0.0150	-0.0149
	(0.0060)	(0.0059)	(0.0060)	(0.0060)

[a] Weights are the inverse of the estimated dependent variable's standard error
[b] Weights incorporate both estimated dependent variable's standard error, as well as variance of stage 2 random shock component. The estimated dependent variable's standard errors are assumed to be known.
[c] Weights incorporate both estimated dependent variable's standard error, as well as variance of stage 2 random shock component. The estimated dependent variable's standard errors are assumed known up to a proportion.

Table F.2 Standard Error Sensitivities, Stage 2 Regressions, Hedonic Model

	QOL (Adjusted-Weights)		QOL (Traditional Weights)	
	Base Model (OLS, Robust SEs)	FGLS (Version 2)[c]	Base Model (OLS, Robust SEs)	FGLS (Version 2)[c]
2nd Stage Estimates				
Variable	Coef (Std Err)	Coef (Std Err)	Coef (Std Err)	Coef (Std Err)
Avg Winter Temperature	0.0015	0.0015	0.0030	0.0030
	(0.0005)	(0.0005)	(0.0006)	(0.0006)
Avg Summer Temperature	-0.0052	-0.0052	-0.0033	-0.0033
	(0.0009)	(0.0009)	(0.0010)	(0.0010)
July Humidity	0.0010	0.0010	0.0012	0.0012
	(0.0003)	(0.0003)	(0.0005)	(0.0005)
Annual Snowfall	-0.0002	-0.0002	0.0004	0.0004
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Ln(Summer Precipitation)	-0.0031	-0.0032	0.0128	0.0122
	(0.0067)	(0.0067)	(0.0080)	(0.0080)
Annual Sunshine	0.0028	0.0028	0.0019	0.0018
	(0.0005)	(0.0005)	(0.0006)	(0.0006)

[c] Weights incorporate both estimated dependent variable's standard error, as well as variance of stage 2 random shock component. The estimated dependent variable's standard errors are assumed known up to a proportion.

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