Preliminary Draft – Please Do Not Cite or Quote

Why Do Discrete Choice Approaches to Valuing Urban Amenities Yield Different Results than Hedonic Models?

Paramita Sinha, RTI International; Martha Caulkins, University of Maryland; Maureen Cropper, University of Maryland and Resources for the Future

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., 2013) or 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 second, 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 produced by the continuous hedonic approach. Bayer, Keohane and Timmins (2009) estimate marginal willingness to pay (MWTP) to reduce air pollution damages that is three times greater using a discrete choice approach than an hedonic approach. Sinha and Cropper (2013) estimate higher damages associated with predicted changes in climate in U.S. cities than Albouy et al. (2013)'s hedonic model. Both sets of authors attribute this to moving costs: the continuous hedonic approach assumes that consumers are perfectly mobile; 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' marginal amenity values.

In this paper we examine differences between the continuous hedonic and discrete choice approaches in the context of valuing climate amenities. Specifically we use the 2000 PUMS to estimate hedonic and discrete choice models that value winter and summer temperature. Our 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 MSAs as the geographic unit (Albouy, 2012). Wage and housing price indices are estimated, following Albouy et al. (2013), assuming national labor and housing markets. We construct a weighted sum of wage and housing price indices for each MSA using the same weights as in Albouy et al. (2013) and, alternately, using a traditional set of weights (Roback, 1982). We allow the marginal price of winter and summer temperature to vary by city using local linear regressions (Bajari and Benkard, 2005).

In discrete location choice models 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. 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) and older heads (> 55 years old). We estimate random parameter logit models 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. We 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 we are measuring. Mean MWTP estimates from the hedonic and discrete choice approaches (not conditional on location) are closest when we compare the preferences of prime-aged households estimated using the discrete choice model to hedonic estimates using Roback weights. When the discrete choice model is estimated using prime-aged households the mean MWTP for a one degree increase in winter temperature is $320; it is -$180 for a one degree increase in summer temperature. When we use traditional weights, the hedonic approach yields mean MWTP for winter and summer temperature of $210 and -$230, respectively. The pattern of MWTP conditional on household location differs, however, between the two approaches. The hedonic estimates do not show a positive correlation between MWTP for winter temperature and winter temperature itself.

Why should estimates using the two approaches differ from each other? First, the hedonic and discrete choice models differ in their underlying assumptions about consumer mobility and market integration. The hedonic approach assumes perfect mobility, whereas moving costs are more easily incorporated in discrete models of location choice. The hedonic models assume national labor and housing markets, while discrete choice models, beginning with Cragg and Kahn (1997) do not. Second, 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, focuses on quantities. Wong (2010) suggests that one approach is the dual of the other only under quite restrictive conditions. Third, the two models use fundamentally different econometric approaches to capture heterogeneity in tastes.

When we estimate our discrete choice model without moving costs, the value of warmer winters falls significantly. And, the positive correlation between higher MWTP for warmer winters and the temperature of the chosen city disappears. Moving costs do not, however, completely explain differences in taste sorting implied by the two sets of models.

The paper is organized as follows. Section 2 describes the hedonic model of amenity valuation as originally developed by Roback (1982) and modified by Albouy (2012) and Albouy et al. (2013). We present the discrete location choice model that we estimate in section 3 and describe our data in section 4. Section 5 presents the results of both modeling approaches. This includes estimates of mean MWTP for winter and summer temperature and the implications of both models for taste sorting. Section 6 concludes.

2. Hedonic Models of Amenity Valuation

The Roback and Albouy Models

The hedonic approach to valuing location-specific amenities dates from Jennifer Roback's (1982) seminal article "Wages, Rents and the Quality of Life." Roback posited that, in a world of perfectly mobile individuals, wages and land prices would adjust to equalize utility in all locations. Consider a world of homogeneous individuals who receive utility from housing h, a traded good, C and a location-specific amenity, a.[1] In each location, j, the individual selects C and h to maximize utility subject to a budget constraint,

$$\max_{C_j, h_j} U(C_j, h_j; a_j) \quad s.t. \quad W_j + I = r_j h_j + C_j \tag{1}$$

where r_j is the rental price of housing, W_j is wage income, I is non-wage income, which is independent of location, and the price of traded the good, C, has been normalized to 1.[2] This yields an indirect utility function $V(W_j, r_j, a_j)$. If individuals are perfectly mobile, locational equilibrium requires that utility be everywhere equal,

$$V(W_j, r_j, a_j) = k \tag{2}$$

implying that housing prices and wages will adjust to equalize utility. The value to consumers of a small change in a_j is given by

$$MWTP_a \equiv \frac{V_a}{V_W} = h\frac{dr}{da} - \frac{dW}{da} \quad and \quad \frac{MWTP_a}{W} \equiv \frac{V_a}{V_W}\frac{1}{W} = s_H\frac{d\log r}{da} - \frac{d\log W}{da} \tag{3}$$

where s_H is the share of the consumer's budget spent on housing.

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,

$$\ln w_{mj} = \gamma^0 + \boldsymbol{X}_{mj}^{w}\boldsymbol{\Gamma}^{X,0} + \boldsymbol{A}_j\Gamma^{A,0} + \nu_{mj}^0 \tag{4}$$
$$\ln P_{ij} = \delta^0 + \boldsymbol{X}_{ij}^{P}\boldsymbol{\Delta}^{X,0} + \boldsymbol{A}_j\boldsymbol{\Delta}^{A,0} + \omega_{mj}^0 \tag{5}$$

[1] Roback's model deals with land, not housing. In the subsequent literature, r is treated as the rental rate on housing.
[2] It is assumed that each individual offers a single unit of labor in each location.

where w_{mj} is the hourly wage earned by worker m in location j, $\boldsymbol{X}^{w}_{mj}$ is a vector measuring the education, experience, demographic characteristics, industry and occupation of worker m, P_{ij} is housing expenditure by household i in location j, and $\boldsymbol{X}^{P}_{ij}$ is a vector of dwelling characteristics. $\boldsymbol{A}_j$ is a vector of attributes characterizing location j. In using eqs. (4) and (5) to infer the value of location-specific amenities, Blomquist et al. (1988) multiply the hourly wage by the average number of workers per household and the average number of hours worked per week and weeks worked per year, and monthly housing expenditure by 12. Implicitly, wage differentials across counties are weighted ~3 times as large as housing price differentials.

Albouy (2012) makes significant modifications to Roback's approach. He argues that the weight placed on wage income is too high, relative to the cost of non-traded goods, and, he suggests an alternate approach to estimating the value of local amenities. 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 raises the weight placed on non-traded goods (proxied by housing) relative to wages. Second, Albouy estimates wage and housing price indices for each geographic area and combines them into a quality of life (QOL) index, using his adjusted weights. The QOL index is then regressed on site-specific amenities to estimate marginal amenity values.

Albouy's approach estimates equations (4) and (5) in two stages, including location-specific fixed effects in the hourly wage and housing rent equations in the first stage to construct wage and housing price indices, λ^{w}_{j} and λ^{P}_{j},[3]

$$\ln w_{mj} = \boldsymbol{X}^{w}_{mj}\boldsymbol{\Gamma}^{X,1} + \lambda^{w}_{j} + \nu^{1}_{mj} \tag{4′}$$
$$\ln P_{ij} = \boldsymbol{X}^{P}_{ij}\boldsymbol{\Delta}^{X,1} + \lambda^{P}_{j} + \omega^{1}_{mj} \tag{5′}$$

These indices are then weighted to form a QOL index (see equation (6)), which is then regressed on location-specific amenities.

$$QOL_j \equiv 0.33\lambda^{P}_{j} - 0.51\lambda^{w}_{j} = \boldsymbol{A_j}\boldsymbol{\theta} + \xi_j \tag{6}$$

Albouy and co-authors (2013) apply this approach to PUMA-level data from the 2000 US Census to estimate the value of changes in temperature in the US. They use flexible functional forms to relate binned temperature data to the QOL index, while 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.

Hedonic Models that We Estimate

We estimate two sets of hedonic models—one using traditional weights on the wage and housing price indices generated by equations (4') and (5') (i.e., the weights in equation (3)) and the other applying the weights proposed by Albouy to the same wage and housing price indices (i.e., the

[3] This is similar to the approach followed by Bieri, Kuminoff and Pope (2013).

adjusted weights in equation (6)). The national wage and property value equations estimated using the 2000 PUMS use the same set of explanatory variables as the wage and housing cost hedonic equations that we use in the discrete choice model (see Appendix), and use the same samples of workers and houses.

We regress each set of QOL indices (traditional and adjusted) on the same set of amenity variables used in estimating the discrete choice model. Our estimates of equations (4') and (5') yield price indices for 284 MSAs; hence we have 284 observations for our QOL regressions.[4] To allow the coefficients on temperature variables to vary by MSA, we use a modified local linear regression, in the spirit of Bajari and Benkard (2005) and Bajari and Kahn (2005). Specifically, we 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 local linear regression with kernel weights, as described in (7), 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 (7) emphasizes this.

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

$$\hat{\boldsymbol{e}} = [\hat{e}_j] \qquad \boldsymbol{T} = [[wt_j]\,[st_j]] \qquad \boldsymbol{W} = [diag(K_h(\boldsymbol{T}_j - \boldsymbol{T}_{j^*}))]$$

$$K(Z) = \prod_{z=wt,st} N\big((z_j - z_{j^*})/\hat{\sigma}_z\big)$$

$$K_h(Z) = K(Z/h)/h$$

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, which 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 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 marginal willingness to pay (MWTP) for an amenity (equation (3)). Bayer, Keohane and Timmins (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. 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).

[4] We estimate these models using OLS, and compute robust standard errors. Albouy et al. (2013) indicate that they weight observations by population in their QOL models. We have also estimated Albouy QOL models using population weights. The results are not significantly different from the unweighted results reported below.

The Discrete Choice Model

Our discrete choice model builds on the work of Bayer, Keohane and Timmins (2009) and Cragg and Kahn (1997). We model household location in 2000 assuming that each household selected its preferred MSA from the set of MSAs in the United States in 2000. Household utility depends on income minus the cost of housing, location-specific amenities and moving costs from the birthplace of the household head. Specifically, we assume that the utility that household *i* receives from city *j* is given by

$$U_{ij} = \alpha_i\left(Y_{ij} - P_{ij}\right) + \boldsymbol{A}_j\boldsymbol{\beta}_i + MC_{ij} \tag{8}$$

where Y_{ij} is household *i*'s income and P_{ij} its housing expenditure in city j. MC_{ij} represents the costs—psychological and other—of moving from the head of household's birthplace to city *j*. $\boldsymbol{A}_j$ is a vector of location-specific amenities. We allow the coefficients on the Hicksian bundle, Y_{ij}-P_{ij}, moving costs and amenities to vary across households.[5] Household income is the sum of the wages of all workers in the household, W_{ij} , plus non-wage income, which is assumed not to vary by residential location. To predict the earnings of household workers in locations not chosen we estimate hedonic wage and housing price equations for each MSA, as described below.

Moving costs capture the psychological, search, and out-of-pocket costs of leaving a household's place of origin. Seventy-four percent of households in our sample (see Table 1, full sample) live in the Census region in which the head was born; 67% live in 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), we represent moving costs as a series of dummy variables that reflect whether city *j* is outside of the state, Census division, and/or Census region in which household *i*'s head was born. Formally,

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

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 household head *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.

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

[5] In this paper we allow only the coefficients on summer and winter temperature to vary across households. In a companion paper we allow coefficients on moving costs, the Hicksian bundle and other climate variables to vary across households.

chosen location, we estimate a hedonic wage equation for each MSA and use it to predict W_{ij}. The hedonic wage equation for MSA j regresses the logarithm of the hourly wage rate for worker m in MSA j on variables ($\boldsymbol{X}_{mj}^{w}$) measuring the demographic characteristics—education, experience, and industry and occupation—of worker m.

$$\ln w_{mj} = \gamma_j^2 + \boldsymbol{X}_{mj}^{w}\boldsymbol{\Gamma}^{X,2} + \nu_{mj}^2 \quad \forall\, j = 1, \ldots, J \tag{10}$$

Equation (10) is estimated using data on full-time workers in the Public Use Microdata sample (PUMS).[6] The coefficients of (10) are used to calculate the earnings of each worker in the sample used to estimate the discrete choice model (see Table 1), under the assumption that individuals work the same number of hours and weeks in all locations. Summing earnings over all individuals in each household, we obtain predicted household wages for household i in location j ($\hat{W}_{ij}$).

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

$$\ln P_{ij} = \delta_j^2 + \boldsymbol{X}_{ij}^{P}\boldsymbol{\Delta}^{X,2} + \omega_{mj}^2 \quad \forall\, j = 1, \ldots, J \tag{11}$$

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

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

To estimate the discrete location choice model we assume that the coefficients in $\boldsymbol{\beta}_i$ are jointly normally distributed, with mean vector $\boldsymbol{\mu}$ and variance-covariance matrix $\boldsymbol{\Sigma}$.[7] The household's utility function is observed with 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 logit model,

---

[6] 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 (4′).

[7] In this paper we report results allowing only the coefficients on winter and summer temperature to be jointly normally distributed. Allowing the coefficients on other amenities (and moving costs) to be random does not substantially alter the results reported here.

$$P(i \; selectes \; j) \quad = \int_{-\infty}^{\infty} \frac{\exp(V_{ij}(\alpha, \boldsymbol{\beta}_i, \boldsymbol{\pi}))}{\sum_k \exp(V_{ik}(\alpha, \boldsymbol{\beta}_i, \boldsymbol{\pi}))} f(\boldsymbol{\beta}|\boldsymbol{\mu}, \boldsymbol{\Sigma}) d\beta \qquad (12)$$

Equation (12) is estimated via simulated maximum likelihood techniques, using the McFadden sampling procedure to reduce the size of each household's choice set (McFadden, 1978). Each household's choice set consists of the chosen MSA and 19 MSAs chosen at random from the universal choice set of 284 MSAs.

4. Data

The data used to estimate our discrete choice and hedonic models come from the 5 percent PUMS of the 2000 Census as well as other publicly available data sources.

Households Used to Estimate the Discrete Choice Model

The PUMS contains information on more than 5.6 million households. In estimating the discrete choice model we focus on households residing in one of the 284 MSAs for which we have complete amenity data. These MSAs contained 80% of the total US population in 2000. In order to be included in our sample, a household must be headed by a person 16 years of age or older who was born in the continental US. We exclude households whose heads are in the military, or who are in certain occupations (e.g., logging, mining) which would restrict locational choices. We also eliminate households whose members are self-employed, due to difficulty in predicting the wages of the self-employed, and drop households with negative Hicksian bundles at their chosen locations.[8] This leaves over 2 million households. A 10% sample of these households yields the 216,257 households described in Table 1.

We have estimated the discrete choice model for the full sample of households, and also for the two sub-samples described in Table 1: households with prime-aged heads (i.e., heads between 25 and 55) and households with heads over age 55. The results presented in this paper focus on households with prime-aged heads. As Table 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, especially when traditional weights are used.[9] Our 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.

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

[9] In adjusting the weights on wages and rents, Albouy (2012) weights the percent of wage income received by different demographic groups in the PUMS. Wage estimates in Albouy et al. (2013) are, however, based on prime-aged workers.

Climate Variables

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

We focus on mean temperature, measured for the winter (December–February) and summer (June–August) seasons. Previous studies of climate amenities have primarily used mean winter and summer temperature or annual heating and cooling degree days.[11,12] In studying the impact of climate on agriculture, health, and electricity usage, temperature has been measured by the number of days in various temperature bins (Schlenker and Roberts, 2009; Deschenes and Greenstone, 2011; Albouy et al., 2013). The advantage of mean winter and summer temperature is that they capture seasonality, which annual heating and cooling degree days and temperature bins do not.

At the same time, correlation between winter and summer temperature and temperature during other seasons of the year means that winter and summer temperature will pick up other temperature impacts: the correlation between mean winter temperature and mean March temperature is 0.98, as is the correlation between mean winter temperature and mean November temperature. Collinearity among mean winter, summer, fall, and spring temperatures, however, makes it impossible to include all four measures in our models.

The precision with which the impact of temperature on location decisions can be estimated depends on temperature variation. Mean winter temperature across the 284 MSAs in our data averages 37°F, with a standard deviation (s.d.) of 12°; summer temperature averages 73°, with an s.d. of 6°. Winter and summer temperature 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 −0.35), and snow is likely to be more of a disamenity than rain.

Summer precipitation, which averages 11 inches (s.d. = 5 inches), is heaviest in the southeastern United States. Surprisingly, the correlation between summer precipitation and winter precipitation is very low (r = 0.03), as is the correlation between summer precipitation and

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

[11] Heating and cooling degree days are computed by the National Climatic Data Center using the average of the high and low temperatures for a day. If this is greater than 65°F, it results in (average temperature−65) cooling degree days. If the average temperature is less than 65°, it results in (65−average temperature) heating degree days.

[12] 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).

annual snow (r = −0.02). Mean July relative humidity is 66 percent (s.d. = 11 percent) and is not highly correlated with either winter temperature (r = 0.07) or summer temperature (r = 0.14).

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

Nonclimate Amenities

The nonclimate amenity variables used in the second stage of the model are also summarized in Table 2. These include amenity measures typically used in quality-of-life studies as well as variables that are likely to be correlated with climate, such as elevation, visibility, and measures of parks and recreation opportunities. Our desire is to avoid problems of omitted variable bias by including a variety of location-specific amenities in our models and by using different functional forms for our temperature variables.

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

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

5. Estimation Results

In the spirit of Cragg and Kahn (1997) and Bayer, Keohane and Timmins (2009) we 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. We are, however, also interested in taste sorting. From the perspective of valuing climate, it matters how MWTP for temperature changes varies geographically—are households living 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? We approach this by measuring MWTP for temperature changes conditional a household's current location.

Discrete Choice Results

As noted above, we 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, and households headed by persons 16 years of age and older (full sample). In comparing the discrete choice and continuous hedonic approaches we focus on prime-aged households because of their strong labor-force attachment (see Table 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.

Table 3 describes the results of our base model for three samples: all households, prime-aged households and households with heads older than 55. The base model is a mixed logit model that allows the coefficients on winter and summer temperature to be jointly normally distributed and controls for all attributes in Table 2, as well as the Hicksian bundle and moving costs. Coefficients have been converted to MWTP by dividing by the coefficient on the Hicksian bundle. For winter and summer temperature we report the mean and standard deviation of the distribution of MWTP, as well as the correlation coefficient between the winter and summer temperature coefficients. Standard errors are reported for all MWTP estimates.[13]

The most striking result in the table is that the mean MWTP for winter and summer temperature differ 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 ($627 v. $319). At the same time, older households are, on average, willing to pay much more to decrease summer temperature than prime-aged households ($918 v. $183). This suggests the importance of considering all households when evaluating climate impacts for policy purposes.

We focus henceforth on prime-aged households. Table 4 presents estimates of MWTP for winter and summer temperature and other climate amenities based on four mixed logit models. Our base model (model M.1) controls for all of the amenities in Table 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 to model M.1, except for dropping population density. Both models suggest that, on average, higher winter temperature is an amenity, and warmer summer temperature a disamenity. Mean MWTP to increase winter temperature by one degree is higher than mean MWTP to reduce summer temperature ($319 v. $183 in model M.1; $302 v. $188 in model M.2). There is, however, considerable variation in tastes. Interestingly, the coefficients on winter and summer temperature are negatively correlated: most (but not all) households who prefer milder winters also prefer milder summers, while those who favor colder winters like hotter summers.

[13] Tables 3-6 in the text report MWTP only for climate variables. MWTPs for all model coefficients are reported in the Appendix.

To examine how households sort across locations in relation to their taste for winter and summer temperature we 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 in Figures 1 and 2.[14]

Households with higher MWTP for warmer winters tend to locate in warmer cities (the correlation coefficient between winter temperature and mean MSA MWTP is 0.90); however, there is some variation in mean MWTP across cities at a given temperature. For example, at a mean winter temperature of 40 degrees, households in Oregon and Washington state have a willingness to pay for a warmer winter that is over twice as high as the MWTP of households in Texas. At a mean winter temperature of 50 degrees, households on the Pacific coast are willing to pay approximately $180 more for warmer winter temperature than households in the East South Central division. Preferences for summer temperature (Figure 2) are even more varied: at a temperature of 70 degrees, households on the Pacific coast find warmer summers a disamenity; however, this is less so for people in the West North Central division (e.g., the Dakotas). This is also true at mean summer temperatures above 80—households in the South Atlantic division find warmer summers a disamenity but residents of Texas are willing to pay less to avoid hotter summers than residents of Florida.

Figures 1 and 2 suggest that, holding temperature constant, MWTP for winter and summer temperature varies by region: households in the East North Central Census division appear to find hotter summers less of a disamenity that households who have located on the Pacific coast. Households in the Mountain states appear to favor colder winters than households in the Pacific division. Some of this might appear to reflect differences in other climate variables besides temperature—such as differences in summer humidity, precipitation and snowfall. Our base model, however, controls for summer humidity, and precipitation, as well as snowfall and sunshine. Indeed, model M.4 indicates the importance of controlling for other climate variables: when they are omitted from the model, the mean of the coefficient distribution on winter temperature doubles, while the mean of the summer temperature becomes positive.

Failure to control for moving costs has a huge effect on the estimated value of climate amenities, as well as on the spatial distribution of MWTP for winter and summer temperature. Model M.3 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 almost 75%. The mean of the distribution on the coefficient of summer temperature becomes positive. The magnitude of the coefficients on other climate variables is also altered—snowfall becomes less of a disamenity and July precipitation less of an amenity.

Figures 3 and 4 show the impact of removing moving costs on taste sorting. Figure 3 suggests that mean MWTP for winter temperature is negatively correlated with winter temperature—a

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

pattern that also occurs in the hedonic results reported below. And, Figure 4 suggests that MWTP for warmer summers is positively associated with summer temperature. We present these results to show the importance of controlling for moving costs. Moving costs are highly significant in all discrete choice models and clearly belong in the models.

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 2. Not surprisingly, the traditional (Roback) weights, which are closer to the Hicksian bundle used in the discrete location choice model than the adjusted (Albouy) weights, lead to estimates that are closer to estimates produced by the discrete choice model. The taste sorting implied by the two hedonic models are, however, quite different from the taste sorting implied by the discrete choice model.

Table 5 displays MWTP for climate amenities implied by the QOL models, using, alternately, adjusted and traditional weights. Each model controls for all of the amenities listed in Table 2.[15] Models H.1, H.2 and H.3 allow winter and summer temperature to enter in linear, quadratic and cubic form. In each model, MWTP is computed at the means of each climate variable. 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 adjusted weights indicate that summer temperature is more of a disamenity than winter temperature is an amenity when evaluated at temperature means. MWTP to avoid an increase in summer temperature is, on average over three times as great as MWTP for an increase in winter temperature ($104 to $159 for winter temperature and -$358 to -$599 for summer temperature). In contrast, the two values are approximately equal in magnitude when traditional weights are used (e.g., $229 and -$257 in model H.3t).[16] As Table 6 shows, the results in Table 5 are robust to dropping population density as an amenity.

Table 5 suggests that the mean MWTP for winter and summer temperature produced by the hedonic and discrete models are close, when the hedonic model is estimated using traditional weights. The relationship between MWTP and temperature differs, however, between the discrete choice model and each of the hedonic models. The relationship between MWTP for winter and summer temperature and temperature is shown in Figures 5 and 6 for the quadratic and cubic hedonic models. The sorting pattern differs significantly from the discrete choice model for both sets of hedonic weights. MWTP for warmer winters decreases as winter temperature increases rather than increasing, as in Figure 1. In none of the hedonic models does MWTP display the inverted-U shape seen in Figure 2. Interestingly, the sorting patterns exhibited by the hedonic model with traditional weights are similar in shape to what is seen in the discrete choice model when moving costs are dropped from the model (Figures 3 and 4).

[15] MWTP in Tables 5 and 6 is calculated by multiplying the relevant coefficient by the mean income of prime-aged households.

[16] 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.

We 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, we regress the QOL index on all amenities except for winter and summer temperature and then use the residuals from this equation in a local linear regression with the 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. The marginal hedonic prices for winter and summer temperature are plotted in Figures 7-10 for the adjusted weight models using bandwidths of 0.5 and 1.0 and in Figures 11-14 for the models estimated using traditional weights, using the same bandwidths.[17]

The results of the local linear regressions are interesting, although we believe that they should be interpreted with caution, in view of the small number of observations involved. When traditional weights are used, the sorting pattern in Figures 11-14 resembles what is shown in Figures 5 and 6—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 resembles neither the pattern when traditional weights are used nor the pattern in Figures 5 or 6.

How do the results using the traditional hedonic weights compare with the discrete choice results? As in Figures 5 and 6, the marginal hedonic prices from the local linear regressions and the conditional means of MWTP from the discrete choice model have the same general shape when moving costs are dropped from the discrete choice model. However, there are important differences between the two sets of results. At first glance the range and shape of winter temperature results in Figures 3 and 12 (bandwidth = 1) are quite close. But, there are important differences: MWTP in Figure 3 is highest in the Pacific census division, while it is the lowest in that division in Figure 12. The value of increases in summer temperature is generally increasing in temperature in Figures 4 and 14 (bandwidth = 1) but there are important regional differences in this case as well. This leads us to conclude that, although moving costs are an important component of discrete choice location models, eliminating them does not cause these models to yield the same results as continuous hedonic models based on differences in wages and rents.

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. While previous comparisons of the two methods have focused on comparing mean MWTP estimates produced by the two approaches (Cragg and Kahn, 1997; Bayer, Keohane and Timmins, 2009) we have focused on comparing how MWTP for small changes in winter and summer temperature vary

[17] We have also estimated each model using bandwidths of 2 and 4; however, there is little variation in marginal hedonic prices in these cases. To illustrate, marginal prices for winter temperature using Albouy weights vary across cities between $40 and $50 when the bandwidth equals 2, and between $43 and $45 when the bandwidth equals 4.

with a household's current location. 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.[18]

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 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 by people living in North Dakota is higher than it is in Florida. The hedonic results with Albouy weights (bandwidth = 1) are a U-shaped function of temperature: MWTP is highest for people living in the West North Central census division, where it is very cold, and in Florida, where winters are mild, and 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 (bandwidth = 1) 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. The hedonic local linear regressions with traditional hedonic weights suggests that people living in the South Atlantic, West South Central and East South Central Census divisions are actually willing to pay less to avoid an increase in mean summer temperature than people in other parts of the country. The discrete choice model estimates that MWTP to avoid warmer summers is highest in the Pacific and mountain states.

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 approximately \$200 in the hedonic model with traditional weights and \$100 in the hedonic model with Albouy weights, but \$320 in the discrete choice model. Mean MWTP to avoid warmer summers is higher in the hedonic model with Albouy weights (~\$350) than in either the discrete choice or traditional hedonic models, where it is approximately \$200.[19]

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 we omit moving costs from the discrete choice model, the sorting pattern for winter temperature (Figure 3) resembles that of the hedonic model with traditional weights (Figure 12); i.e., MWTP for winter temperature decreases with temperature. The sorting pattern for summer temperature in the discrete choice model shows a close positive correlation between MWTP for summer temperature and summer

[18] We interpret both the mean of the coefficient on winter (summer) temperature conditional on location (conditional means, 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.

[19] The mean estimate for the hedonic models varies with bandwidth in the case of local linear regressions, and with the functional form of winter and summer temperature in Tables 5 and 6.

temperature when moving costs are omitted (Figure 4). The positive relationship is also suggested by the hedonic model with traditional weights (Figure 14) although there are important regional differences between the two models. So, moving costs appear to be an important factor explaining differences between hedonic and discrete choice models, but they are not the only one.

The hedonic and discrete choice approaches differ in other ways. 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 the same in all locations. 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. The econometric models underlying the two approaches also make different distributional assumptions. It is more difficult to judge the impact of these factors.

What we have not answered in this paper is the question that is of key importance to policymakers: which of the approaches yields the most reliable estimates of the value of climate amenities for use in evaluating climate policy? This is a question that clearly deserves more research.

References

Albouy, D. Y. (2012). “Are Big Cities Bad Places to Live? Estimating Quality of Life Across Metropolitan Areas.” NBER Working Paper 14472. Original 2008, revised May 29, 2012.

Albouy, D.; Graf, W.; Kellogg, R.; Wolff, H. (2013). “Climate Amenities, Climate Changes and American Quality of Life.” NBER Working Paper 18925.

Bajari, P. and Benkard, L. (2005). “Demand Estimation with Heterogeneous Consumers and Unobserved Product Characteristics: A Hedonic Approach.” Journal of Political Economy 113, no. 6: 1239-1276.

Bajari, P.; Kahn, M. (2005). “Estimating Housing Demand with an Application to Explaining Racial Segregation in Cities.” Journal of Business & Economic Statistics 23, no. 1: 20-33.

Bayer, P.; Keohane, N.; Timmins, C. (2009). “Migration and Hedonic Valuation: The Case of Air Quality.” Journal of Environmental Economics and Management 58: 1-14.

Bieri, D. S.; Kuminoff, N. V.; Pope, J. C. (2013). “The Role of Local Amenities in the National Economy.” Mimeo.

Blomquist, G. C.; Berger, M. C.; Hoehn, J. P. (1988). “New Estimates of Quality of Life in Urban Areas.” American Economic Review 78, no. 1: 89-107.

Cragg, M.; Kahn, M. (1997). “New Estimates of Climate Demand: Evidence from Location Choice.” Journal of Urban Economics 42: 261-284.

Cragg, M.; Kahn, M. (1999). “Climate Consumption and Climate Pricing from 1940 to 1990.” Regional Science and Urban Economics 29: 519–539.

Deschenes, O.; Greenstone, M. (2011). “Climate Change, Mortality, and Adaptation: Evidence from Annual Fluctuations in Weather in the US.” American Economic Journal: Applied Economics 3 no. 4: 152–185.

Graves, P.; Mueser, P. (1993). “The Role of Equilibrium and Disequilibrium in Modeling Regional Growth and Decline: A Critical Reassessment.” Journal of Regional Science 33 no. 1: 69–84.

Gyourko, J.; Tracy, J. (1991). “The Structure of Local Public Finance and the Quality of Life.” Journal of Political Economy 99, no. 4: 774–806.

Kahn, M. (2009). “Urban Growth and Climate Change.” Annual Review of Resource Economics 1: 333–350.

McFadden, D. (1978). “Modeling the Choice of Residential Location.” In Spatial Interaction Theory and Planning Models. Edited by A. Karlqvist, L. Lundquist, F. Snickars, and J. Weibull. Amsterdam: North Holland.

Rappaport, J. (2007). “Moving to Nice Weather.” Regional Science and Urban Economics 37, no. 3:

Roback, J. (1982). “Wages, Rents, and the Quality of Life.” Journal of Political Economy 90, no. 6: 1257-1278.

Savageau, D.; D’Agostino, R. (2000). Places Rated Almanac: Millennium Edition. New York: Hungry Minds Inc.

Schlenker, W.; Roberts, M. (2009). “Nonlinear Temperature Effects Indicate Severe Damages to US Crop Yields under Climate Change.” Proceedings of the National Academy of Sciences 106, no. 37: 15594–15598.

Sinha, P.; Cropper, M. (2013). “The Value of Climate Amenities: Evidence from U.S. Migration Decisions.” NBER Working Paper 18756.

Wong, M. (2010). “The Relationship Between Marginal Willingness-To-Pay in the Hedonic and Discrete Choice Models.” Mimeo.

Table 1. Descriptive Statistics for Household Characteristics

Variable	Description	Full Sample (N: 216257)		Prime-Aged (N: 132337)		Greater than 55 (N: 70994)	
		Mean	**Std. Dev.**	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**
Age of Household Head (Mean)	Age	49.15	17.11	40.76	8.18	69.61	9.43
Gender of Household Head (Proportion)	Male	63.83		66.73		60.94	
Marital Status of Household Head (Proportion)	Married	52.02		54.99		51.45	
Race of Household Head (Proportions)	White	82.48		80.86		86.90	
	Black	13.29		14.26		11.06	
	Other	4.23		4.87		2.04	
Education of Household Head (Proportions)	No high school	12.96		7.66		23.07	
	High school	26.04		23.91		30.10	
	Some college	30.94		33.88		23.75	
	College graduate	19.21		22.58		12.70	
	Postgraduate education	10.85		11.97		10.38	
Household Head Movement from Place of Birth (Proportions)	Left state of birth	42.63		40.95		47.32	
	Left Census division of birth	32.61		31.12		36.68	
	Left Census region of birth	26.33		24.86		30.40	
Household Wage Earnings (Mean)	Sum of the wage earnings of all household members	$49,781	$54,314	$64,159	$55,209	$25,885	$46,409
Household Wage Earnings (Proportion)	Households with zero wage earnings	16.89		2.18		47.20	
Total Household Income (Mean)	Sum of wage, business, and farm incomes and income from other sources[a] of all household members	$63,123	$58,320	$69,188	$59,658	$56,827	$57,624

Table 1. Descriptive Statistics for Household Characteristics

		Full Sample (N: 216257)		Prime-Aged (N: 132337)		Greater than 55 (N: 70994)	
Variable	**Description**	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**	**Mean**	**Std. Dev.**
Household Annual Housing Expenditures (Mean)	Sum of monthly mortgage payment or rent, cost of utilities, insurance, and property taxes	$15,544	$9,117	$16,186	$9,447	$15,487	$8,648
Size of Household (Proportions)	1 member	26.38		21.68		35.48	
	2 members	34.63		26.99		47.98	
	3 or more members	38.99		51.34		16.54	

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

Table 2. Descriptive Statistics of Amenity Variables

Variable	N	Mean	Std. Dev.	Minimum	Maximum	Median
Avg Winter Temperature (°F)	284	37.339	12.158	9.442	67.922	34.996
Avg Summer Temperature (°F)	284	73.309	5.817	60.848	89.733	72.517
Annual Snowfall (inches)	284	20.360	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

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

	Model M.1 (Prime)		Model M.1 (Full)		Model M.1 (>55)	
Sample	Prime-Aged (Base Model)		All Ages		Over 55 Years	
Variable	Mean	SE	Mean	SE	Mean	SE
Means:						
Avg Winter Temperature	$319	$23	$426	$20	$627	$35
Avg Summer Temperature	-$183	$39	-$382	$34	-$918	$60
Annual Snowfall	-$378	$11	-$410	$9	-$369	$15
Summer Precipitation	$369	$26	$403	$22	$392	$36
July Humidity	-$395	$19	-$607	$18	-$819	$33
Annual Sunshine	-$120	$26	-$86	$22	$134	$37
Standard Deviations:						
Avg Winter Temperature	$1,093	$33	$1,376	$29	$1,408	$53
Avg Summer Temperature	$1,568	$71	$1,570	$67	$951	$165
Correlation Coefficient	-0.63		-0.70		-0.79	

Note: MWTP estimates for all model covariates are presented in Appendix Table A. 1.

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

	Model M.1		Model M.2		Model M.3		Model M.4	
Sensitivity	Base Model		Omit population density		Omit moving costs		Omit other climate variables	
Variable	Mean	SE	Mean	SE	Mean	SE	Mean	SE
Means:								
Avg Winter Temperature	$319	$23	$302	$21	$65	$19	$576	$17
Avg Summer Temperature	-$183	$39	-$188	$37	$125	$33	$117	$36
Annual Snowfall	-$378	$11	-$359	$10	-$201	$8		
Summer Precipitation	$369	$26	$201	$23	$132	$21		
July Humidity	-$395	$19	-$338	$18	-$383	$17		
Annual Sunshine	-$120	$26	-$181	$24	-$238	$22		
Standard Deviations:								
Avg Winter Temperature	$1,093	$33	$1,110	$30	$67	$56	$1,019	$31
Avg Summer Temperature	$1,568	$71	$1,376	$70	$965	$114	$1,866	$59
Correlation Coefficient	-0.63		-0.66		-0.98		-0.71	

Note: MWTP estimates for all model covariates are presented in Appendix Table A. 2.

Table 5. Marginal Willingness To Pay for Climate Amenities (Base Hedonic Models)

	Adjusted Hedonic Weights						Traditional Hedonic Weights					
	Model H.1a		Model H.2a		Model H.3a		Model H.1t		Model H.2t		Model H.3t	
Temperature Specification	Linear		Quadratic		Cubic		Linear		Quadratic		Cubic	
Variable	Mean	SE	Mean	SE	Mean	SE	Mean	SE	Mean	SE	Mean	SE
Avg Winter Temperature	$104	$33	$110	$41	$159	$56	$207	$42	$186	$46	$229	$76
Avg Summer Temperature	-$358	$64	-$355	$65	-$599	$103	-$228	$68	-$228	$68	-$257	$148
Annual Snowfall	-$16	$11	-$10	$11	-$25	$11	$29	$16	$33	$16	$36	$16
Summer Precipitation	-$19	$42	-$9	$44	$30	$50	$81	$50	$99	$55	$111	$62
July Humidity	$71	$24	$71	$23	$70	$25	$84	$35	$84	$35	$75	$36
Annual Sunshine	$191	$35	$205	$45	$185	$43	$129	$44	$172	$57	$162	$59

Note: MWTP is computed at mean household income for the prime-aged sample ($69,188). MWTP is computed at temperature means for the quadratic and cubic models. MWTP estimates for all model covariates are presented in Appendix Table A. 3.

Table 6. Marginal Willingness To Pay for Climate Amenities (Hedonic Models Sensitivities)

	Adjusted Hedonic Weights						Traditional Hedonic Weights					
	Model H.1a		Model H.4a		Model H.5a		Model H.1t		Model H.4t		Model H.5t	
Sensitivity	Base Model		Omit population density		Omit other climate variables		Base Model		Omit population density		Omit other climate variables	
Variable	Mean	SE	Mean	SE	Mean	SE	Mean	SE	Mean	SE	Mean	SE
Avg Winter Temperature	$104	$33	$111	$37	$218	$28	$207	$42	$200	$44	$167	$26
Avg Summer Temperature	-$358	$64	-$353	$62	-$377	$64	-$228	$68	-$233	$72	-$164	$57
Annual Snowfall	-$16	$11	-$9	$13			$29	$16	$22	$17		
Summer Precipitation	-$19	$42	-$40	$42			$81	$50	$103	$49		
July Humidity	$71	$24	$82	$24			$84	$35	$72	$34		
Annual Sunshine	$191	$35	$173	$36			$129	$44	$148	$43		

Note: MWTP is computed at mean household income for the prime-aged sample ($69,188). MWTP estimates for all model covariates are presented in Appendix Table A. 4.

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

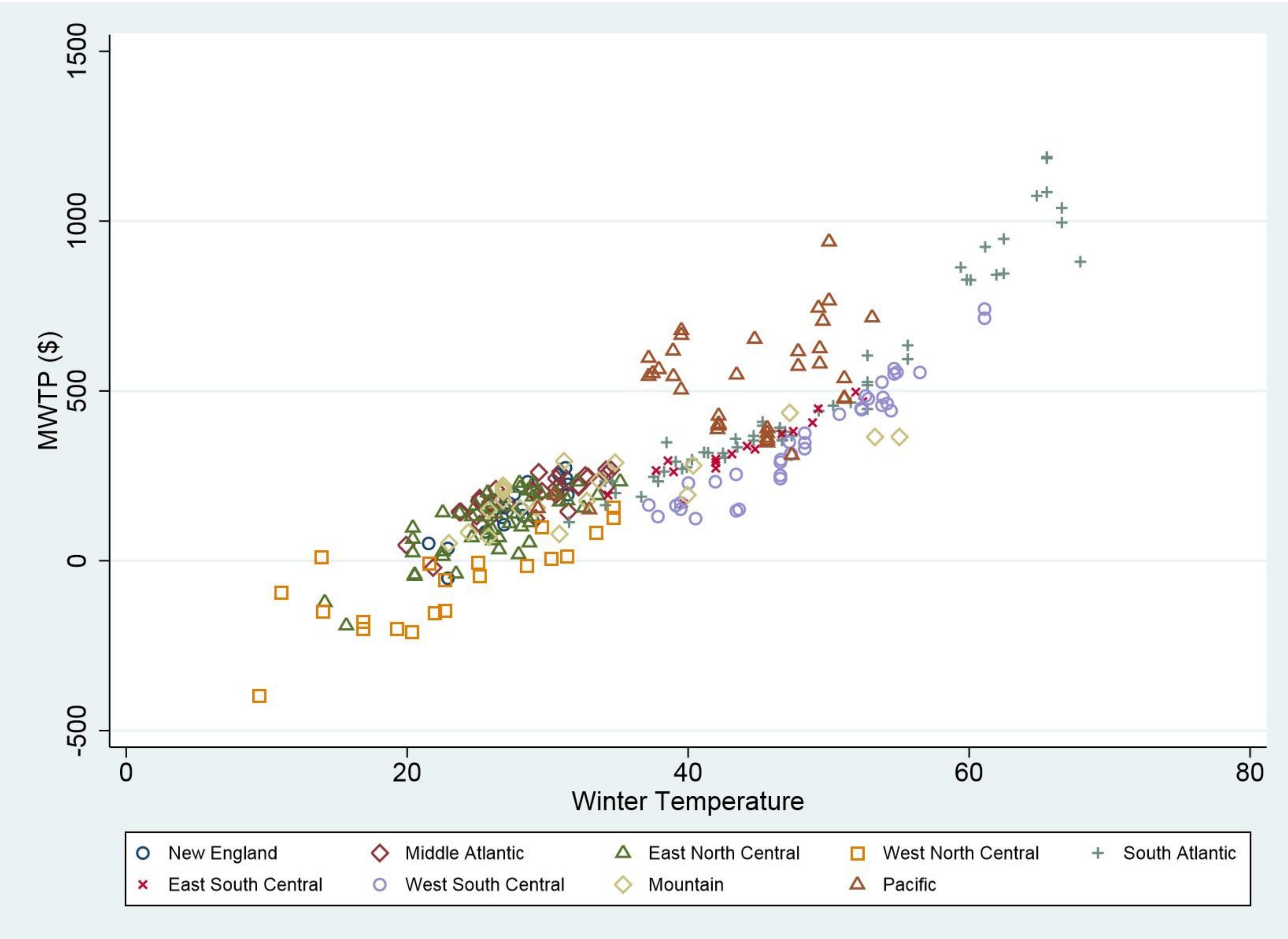

Figure 2. Taste-Sorting for Summer Temperature by Metropolitan Area (Base Discrete Choice Model – Model M.1)

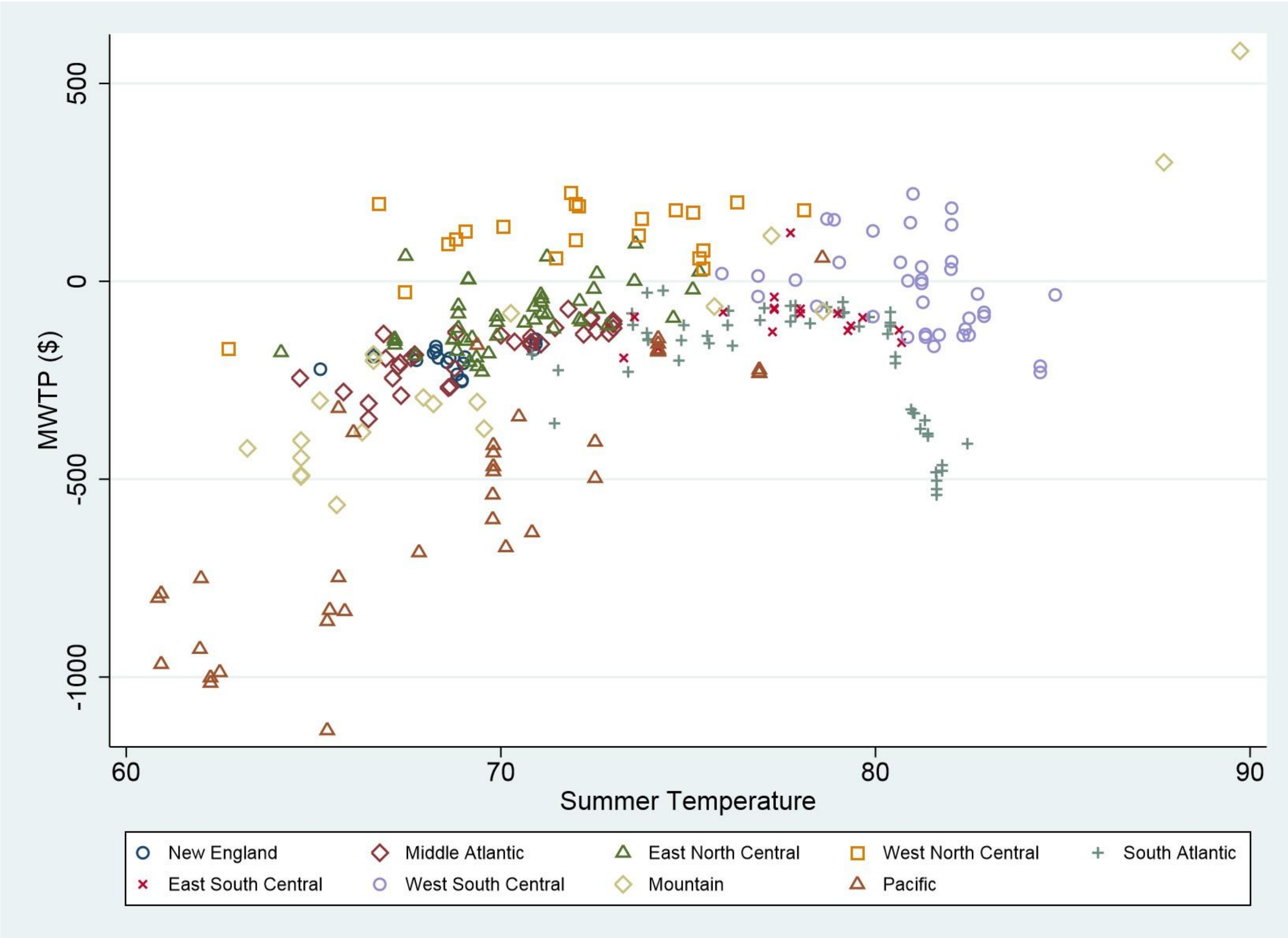

Figure 3. Taste-Sorting for Winter Temperature by Metropolitan Area (Discrete Choice Model with No Moving Costs – Model M.3)

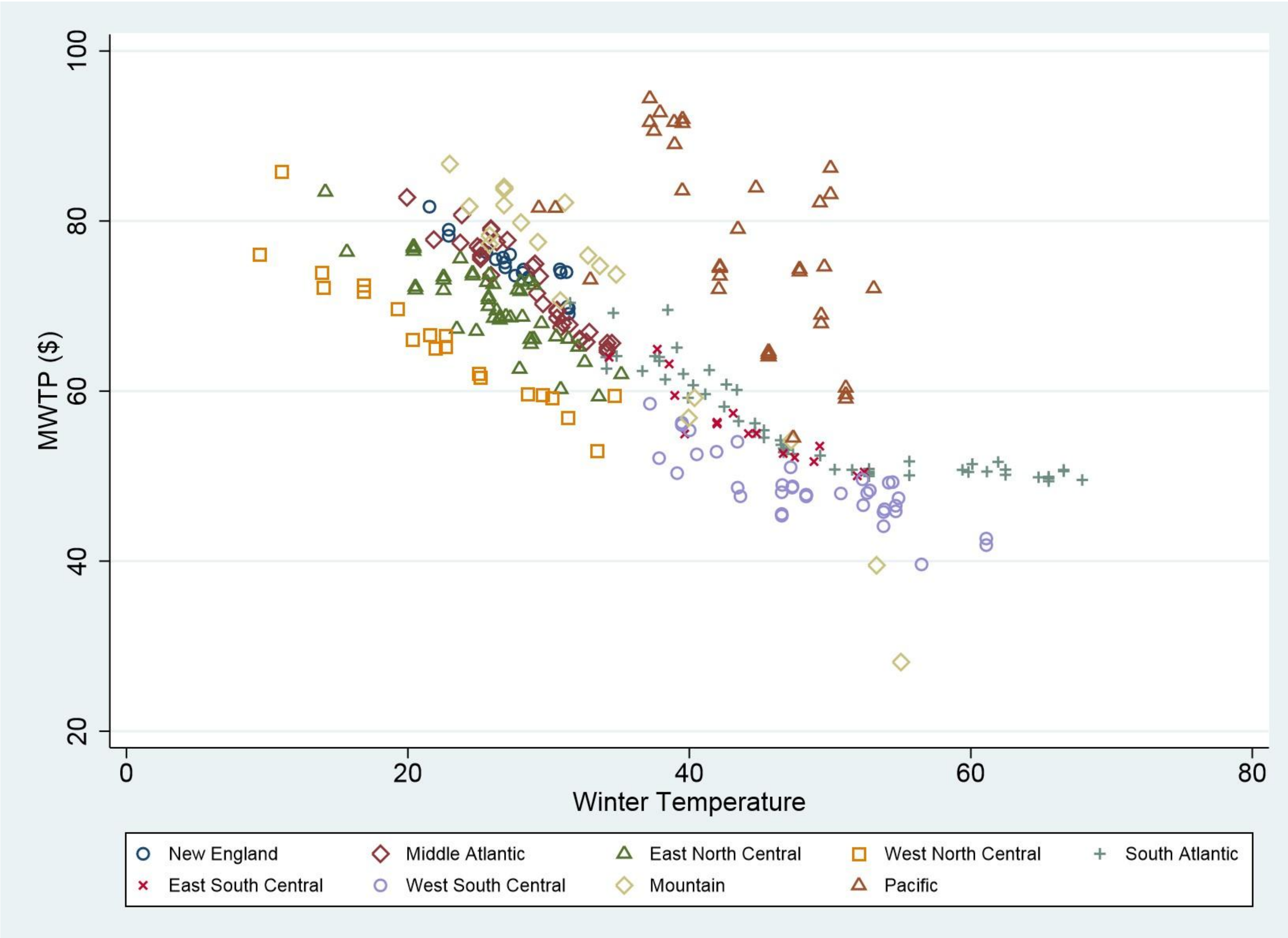

Figure 4. Taste-Sorting for Summer Temperature by Metropolitan Area (Discrete Choice Model with No Moving Costs – Model M.3)

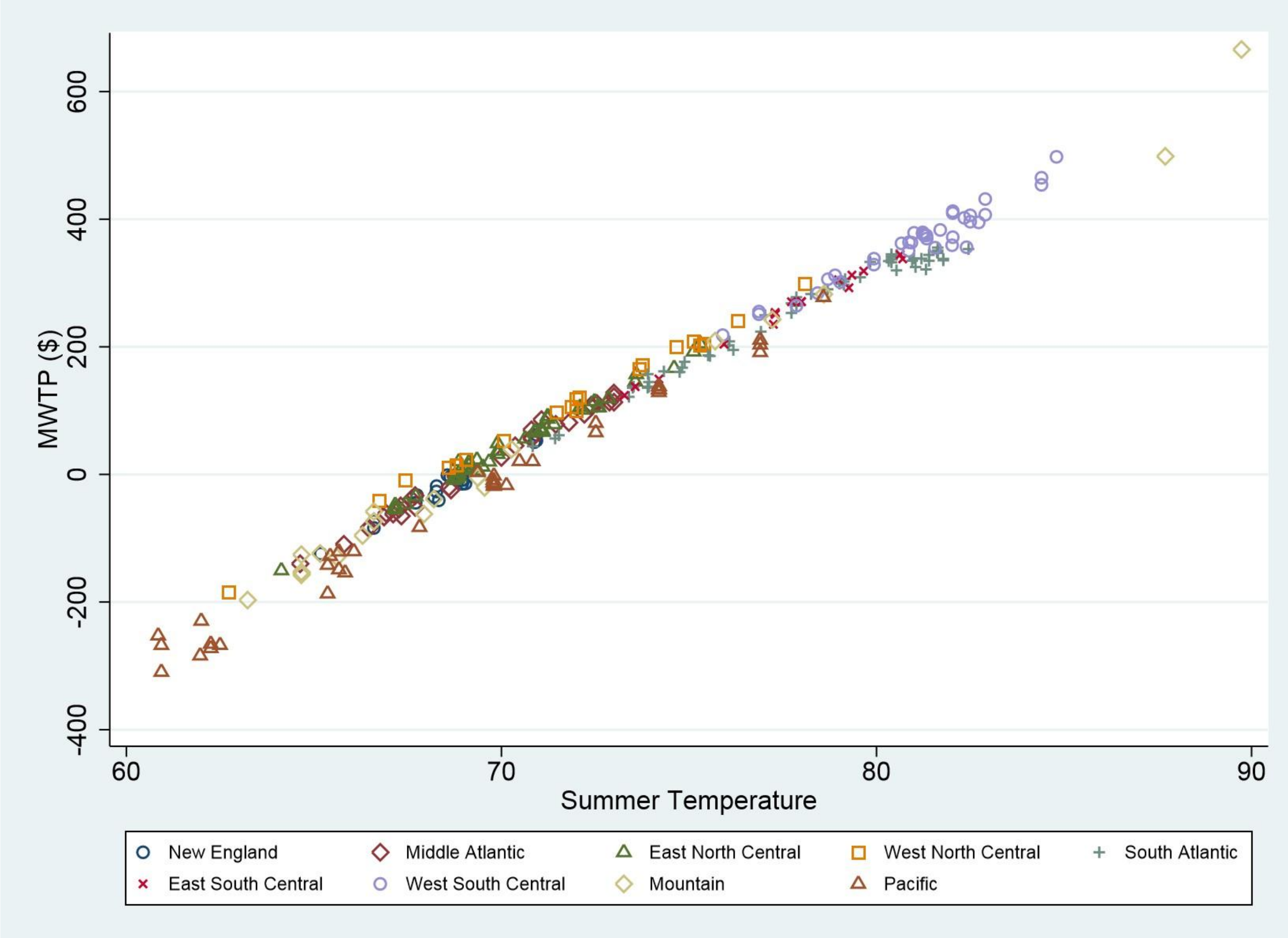

Figure 5. MWTP for Winter Temperature (Hedonic Models - Models H.2 and H.3)

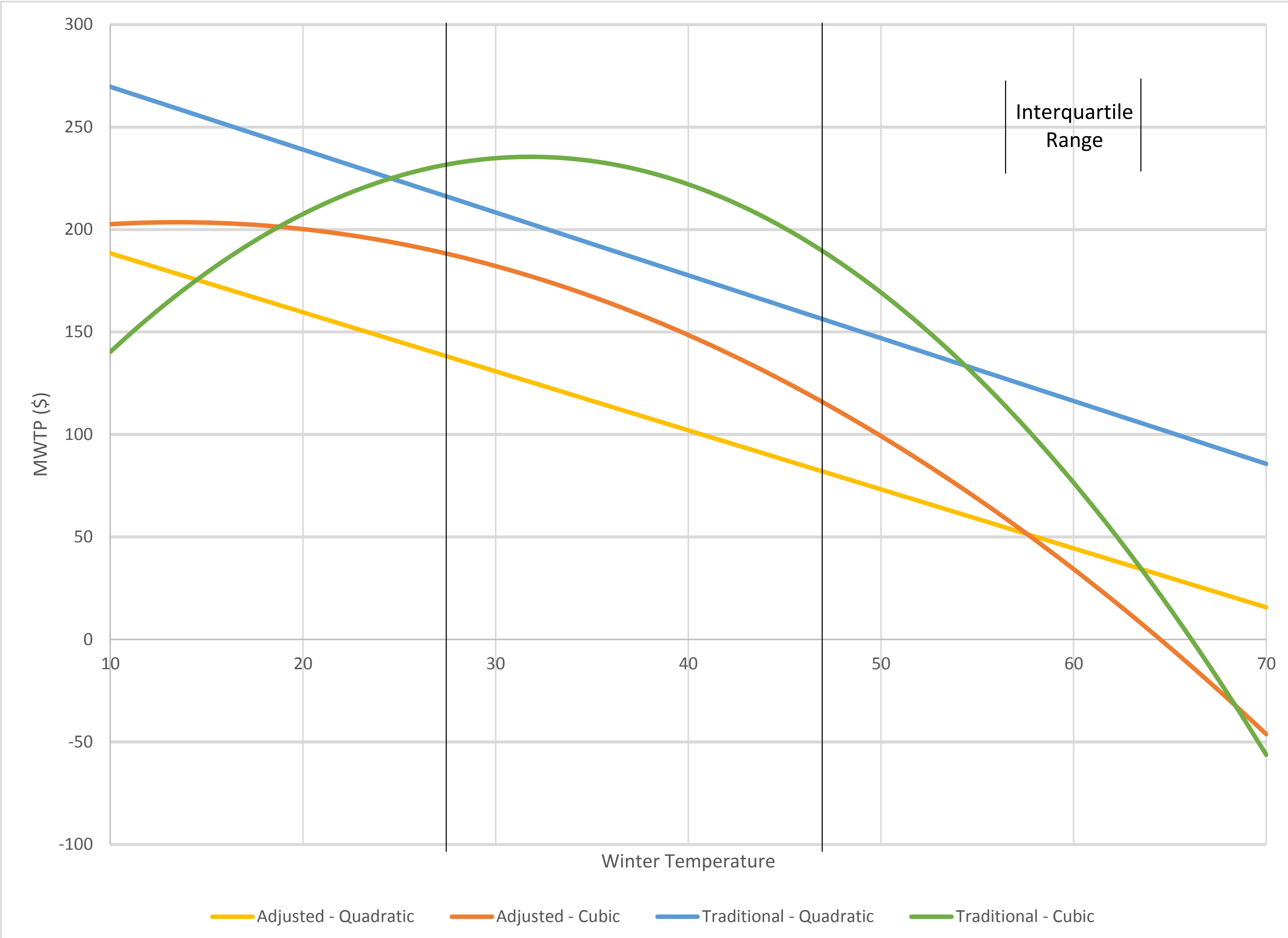

Figure 6. MWTP for Summer Temperature (Hedonic Models - Models H.2 and H.3)

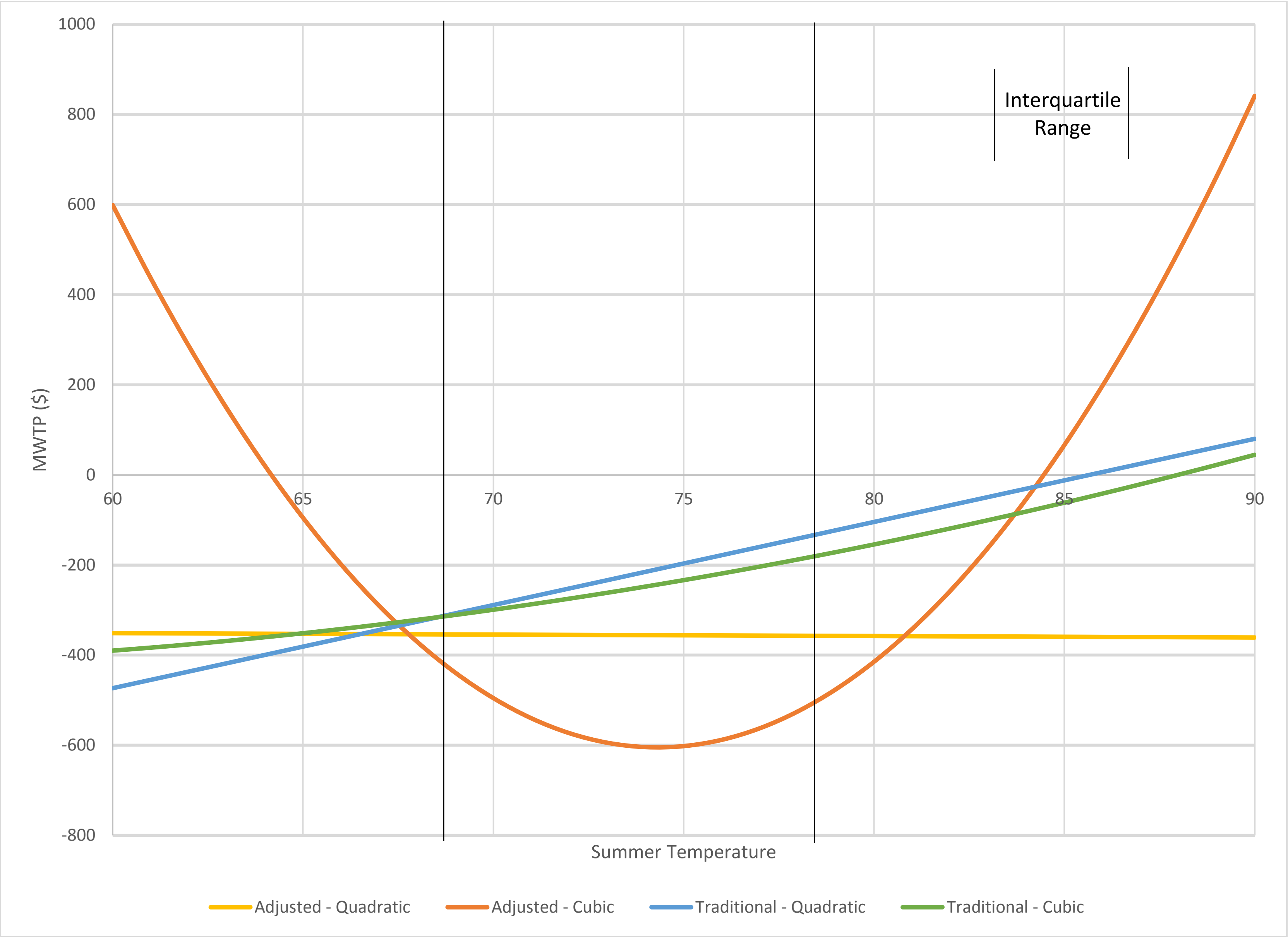

Figure 7. Taste-Sorting for Winter Temperature by Metropolitan Area (Local Linear Hedonic Model, Adjusted Weights, Bandwidth = 0.5)

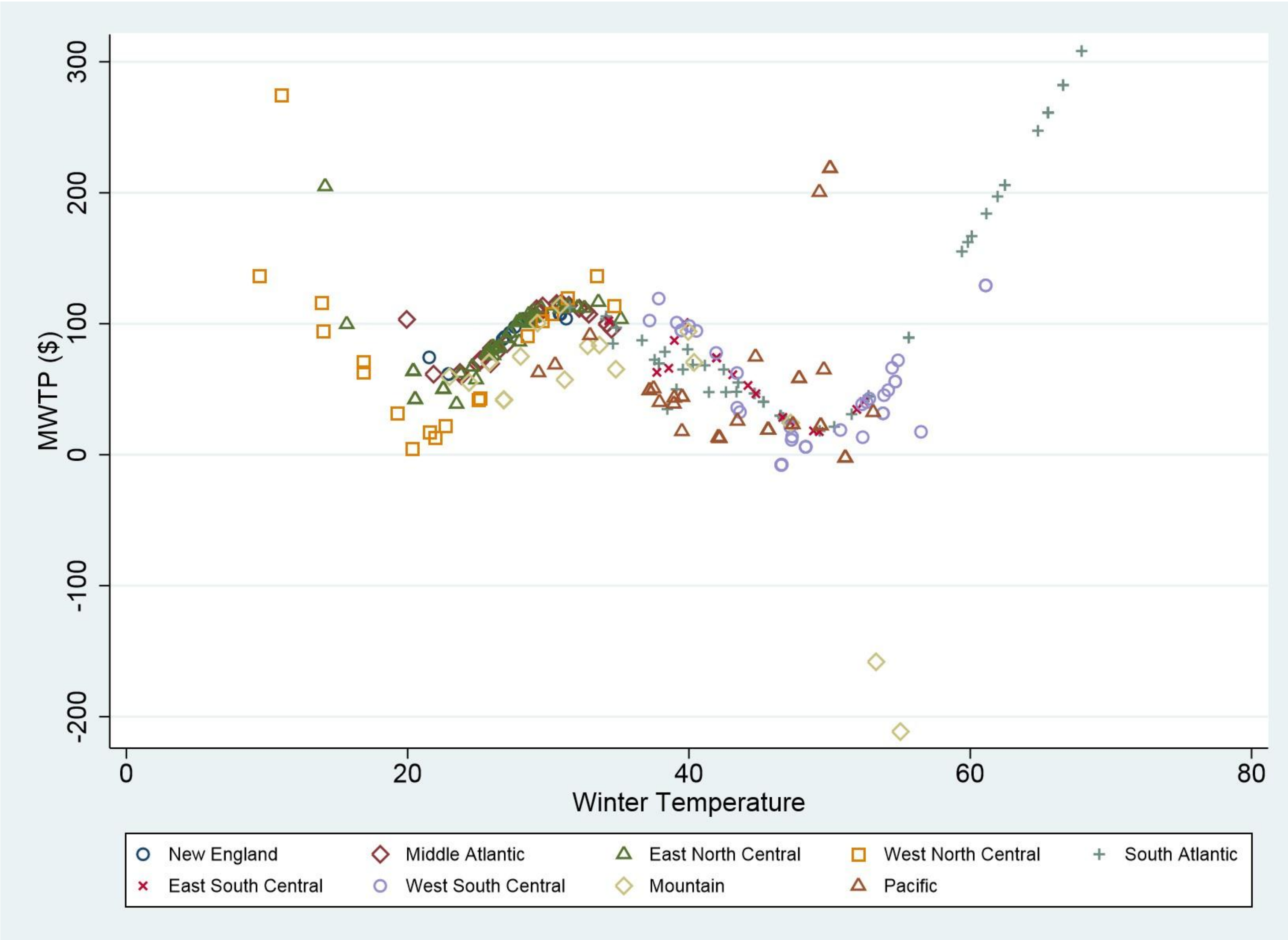

Figure 8. Taste-Sorting for Winter Temperature by Metropolitan Area (Local Linear Hedonic Model, Adjusted Weights, Bandwidth = 1.0)

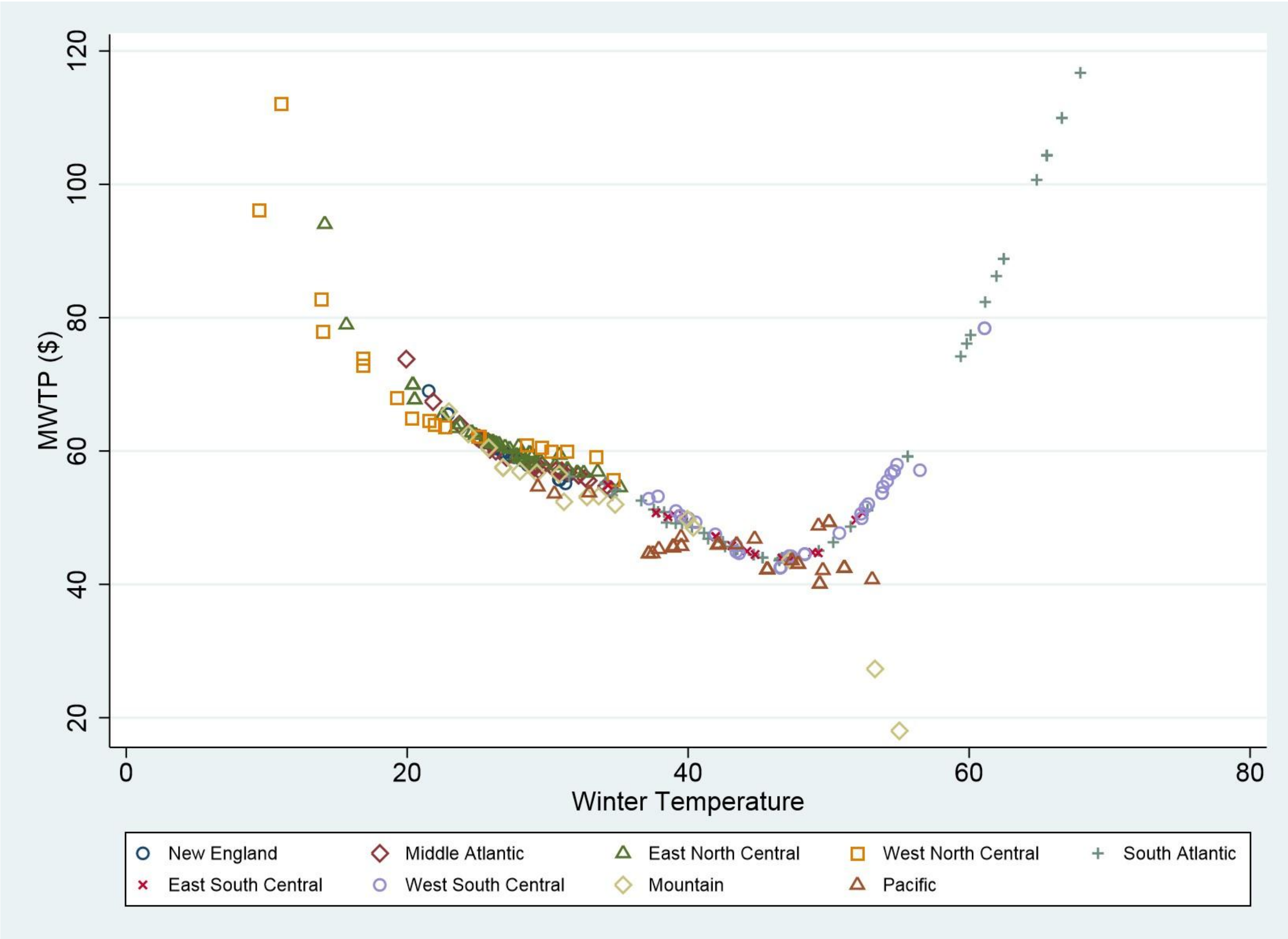

Figure 9. Taste-Sorting for Summer Temperature by Metropolitan Area (Local Linear Hedonic Model, Adjusted Weights, Bandwidth = 0.5)

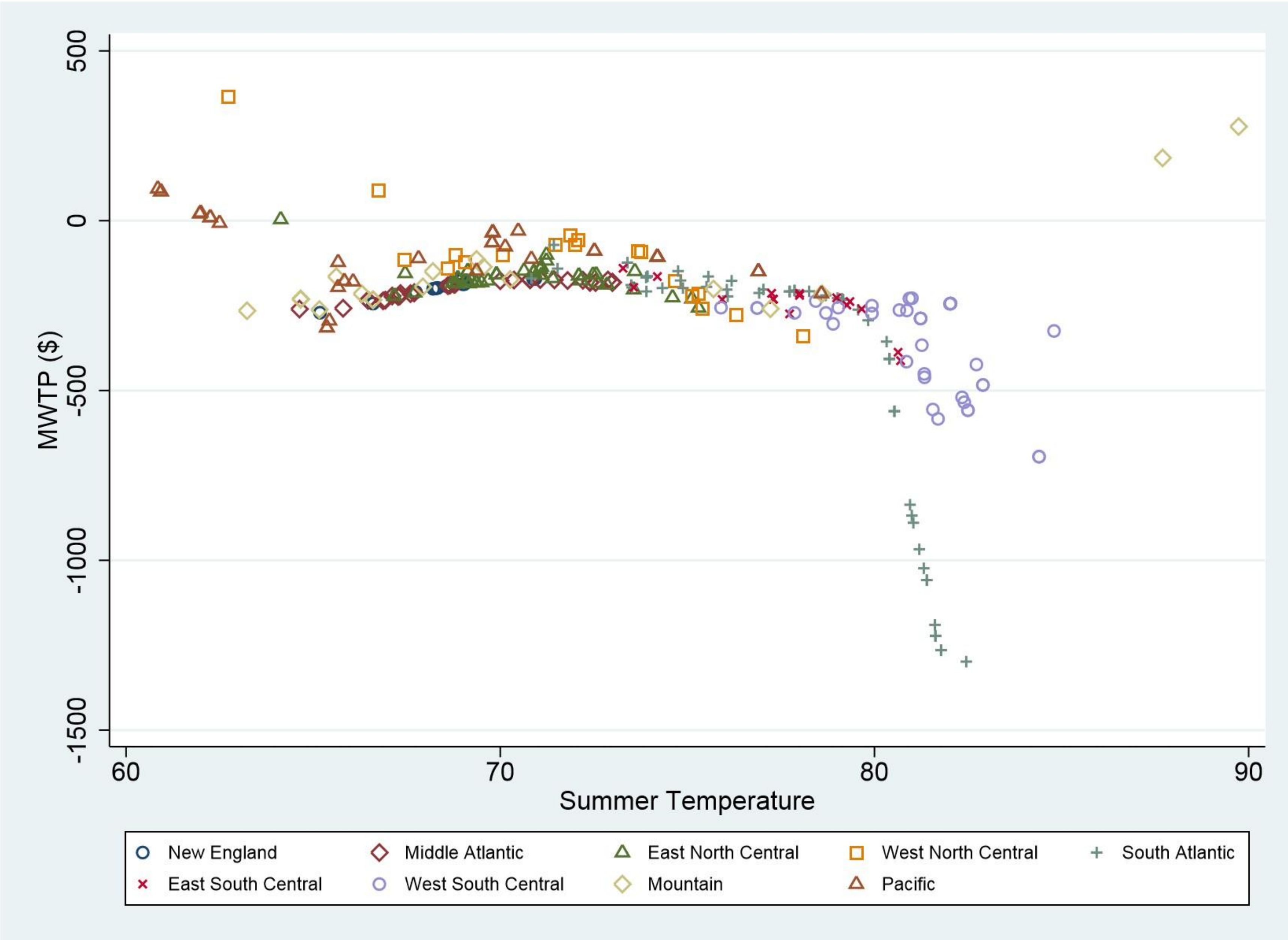

Figure 10. Taste-Sorting for Summer Temperature by Metropolitan Area (Local Linear Hedonic Model, Adjusted Weights, Bandwidth = 1.0)

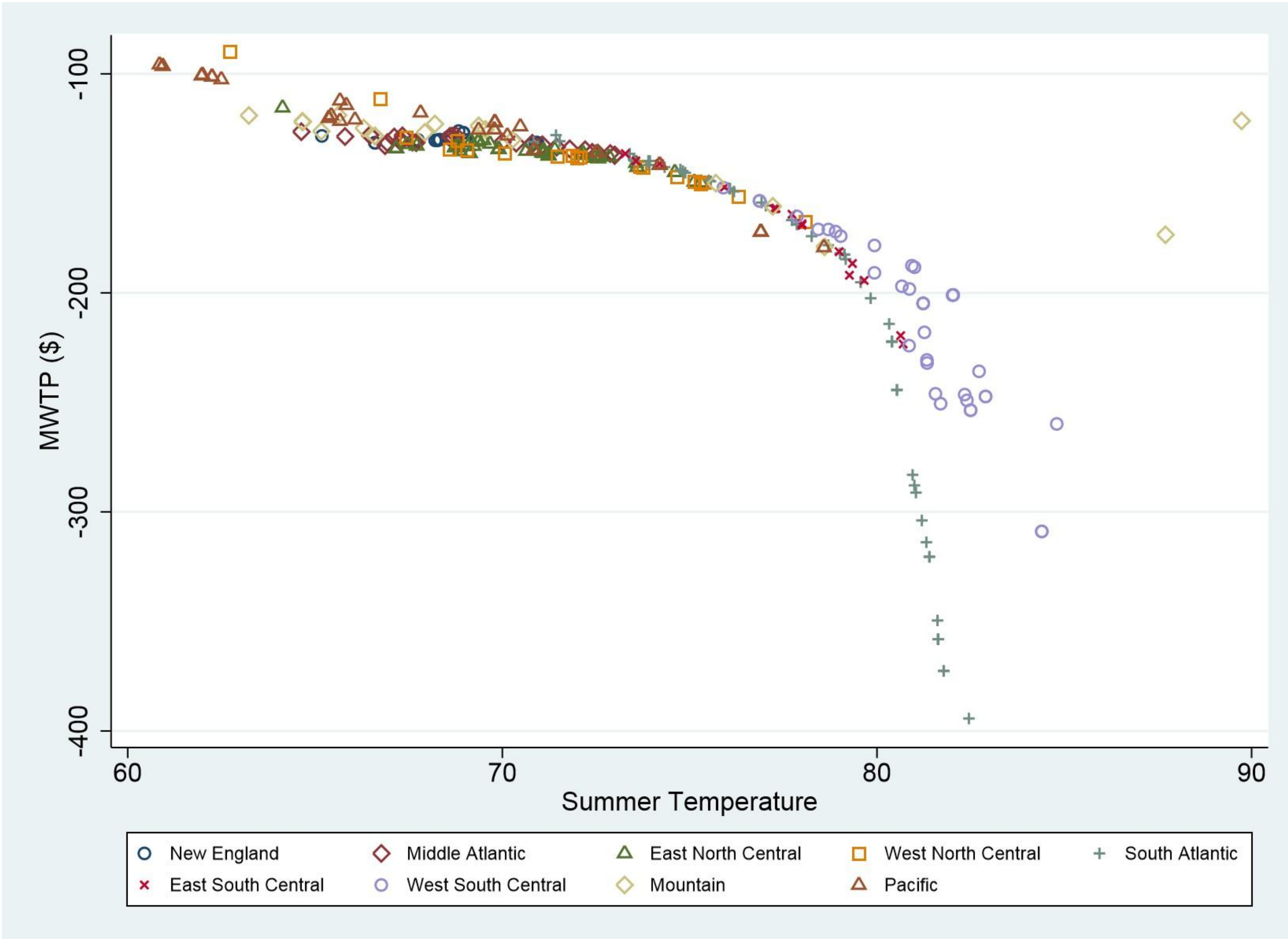

Figure 11. Taste-Sorting for Winter Temperature by Metropolitan Area (Local Linear Hedonic Model, Traditional Weights, Bandwidth = 0.5)

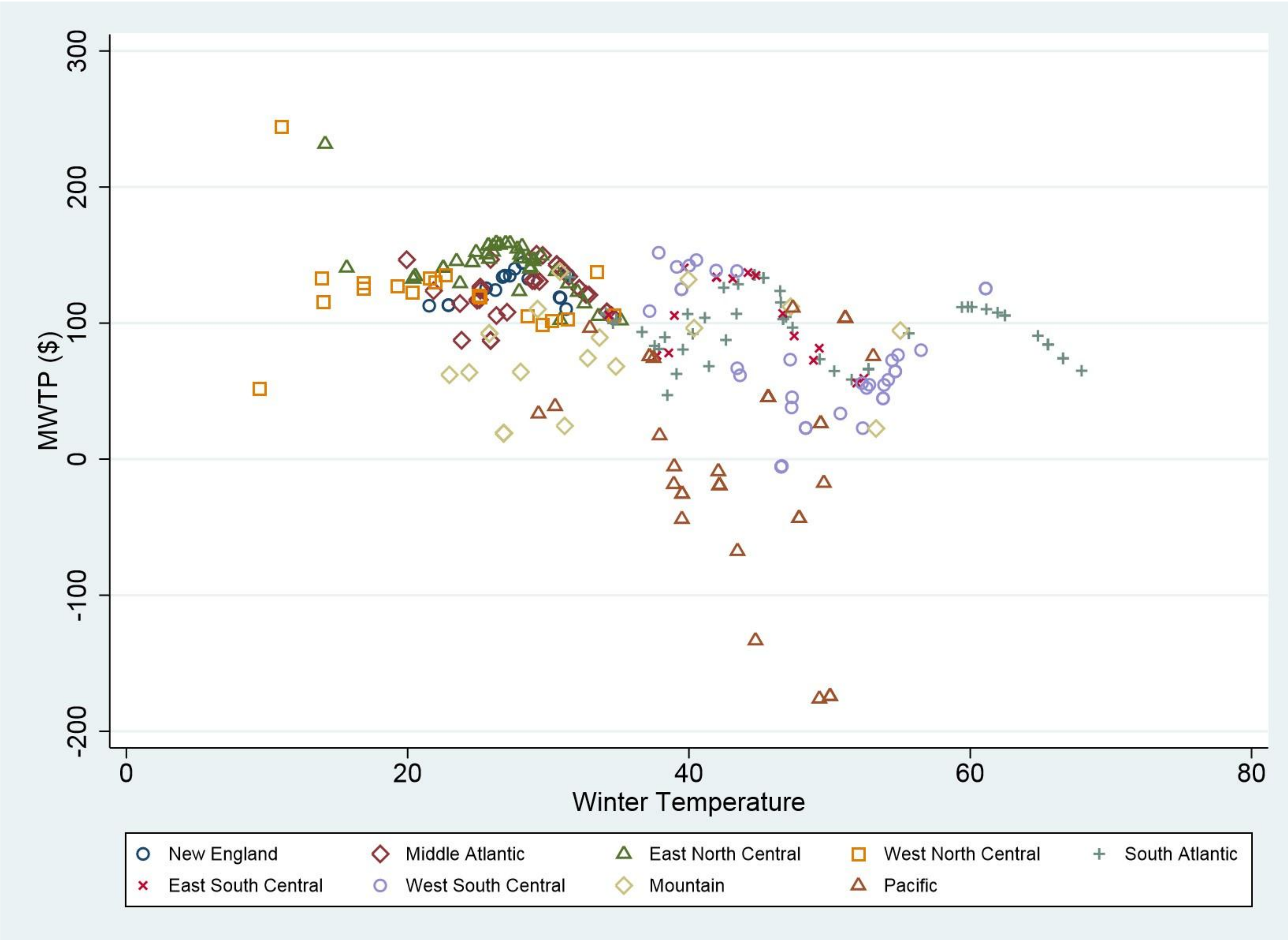

Figure 12. Taste-Sorting for Winter Temperature by Metropolitan Area (Local Linear Hedonic Model, Traditional Weights, Bandwidth = 1.0)

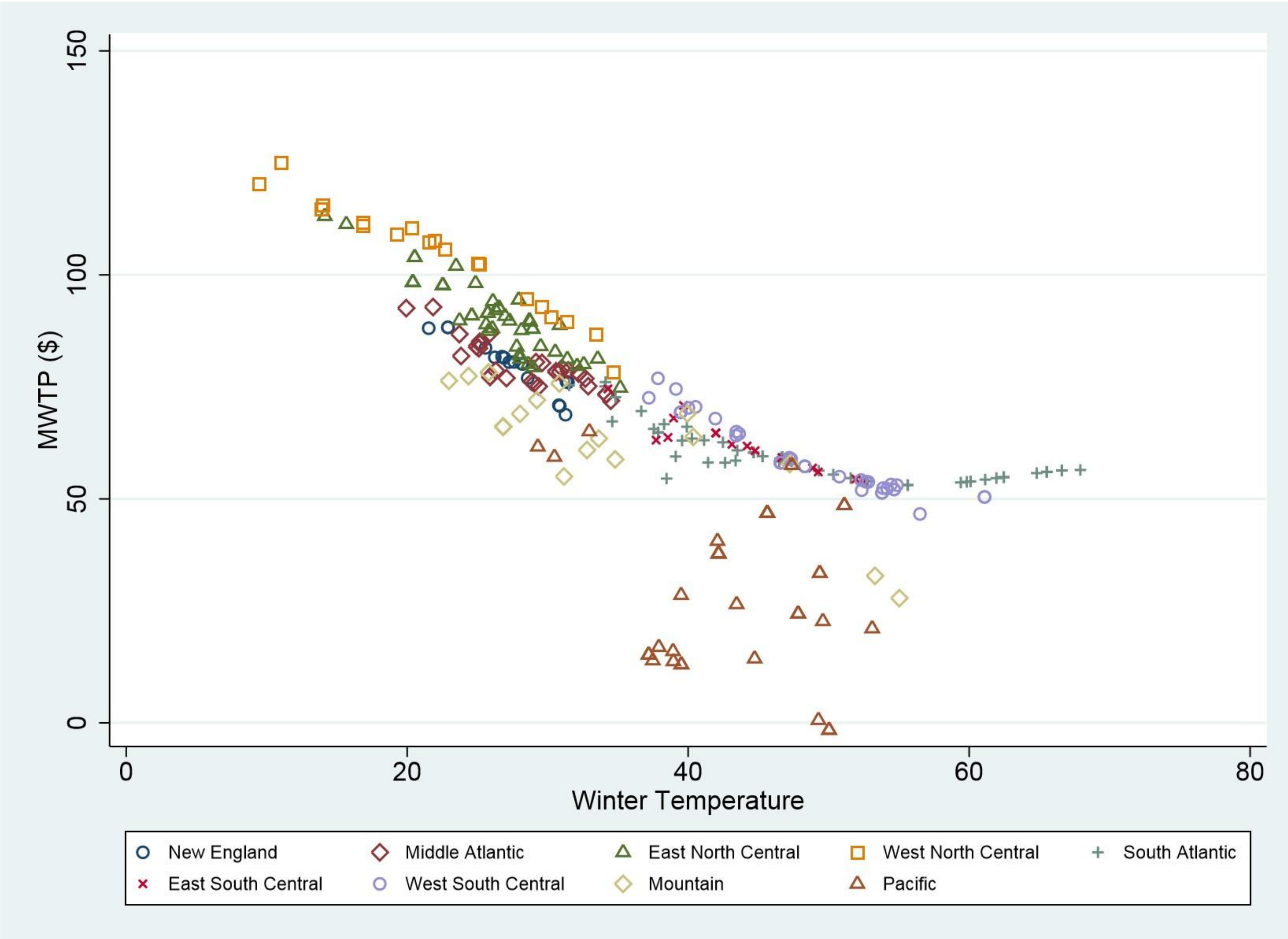

Figure 13. Taste-Sorting for Summer Temperature by Metropolitan Area (Local Linear Hedonic Model, Traditional Weights, Bandwidth = 0.5)

Figure 14. Taste-Sorting for Summer Temperature by Metropolitan Area (Local Linear Hedonic Model, Traditional Weights, Bandwidth = 1.0)

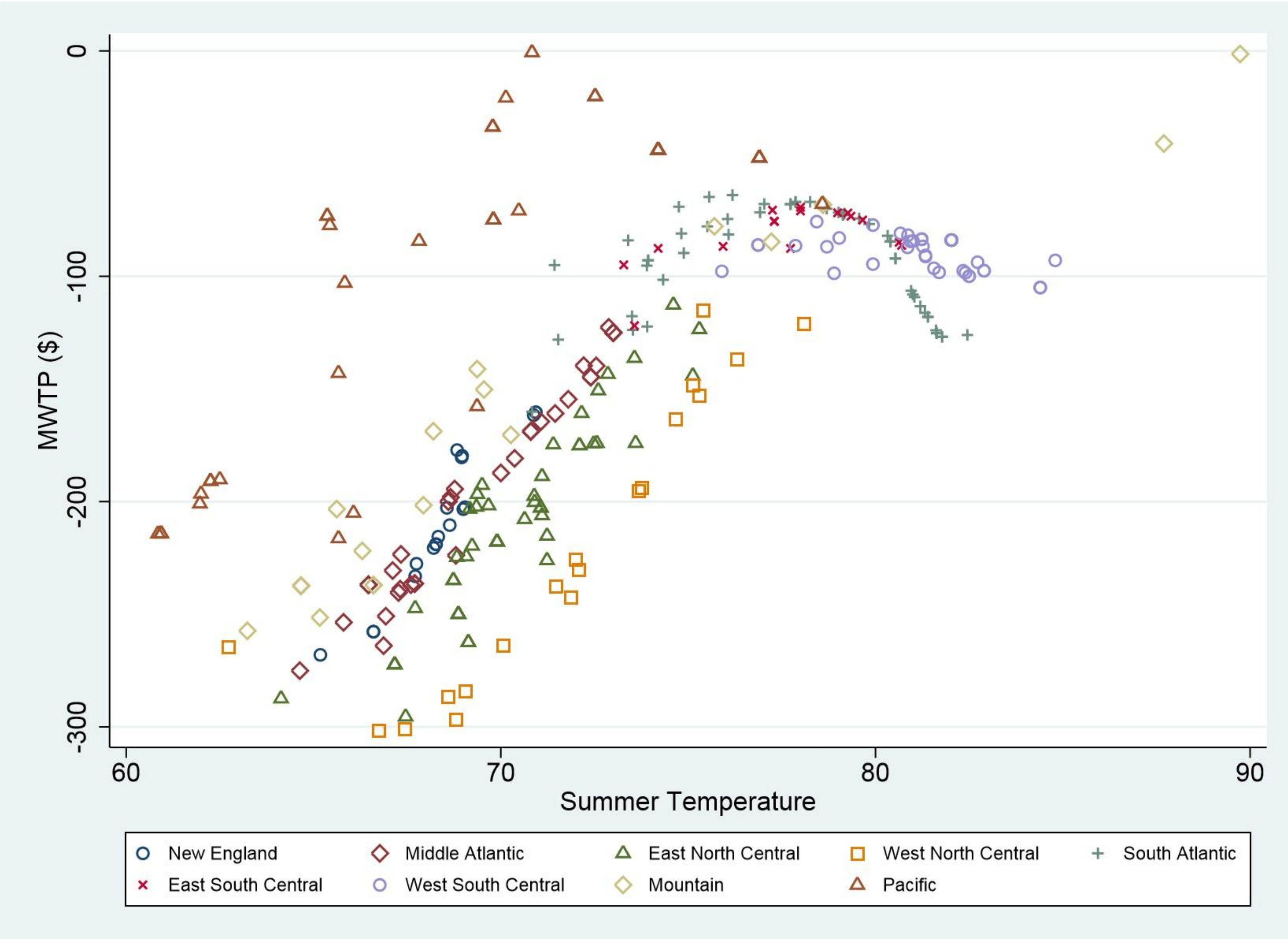

Table A.1. Marginal Willingness To Pay for Climate Amenities (Base Discrete Choice Models)

	Model M.1 (Prime)		Model M.1 (Full)		Model M.1 (>55)	
Sample	Prime-Aged (Base Model)		All Ages		Over 55 Years	
Variable	Mean	SE	Mean	SE	Mean	SE
Means:						
Moved from State of Birth	-$70,164	$964	-$77,854	$952	-$74,938	$1,777
Moved from Division of Birth	-$19,533	$450	-$23,272	$421	-$26,314	$809
Moved from Region of Birth	-$11,441	$361	-$11,036	$313	-$7,047	$511
Mean PM2.5	$1,577	$58	$1,826	$52	$1,853	$89
Violent Crime Rate	-$384	$56	-$340	$48	-$289	$78
Transportation Score	$254	$7	$252	$6	$198	$9
Education Score	$77	$6	$75	$5	$34	$8
Arts Score	$168	$7	$184	$6	$167	$10
Healthcare Score	$10	$5	$14	$4	$21	$7
Recreation Score	$352	$8	$411	$7	$446	$13
Park Area	$3	$0	$3	$0	$3	$0
Visibility > 10 Miles	$232	$11	$212	$9	$118	$15
July Humidity	-$395	$19	-$607	$18	-$819	$33
Distance to Coast	-$30	$2	-$40	$2	-$51	$3
Annual Snowfall	-$378	$11	-$410	$9	-$369	$15
Summer Precipitation	$369	$26	$403	$22	$392	$36
Annual Sunshine	-$120	$26	-$86	$22	$134	$37
Elevation	$8,108	$702	$8,975	$600	$9,825	$985
Population Density	$10	$0	$13	$0	$16	$1
Avg Winter Temperature	-$183	$39	-$382	$34	-$918	$60
Avg Summer Temperature	$319	$23	$426	$20	$627	$35

Table A.1. Marginal Willingness To Pay for Climate Amenities (Base Discrete Choice Models)

	Model M.1 (Prime)		Model M.1 (Full)		Model M.1 (>55)	
Sample	Prime-Aged (Base Model)		All Ages		Over 55 Years	
Variable	Mean	SE	Mean	SE	Mean	SE
Standard Deviations:						
Avg Winter Temperature	$1,093	$33	$1,376	$29	$1,408	$53
Avg Summer Temperature	$1,568	$71	$1,570	$67	$951	$165
Correlation Coefficient	-0.63		-0.70		-0.79	

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 A.2. Marginal Willingness To Pay for Climate Amenities (Discrete Choice Model Sensitivities)

	Model M.1		Model M.2		Model M.3		Model M.4	
Sensitivity	Base Model		Omit population density		Omit moving costs		Omit other climate variables	
Variable	Mean	SE	Mean	SE	Mean	SE	Mean	SE
Means:								
Moved from State of Birth	-$70,164	$964	-$66,526	$865			-$65,836	$857
Moved from Division of Birth	-$19,533	$450	-$18,671	$420			-$19,099	$424
Moved from Region of Birth	-$11,441	$361	-$11,050	$340			-$10,584	$338
Mean PM2.5	$1,577	$58	$1,885	$56	$1,438	$50	$1,736	$56
Violent Crime Rate	-$384	$56	-$26	$52	-$357	$47	$55	$51
Transportation Score	$254	$7	$234	$6	$328	$6	$267	$6
Education Score	$77	$6	$85	$6	$74	$5	$42	$6
Arts Score	$168	$7	$235	$7	$144	$7	$193	$7
Healthcare Score	$10	$5	$3	$5	-$2	$4	$18	$5
Recreation Score	$352	$8	$339	$8	$343	$7	$268	$7
Park Area	$3	$0	$1	$0	$2	$0	$4	$0
Visibility > 10 Miles	$232	$11	$272	$11	$78	$9	$326	$10
July Humidity	-$395	$19	-$338	$18	-$383	$17		
Distance to Coast	-$30	$2	-$39	$2	-$31	$1	-$10	$2
Annual Snowfall	-$378	$11	-$359	$10	-$201	$8		
Summer Precipitation	$369	$26	$201	$23	$132	$21		
Annual Sunshine	-$120	$26	-$181	$24	-$238	$22		
Elevation	$8,108	$702	$4,415	$650	$9,609	$616	$2,159	$595
Population Density	$10	$0			$15	$0	$8	$0
Avg Winter Temperature	-$183	$39	-$188	$37	$125	$33	$117	$36
Avg Summer Temperature	$319	$23	$302	$21	$65	$19	$576	$17

Table A.2. Marginal Willingness To Pay for Climate Amenities (Discrete Choice Model Sensitivities)

	Model M.1		Model M.2		Model M.3		Model M.4	
Sensitivity	Base Model		Omit population density		Omit moving costs		Omit other climate variables	
Variable	Mean	SE	Mean	SE	Mean	SE	Mean	SE
Standard Deviations:								
Avg Winter Temperature	$1,093	$33	$1,110	$30	$67	$56	$1,019	$31
Avg Summer Temperature	$1,568	$71	$1,376	$70	$965	$114	$1,866	$59
Correlation Coefficient	-0.63		-0.66		-0.98		-0.71	

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 A.3. Marginal Willingness To Pay for Climate Amenities (Base Hedonic Models)

	Adjusted Weights						Traditional Weights					
	Model H.1a		Model H.2a		Model H.3a		Model H.1t		Model H.2t		Model H.3t	
Temperature Specification	Linear		Quadratic		Cubic		Linear		Quadratic		Cubic	
Variable	Mean	SE	Mean	SE	Mean	SE	Mean	SE	Mean	SE	Mean	SE
Mean PM2.5	-$303	$75	-$350	$84	-$396	$84	-$384	$95	-$387	$110	-$402	$117
Violent Crime Rate	-$288	$87	-$307	$89	-$281	$90	-$301	$116	-$312	$120	-$316	$120
Transportation Score	-$9	$8	-$8	$8	-$8	$8	$23	$10	$23	$10	$24	$10
Education Score	$1	$9	$0	$9	$0	$9	$2	$10	$1	$10	$0	$10
Arts Score	$5	$9	$6	$9	$6	$9	-$26	$12	-$26	$12	-$26	$12
Healthcare Score	$24	$7	$24	$7	$25	$7	$11	$8	$12	$8	$12	$8
Recreation Score	$4	$9	$4	$9	$5	$9	-$17	$12	-$16	$12	-$17	$12
Park Area	$0	$0	$0	$0	$0	$0	-$1	$0	-$1	$0	-$1	$0
Visibility > 10 Miles	-$1	$16	-$5	$16	-$11	$16	-$68	$21	-$78	$22	-$78	$22
July Humidity	$71	$24	$71	$23	$70	$25	$84	$35	$84	$35	$75	$36
Distance to Coast	-$3	$3	-$3	$3	-$2	$3	$16	$3	$17	$3	$18	$3
Annual Snowfall	-$16	$11	-$10	$11	-$25	$11	$29	$16	$33	$16	$36	$16
Summer Precipitation	-$19	$42	-$9	$44	$30	$50	$81	$50	$99	$55	$111	$62
Annual Sunshine	$191	$35	$205	$45	$185	$43	$129	$44	$172	$57	$162	$59
Elevation	$740	$1,126	$614	$1,123	$735	$1,103	$965	$1,531	$731	$1,554	$698	$1,558
Population Density	$2	$1	$2	$1	$2	$1	-$3	$1	-$2	$1	-$2	$1
Avg Winter Temperature	$104	$33	$110	$41	$159	$56	$207	$42	$186	$46	$229	$76
Avg Summer Temperature	-$358	$64	-$355	$65	-$599	$103	-$228	$68	-$228	$68	-$257	$148

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 A.4. Marginal Willingness To Pay for Climate Amenities (Hedonic Model Sensitivities)

	Adjusted Hedonic Weights						Traditional Hedonic Weights					
	Model H.1a		Model H.4a		Model H.5a		Model H.1t		Model H.4t		Model H.5t	
Sensitivity	Base Model		Omit population density		Omit other climate variables		Base Model		Omit population density		Omit other climate variables	
Variable	Mean	SE	Mean	SE	Mean	SE	Mean	SE	Mean	SE	Mean	SE
Mean PM2.5	-$303	$75	-$183	$82	-$286	$81	-$384	$95	-$508	$93	-$456	$96
Violent Crime Rate	-$288	$87	-$212	$87	-$207	$92	-$301	$116	-$380	$118	-$275	$119
Transportation Score	-$9	$8	-$13	$9	-$16	$8	$23	$10	$28	$10	$15	$11
Education Score	$1	$9	$6	$9	-$2	$9	$2	$10	-$3	$11	$6	$10
Arts Score	$5	$9	$23	$10	$11	$9	-$26	$12	-$44	$13	-$29	$12
Healthcare Score	$24	$7	$22	$7	$30	$7	$11	$8	$13	$8	$16	$8
Recreation Score	$4	$9	$7	$9	$3	$9	-$17	$12	-$20	$12	-$9	$11
Park Area	$0	$0	$0	$0	$0	$0	-$1	$0	-$1	$0	-$1	$0
Visibility > 10 Miles	-$1	$16	$17	$16	$9	$15	-$68	$21	-$86	$21	-$99	$18
July Humidity	$71	$24	$82	$24			$84	$35	$72	$34		
Distance to Coast	-$3	$3	-$6	$3	-$3	$3	$16	$3	$19	$3	$17	$3
Annual Snowfall	-$16	$11	-$9	$13			$29	$16	$22	$17		
Summer Precipitation	-$19	$42	-$40	$42			$81	$50	$103	$49		
Annual Sunshine	$191	$35	$173	$36			$129	$44	$148	$43		
Elevation	$740	$1,126	-$129	$1,241	$1,543	$1,294	$965	$1,531	$1,863	$1,497	$345	$1,515
Population Density	$2	$1			$2	$1	-$3	$1			-$2	$1
Avg Winter Temperature	$104	$33	$111	$37	$218	$28	$207	$42	$200	$44	$167	$26
Avg Summer Temperature	-$358	$64	-$353	$62	-$377	$64	-$228	$68	-$233	$72	-$164	$57

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 A.5. Summary of Hedonic Wage Coefficients

Variables (Dependent Variable: log(wage rate))	Mean of Estimates from 284 MSAs	Std Dev of Estimates from 284 MSAs
High School (left out category is no high school)	0.098	0.038
Some College	0.180	0.045
College Graduate	0.382	0.069
Higher Education	0.546	0.074
Age	0.048	0.007
Age squared (divided by 100)	0.000	0.000
Married	0.092	0.021
Male	0.215	0.040
Black (left out category is white)	-0.070	0.070
Other Race	-0.055	0.054
Speaks English Well	0.126	0.103
Hispanic	-0.057	0.074
Business Operations Occupation (left out category is Management Occupation)	-0.122	0.067
Financial Specialists Occupation	-0.116	0.072
Computer and Math Occupation	0.004	0.089
Engineering Occupation	-0.073	0.083
Life, Physical, & Social Sciences Occupation	-0.180	0.100
Social Services Occupation	-0.328	0.078
Legal Occupation	-0.039	0.127
Teachers Occupation	-0.190	0.093
Other Educational Occupation	-0.473	0.129
Arts, Sports & Media Occupation	-0.243	0.094
Healthcare Practitioners Occupation	0.062	0.078
Healthcare Support Occupation	-0.330	0.078
Protective Services Occupation	-0.240	0.106
Food and Serving Occupation	-0.428	0.077
Maintenance Occupation	-0.472	0.074

Table A.5. Summary of Hedonic Wage Coefficients

Variables (Dependent Variable: log(wage rate))	Mean of Estimates from 284 MSAs	Std Dev of Estimates from 284 MSAs
Personal Care Service Occupation	-0.423	0.114
High Skill Sales Occupation	-0.136	0.067
Low Skill Sales Occupation	-0.228	0.062
Office Support Occupation	-0.298	0.049
Construction Trades & Extraction Workers Occupation	-0.246	0.090
Maintenance Workers Occupation	-0.192	0.065
Production Occupation	-0.317	0.084
Transportation Occupation	-0.357	0.075
Construction Industry (left out category is Mining and Utilities)[a]	-0.180	0.095
Manufacturing Industry	-0.120	0.107
Wholesale Industry	-0.185	0.097
Retail Industry	-0.339	0.094
Transportation Industry	-0.084	0.107
Information & Communications Industry	-0.134	0.109
Finance Industry	-0.175	0.105
Professional and Scientific Management Services Industry	-0.220	0.101
Educational and Health Social Services Industry	-0.267	0.092
Recreation and Food Services Industry	-0.370	0.110
Other Services Industry	-0.343	0.101
Public Administration Industry	-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.6. Summary of Hedonic Housing Coefficients

Variables (Dependent Variable: log(user costs including insurance and utility costs))	Mean of Estimates from 284 MSAs	Std Dev of Estimates from 284 MSAs
House is Owned	0.464	0.144
3 Bedrooms (left out category is less than three bedrooms)	0.160	0.061
4 Bedrooms	0.208	0.082
5 Bedrooms	0.324	0.110
Greater than 5 Bedrooms	0.500	0.163
2 Rooms (left out category is less than two rooms)	0.080	0.133
3 Rooms	0.053	0.140
4 Rooms	0.075	0.146
5 Rooms	0.126	0.154
6 Rooms	0.218	0.156
Greater than 6 Rooms	0.413	0.176
Complete Kitchen	-0.104	0.261
Complete Plumbing	0.221	0.212
1 to 10 Acres	0.246	0.140
0 to 1 years old (left out category is over 61 years old)	0.428	0.157
2 to 5 years old	0.404	0.158
6 to 10 years old	0.358	0.150
11 to 20 years old	0.247	0.127
21 to 30 years old	0.150	0.122
31 to 40 years old	0.093	0.113
41 to 50 years old	0.039	0.089
51 to 60 years old	-0.011	0.075
Number of Units in Structure: Single-Attached (left out category is single family detached)	-0.082	0.105
2 Units in Structure	-0.089	0.107
3 to 4 Units in Structure	-0.135	0.095
5 to 9 Units in Structure	-0.167	0.106
10 to 19 Units in Structure	-0.132	0.127
20 to 49 Units in Structure	-0.154	0.151
Over 50 Units in Structure	-0.190	0.207