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Abstract: Amenities that vary across cities are typically valued using either a hedonic model, in which amenities are capitalized into wages and housing prices, or a discrete model of household location choice. In this paper, we use the 2000 Public Use Microdata Sample (PUMS) to value climate amenities using both methods. We compare estimates of marginal willingness to pay (MWTP), first assuming homogeneous tastes for climate amenities and then allowing preferences for climate amenities to vary by location. We find that mean MWTP for warmer winters is about four times larger using the discrete choice approach than with the hedonic approach; mean MWTP for cooler summers is twice as large. The two approaches also differ in their estimates of taste sorting. The discrete choice model implies that households with the highest MWTP for warmer winters locate in cities with the mildest winters, while the hedonic model does not. Differences in estimates are due to three factors: (1) the discrete choice model incorporates the psychological costs of moving from one's birthplace, which the hedonic models do not; (2) the discrete choice model allows for city-specific labor and housing markets, rather than assuming a national market; (3) the discrete choice model uses information on market shares (i.e., population) in estimating parameters, which the hedonic model does not.

Key words: amenity valuation, location choice, hedonic models, value of climate

JEL codes: Q51; Q54

Do Discrete Choice Approaches to Valuing Urban Amenities Yield Different Results Than Hedonic Models?*

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1. Introduction

To value amenities that vary across cities, researchers have typically followed one of two approaches, they have used either hedonic models of wages and housing prices (Roback 1982; Blomquist et al. 1988; Albouy et al. 2016) or discrete models of location choice (Cragg and Kahn 1997; Bayer et al. 2009; Fan et al. 2016; Sinha et al. 2016). The former approach infers willingness to pay for amenities 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 city in which to live as a function of wages, housing prices, and location-specific attributes.

Cragg and Kahn (1997), Bayer et al. (2009), and Sinha et al. (2016) note that the discrete choice approach typically produces estimates of amenity values that are very different from estimates produced by the continuous hedonic approach. In a discrete choice model where households choose the US state in which to reside, Cragg and Kahn (1997) find the marginal willingness to pay for July and February temperatures exceeds the marginal prices implied by hedonic price functions. Bayer et al. (2009) estimate marginal willingness to pay (MWTP) to reduce air pollution using a discrete choice approach and find MWTP is three times greater than values capitalized into per capita incomes and property values. Sinha et al.'s (2016) discrete choice model estimates higher damages associated with projected climate changes in US cities under the A2 scenario in the Special Report on Emissions Scenarios than comparable estimates from Albouy et al.'s (2016) hedonic model.

While previous research has compared the hedonic and discrete choice approaches in the context of a single housing market (Bayer et al. 2007; Klaiber and Phaneuf 2009), valuing amenities that vary across cities introduces different issues. Hedonic estimates of the value of city-specific amenities involve the capitalization of amenities in both the labor and housing

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markets. An important question is whether these markets should be treated as national markets or city-specific markets. Moving costs across cities are one reason to question the assumption of national labor and housing markets. And moving costs may prevent city-specific amenities from being fully capitalized in wages and housing prices. Hedonic models typically assume perfect mobility, while moving costs are more easily incorporated into discrete choice models.

In this paper, we use the same dataset to value climate amenities using hedonic and discrete choice methods. We compare estimates from each approach, first assuming homogeneous tastes for climate amenities and then allowing preferences for climate amenities to vary by location. Similar to Albouy (2012), our hedonic models regress the weighted sum of wage and housing price indices on climate amenities and various city characteristics using metropolitan statistical areas (MSAs) as the geographic unit. Wage and housing price indices are estimated, following Albouy et al. (2016), 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. (2016) and, alternately, using a traditional set of weights (Roback 1982). We capture preference heterogeneity by allowing the marginal price of climate amenities to vary by city using local linear regressions (Bajari and Benkard 2005; Bajari and Kahn 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 used in the hedonic models. To capture heterogeneity in preferences, we estimate random parameter logit models and calculate the distribution of each household's tastes for climate conditional on the city in which they live. This allows us to estimate mean MWTP for climate amenities by city.

We focus on prime-aged households when comparing the two approaches. Because the hedonic approach assumes that amenities are capitalized into wages, and because a significant fraction of older households have no wage income, Albouy et al. (2016) focus on workers aged 25–55. We estimate discrete location choice models for various age groups and find that preferences for climate amenities vary by the age of the household head; however, we focus on households with heads between 25 and 55 when comparing discrete choice with hedonic estimates.

We find that the two approaches produce different estimates of MWTP for climate amenities when tastes are assumed to be homogeneous and different sorting patterns when we allow preferences to be heterogeneous. Although both approaches find that households have positive MWTP for warmer winters and cooler summers, mean estimates produced by the discrete choice approach are two to three times larger than estimates produced by the hedonic approach. Moreover, the taste sorting patterns produced by the two approaches are very different. The discrete choice model finds that households sort across locations based on their preferences for winter temperature: there is a strong positive correlation between winter temperature and MWTP for warmer winters. The hedonic model with traditional weights finds a negative correlation between MWTP for warmer winters and winter temperature. The discrete choice model thus projects that under most climate scenarios, the parts of the country that will benefit from warmer winters value this less than the average US household. The hedonic model with traditional weights projects the opposite. When adjusted (Albouy) weights are used to estimate the hedonic model, the sorting pattern is closer to that of the discrete choice model but differs for some parts of the country.

We also explore why estimates produced by the two approaches vary. One reason is that the hedonic and discrete choice models differ in their underlying assumptions about consumer mobility. The hedonic approach assumes perfect mobility, whereas moving costs are more easily incorporated in discrete models of location choice. As Bayer et al. (2009) note, moving costs—both psychological and out-of-pocket—may prevent amenities from being fully capitalized into wages and housing values. When we estimate the discrete choice model without moving costs, the value of climate amenities falls significantly. It is also the case that moving costs, which vary by household and city, help identify sorting patterns in the discrete choice model (Berry and Haile 2010). When they are removed, sorting patterns are (incorrectly) reversed.

A related reason for differences in the two sets of estimates is the way in which data on wages and housing prices are used. The hedonic model assumes a single national labor market and a single housing market. The data are used to estimate price indices for each MSA, assuming that the returns to human capital and marginal prices of housing characteristics are the same everywhere. The discrete choice model assumes that each MSA constitutes a separate labor and a separate housing market. It is the variation in wage income and housing costs across MSAs, as well as the variation in moving costs across MSAs, that identifies household preferences in the discrete choice model. This suggests that differences in how the two models use information on housing and labor markets account in part for the difference in estimates.

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. (2016). We present the discrete location choice model that we estimate in section 3 and describe our data and empirical specifications in section 4. Section 5 presents the results of both modeling approaches. This includes estimates of MWTP for climate amenities assuming homogeneous tastes and the implications of both models for taste sorting. Section 6 concludes.

2. Hedonic Models of Amenity Valuation

2.1. 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," which built on Rosen's (1974) model of product differentiation and implicit prices. 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,

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

where r_j is the rental price of housing; W_j is wage income; *I* is nonwage income, which is independent of location; and the price of the traded 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,

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

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

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

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. A common econometric specification in the literature (Gyourko and Tracy 1991) is the semilog[3]

$$\ln w_{mj} = \gamma^0 + \boldsymbol{X}_{mj}^{w}\boldsymbol{\Gamma}^{X,0} + \boldsymbol{A}_j \Gamma^{A,0} + \nu_{mj}^0 \tag{4}$$

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[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.

[3] Blomquist et al. (1988) use Box-Cox transformations of wages and housing prices, i.e., $(w^\lambda-1)/\lambda$ and $(P^\lambda-1)/\lambda$. They estimate a value of $\lambda = 0.2$ for the housing price equation and $\lambda = 0.1$ for the wage equation, in contrast to a logarithmic specification ($\lambda = 0$).

$$\ln P_{ij} = \delta^0 + \boldsymbol{X}_{ij}^P \boldsymbol{\Delta}^{X,0} + \boldsymbol{A}_j \boldsymbol{\Delta}^{A,0} + \eta_{ij}^0 \tag{5}$$

where w_{mj} is the hourly wage earned by worker m in location j; $\boldsymbol{X}_{mj}^w$ 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 $\boldsymbol{X}_{ij}^P$ is a vector of dwelling characteristics. $\boldsymbol{A}_j$ is a vector of attributes characterizing location j. In using equations (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. The two are added together to determine the impact of amenities; thus, implicitly, wage differentials across counties are weighted approximately three times as much 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 nontraded goods, and he suggests an alternate approach to estimating the value of local amenities. Nontraded 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 nontraded 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.

To elaborate, consider the utility maximization problem faced by households, where indirect utility depends on income (both wage and nonwage), the prices of nontraded goods, taxes, and the location-specific amenities in each location. The MWTP for amenity a as a percentage of average total income ($\bar{m}$) can be shown to be equal to the derivative of a QOL index, as described by equation (6),

$$\frac{MWTP_a}{\bar{m}} \equiv \frac{\partial QOL_j}{\partial a} = (s_H + \gamma s_O)\frac{d\ln(p_{j,H})}{da} - (1-\tau)s_w \frac{d\ln(w_j)}{da} \tag{6}$$

where s_H is the share of income spent on housing, s_O is the share of income spent on other nontraded goods, s_w is the share of income that comes from wages, and τ is the marginal tax rate. γ is the ratio of the housing price to the price of nontraded goods. The QOL index corresponding to (6) can be viewed as the consumption a household is willing to forgo to live in city j compared with living in the average city. The weights in the QOL, however, differ from those in Roback. The weight on housing prices now includes the share of income spent on all local goods, and the weight on wage income has been reduced by taxes.[4]

To estimate QOL indices, Albouy et al. (2016) estimate national wage and housing price equations similar to (4) and (5) in two stages. Including location-specific fixed effects in the hourly wage and housing rent equations in the first stage yields wage and housing price indices, λ_j^w and λ_j^P.[5]

$$\ln w_{mj} = \boldsymbol{X}_{mj}^{w}\boldsymbol{\Gamma}^{X,1} + \lambda_j^w + \nu_{mj}^1 \tag{4′}$$

$$\ln P_{ij} = \boldsymbol{X}_{ij}^{P}\boldsymbol{\Delta}^{X,1} + \lambda_j^P + \eta_{ij}^1 \tag{5′}$$

These indices are then used to construct the QOL index in equation (6), where λ_j^w and λ_j^P from equations (4′) and (5′) replace $d\ln(p_{j,H})$ and $d\ln(w_j)$. Based on Albouy (2012), $(s_H + \gamma s_O) = 0.33, \tau = 0.32$ and $s_w = 0.75.$ This yields the QOL index on the left-hand side of equation (7), which is then regressed on location-specific amenities.

$$QOL_j \equiv 0.33\lambda_j^P - 0.51\lambda_j^w = \boldsymbol{A_j\theta} + \xi_j \tag{7}$$

Albouy and coauthors (2016) apply this approach to Public Use Microdata Area (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 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.

2.2. 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 adjusted weights in equation 7). The national wage and property value equations we estimate use the same set of explanatory variables as the wage and housing cost hedonic equations that underpin the discrete choice model described below and are estimated using the same samples of workers and houses.

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[4] To relate this to Roback’s MWTP formulation, if we assume that housing is the only local nontraded good ($s_O = 0$), that all income comes from wages ($s_w = 1$), and that there are no income taxes ($\tau = 0$), this reduces to Roback’s MWTP expression in equation (3).

[5] 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.

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.[6] 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 climate amenities, and then use the residuals ($\hat{e}_j$) from this equation in a local linear regression with kernel weights, as described in equation (8), where $\boldsymbol{T}$ denotes a matrix of climate amenities, $N(\ )$ denotes the normal distribution, b is bandwidth, and $\hat{\sigma}_z$ is the sample standard deviation of characteristic z. This approach yields coefficients for each MSA for climate amenities, where the notation j^* in equation (8) emphasizes this.

$$\boldsymbol{\Phi}_{j^*} = \underset{\boldsymbol{\Phi}}{\operatorname{argmin}}(\hat{\boldsymbol{e}} - \boldsymbol{T\Phi})'\boldsymbol{W}(\hat{\boldsymbol{e}} - \boldsymbol{T\Phi}) \tag{8}$$

$$\hat{\boldsymbol{e}} = \left[\hat{e}_j\right] \qquad \boldsymbol{W} = \left[diag\left(K_b(\boldsymbol{T}_j - \boldsymbol{T}_{j^*})\right)\right]$$

$$K(Z) = \prod_{all\ z} N\left((z_j - z_{j^*})/\hat{\sigma}_z\right)$$

$$K_b(Z) = K(b)/b$$

3. A Discrete Choice Approach to Valuing Climate Amenities

The discrete choice approach to amenity valuation, like the hedonic approach, 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 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 3). Bayer et al. (2009) demonstrate that this equality fails to hold in the

[6] We estimate these models using ordinary least squares (OLS) and compute robust standard errors. Albouy et al. (2016) indicate that they weight observations by population in their QOL models. We believe that using population weights in the estimation of equation (7) is inappropriate, since population is endogenous in an urban location model; however, we do present population-weighted estimates in the appendix for completeness.

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).

3.1. The Discrete Choice Model

Our discrete choice model builds on the work of Bayer et al. (2009) and Cragg and Kahn (1997). We model household location assuming that each household selected its preferred MSA from the set of MSAs in the United States in 2000. Household utility depends on consumption of a numeraire good (the Hicksian bundle), a vector of housing characteristics and amenities, and the psychological costs of leaving the household head's birthplace. Formally, household i's utility from location j is given by

$$U_{ij} = U_i\left(C_{ij}, X_{ij}^P, A_j; MC_{ij}, \xi_j, \varepsilon_{ij}\right) \tag{9}$$

where C_{ij} is consumption of the numeraire good, $\boldsymbol{X^P}$ is a vector of housing characteristics, $\boldsymbol{A}_j$ is a vector of amenities observed by the researcher, and ξ_j is an amenity not observed by the researcher. MC_{ij} represents the psychological cost of moving to city j from the head of household's birthplace. ε_{ij} captures unobserved heterogeneity in preferences. Equation (9) is maximized subject to the household's budget constraint,

$$Y_{ij} = C_{ij} + P_j\left(X_{ij}^P\right) \tag{10}$$

where Y_{ij} is the sum of household i's nonwage income, I_i, which is assumed not to vary by city, and the wages of all family members, W_{ij}. $P_j(\boldsymbol{X^P})$ is the hedonic price function in city j. Following Sinha et al. (2016), we assume that households consume the same bundle of housing characteristics in all cities and thus use $P_{ij} = P_j(X_{i0}^P)$ to represent the expenditure of household i on housing in city j, where X_{i0}^P represents household i's observed housing bundle. Substituting equation (10) into (9) yields the household's indirect utility function, which we assume takes the form

$$V_{ij} = \alpha\left(Y_{ij} - P_{ij}\right) + \boldsymbol{A}_j\boldsymbol{\beta}_i + MC_{ij} + \xi_j + \varepsilon_{ij}. \tag{11}$$

To capture preference heterogeneity, we allow the coefficients on moving costs and amenities to vary across households.[7] To predict the earnings of household workers and housing

[7] In Sinha et al. (2016), we allow the coefficient on $Y_{ij} - P_{ij}$ to vary across households. We also allow $Y_{ij} - P_{ij}$ to enter the utility function in quadratic form.

expenditure in locations not chosen, we estimate hedonic wage and housing price equations for each MSA, as described below.

In equation (11), Y_{ij} represents income before taxes. We also estimate versions of (11) with income measured after taxes. Following Albouy et al. (2016), we use an average tax rate of 32 percent. We acknowledge that this is a very simple way of modeling taxes; however, we adopt it to make our results comparable to Albouy et al. (2016). Ideally, we would like to incorporate tax rates that are MSA-specific, although this is complicated by the fact that some MSAs cross state boundaries.

Moving costs capture the psychological, search, and out-of-pocket costs of leaving the household head's place of origin. Seventy-five percent of households in our prime-aged sample (see Table 1) live in the census region in which the head was born; 69 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 in section 5.2, failure to account for these costs significantly alters the value attached to climate amenities.

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

$$MC_{ij} = \pi_0 d_{ij}^{state} + \pi_1 d_{ij}^{division} + \pi_2 d_{ij}^{region} \tag{12}$$

where d_{ij}^{State} denotes a dummy variable that equals 1 if *j* is in a state that is different from the one in which household head *i* was born, $d_{ij}^{Division} = 1$ if MSA *j* is outside of the census division in which the household head was born, and $d_{ij}^{Region} = 1$ if MSA *j* lies outside of the census region in which the household head was born.[8]

3.2. Estimation of the Discrete Choice Model

Estimating the location choice model requires information on the wages that a household would earn and on the cost of housing in all MSAs. Because wages are observed only in the household's chosen location, we estimate a hedonic wage equation for each MSA and use it to predict W_{ij}. The hedonic wage equation for MSA *j* regresses the logarithm of the hourly wage

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[8] Allowing moving costs to vary by marital status or by presence of children makes little difference to our results (see Sinha et al. 2016).

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.

$$\ln w_{mj} = \gamma_j^2 + \boldsymbol{X}_{mj}^{w}\boldsymbol{\Gamma}_j^{X,2} + \nu_{mj}^2 \;\; \forall\, j = 1, \dots, J \tag{13}$$

Equation (13) is identical to equation (4) above but allows the coefficients on X^w to vary by MSA. It is estimated using data on full-time workers in the PUMS.[9] The coefficients of (13) are used to calculate the 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, 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,

$$\ln P_{ij} = \delta_j^2 + \boldsymbol{X}_{ij}^{P}\boldsymbol{\Delta}_j^{X,2} + \eta_{mj}^2 \;\; \forall\, j = 1, \dots, J \tag{14}$$

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 costs of utilities, property taxes, and property insurance. $\boldsymbol{X}_{ij}^{P}$ contains a dummy variable indicating whether the house was owned or rented, as well as a vector of dwelling characteristics. Utility costs are added both to the costs of owning a home and to rents because heating and cooling requirements vary with climate. We wish to separate these costs from climate amenities. Equation (14) is estimated separately for each MSA 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.

This is clearly a strong assumption. To test its validity, we 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 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 our methodology for predicting housing expenditures.

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[9] We have also estimated equation (13) allowing for nonrandom sorting (Dahl 2002). Specifically, we compute the probability of moving from each birthplace to current location (in terms of census divisions) conditional on each education group listed in Table 1 by taking the appropriate cell counts in our sample of workers (close to 3 million individuals). Including this probability correction term (in quadratic form) in equation (13) has minimal impact on our wage regression results, possibly due to the inclusion of industry and occupation indicators in the equation.

As a sensitivity analysis, we 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 (9′), which is maximized subject to (10′). H is housing consumption, and ρ_j is the housing price index in city j. This implies that indirect utility (11′) is a function of a housing price index ρ_j that varies across cities, not households.[10]

[10] The housing price index for each MSA is the estimated MSA fixed effect in the national hedonic housing price equation, equation (5′).

$$U_{ij} = C_{ij}^{\alpha_C} H_{ij}^{\alpha_H} e^{MC_{ij}} e^{\boldsymbol{A}_j \boldsymbol{\beta}_i} e^{\xi_j} e^{\varepsilon_{ij}} \tag{9'}$$

$$C_{ij} + \rho_j H_{ij} = Y_{ij} \tag{10'}$$

$$\ln V_{ij} = \alpha_0 + \alpha_Y \ln Y_{ij} + MC_{ij} - \alpha_H \ln \rho_j + \boldsymbol{A}_j \boldsymbol{\beta}_i + \xi_j + \varepsilon_{ij} \tag{11'}$$

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

We estimate the discrete location choice model in two stages. In the case of homogeneous preferences, the first stage is a conditional logit model in which the indirect utility function incorporates MSA fixed effects (δ_j):

$$V_{ij} = \alpha\left(\hat{Y}_{ij} - \hat{P}_{ij}\right) + MC_{ij} + \delta_j + \varepsilon_{ij} \tag{15}$$

where

$$\delta_j = \boldsymbol{A_j \beta} + \xi_j \tag{16}$$

In the second stage of our model, equation (16) is estimated by ordinary least squares (Berry et al. 2004).[11]

To allow for heterogeneity in preferences, coefficients on the climate amenities in $\boldsymbol{A}_j$ are allowed to vary across households. We assume that these coefficients are jointly normally distributed, with zero mean vector and variance-covariance matrix $\boldsymbol{\Sigma}$.[12] 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 where

$$P(i\ selectes\ j) \quad = \int_{-\infty}^{\infty} \frac{\exp(V_{ij}(\alpha, \boldsymbol{\beta}_i, \boldsymbol{\pi}))}{\sum_k \exp(V_{ik}(\alpha, \boldsymbol{\beta}_i, \boldsymbol{\pi}))} f(\boldsymbol{\beta} | \boldsymbol{\mu}, \boldsymbol{\Sigma}) d\beta \tag{17}$$

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[11] In the case of the Cobb Douglas utility function,

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

where

$$\delta_j' = -\alpha_H \ln \rho_j + \boldsymbol{A}_j \boldsymbol{\beta} \quad + \xi_j\ .$$

[12] In estimating the mixed logit model, the means of amenity coefficients are constrained to be zero. They are estimated in the second stage of the model (equation 16).

The parameters of equation (17) are estimated via simulated maximum likelihood techniques, using a choice set equal to the household's chosen alterative and a sample of 59 alternatives from the set of 284 MSAs.[13]

To examine how taste heterogeneity varies by location, we compute the distribution of $\boldsymbol{\beta}_i$ for each household, conditioning on where the household has chosen to locate. Specifically, we use Bayes' rule (Revelt and Train 1999) to derive the distribution of $\boldsymbol{\beta}_i$ conditional on chosen location, household attributes, and the population distribution of $\boldsymbol{\beta}$,

$$h(\beta|choice_i, X_i, \boldsymbol{\mu}, \boldsymbol{\Sigma}) = \frac{\Pr(choice_i|X_i, \beta)\, f(\beta|\boldsymbol{\mu}, \boldsymbol{\Sigma})}{\Pr(choice_i|X_i, \boldsymbol{\mu}, \boldsymbol{\Sigma})} \tag{18}$$

Using this conditional distribution yields an expression for mean taste parameters, $\boldsymbol{\mu_i}$, for households of type X_i:

$$\mu_i = E(\beta_i|choice_i, X_i, \boldsymbol{\mu}, \boldsymbol{\Sigma}) = \int \beta_i\, h(\beta|choice_i, X_i, \boldsymbol{\mu}, \boldsymbol{\Sigma})d\beta \tag{19}$$

These household-level parameters are estimated via simulation. 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. A similar method can be used to derive the conditional variance-covariance matrix $\boldsymbol{\Sigma_i}$.

4. Data and Empirical Specifications

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.

4.1. Data Used to Estimate Hedonic Price Functions

The variables that we include in the hedonic wage and housing price equations (equations 4′, 5′, 13, and 14) are listed in Appendix Tables A.1 and A.2, together with coefficient estimates. The hedonic wage equation is estimated using all persons in the 2000 PUMS who live in an MSA for which we have complete amenity data and work at least 40 weeks per year and between

[13] 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. Nerella and Bhat (2004) use simulated data to examine the effect of sampling on the empirical accuracy of parameter estimates in a mixed logit model. They suggest using at least one-quarter of the universal choice set in estimating a mixed logit model. We do, however, face computational trade-offs in estimating the mixed logit model using more than one-quarter of the universal choice set and a sample large enough to estimate 284 fixed effects with precision. Experiments with the size of the choice set indicate that increasing the size of the choice set beyond 60 MSAs does not significantly alter parameter estimates.

30 and 60 hours per week.[14] Persons who are self-employed, in the military, or in farming, fishing, or forestry are excluded from the sample. The housing equations are estimated using data on all households living in one of the 284 MSAs for which we have complete amenity data.

4.2. Households Used to Estimate the Discrete Choice Model

In estimating the discrete choice models, we focus on households residing in one of the 284 MSAs for which we have complete amenity data. 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 United States. We exclude households whose heads are in the military or are in certain occupations (e.g., logging, mining) that would restrict locational choices. We also eliminate households whose members are self-employed, because of the difficulty in predicting their wages, and drop households with negative values of $Y_{ij} - P_{ij}$ at their chosen locations.[15] This leaves over 2 million households. A 2.5 percent sample of these households yields the 54,008 households described in Table 1.[16]

We have estimated the discrete choice model for the full sample of households and also for the two subsamples described in Table 1: households with prime-aged heads (i.e., heads between 25 and 55) and households with heads over age 55. The results presented in this paper focus on households with prime-aged heads. As Table 1 indicates, 98 percent of these households have some labor income, and on average, 93 percent 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. Our results also suggest that preferences for climate amenities 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.

4.3. Climate Variables

Previous studies of the value of climate amenities have used various measures of climate, including temperature, humidity, precipitation, and sunshine. Many studies use average summer

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[14] There were 284 such MSAs in the continental United States in 2000, containing 80 percent of the country's population.

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

[16] Computational difficulties led us to use such a small sample of households. However, we have run the mixed logit model on different samples of this size and find the results to be sufficiently similar.

and winter temperatures (Graves and Mueser 1993; Cragg and Kahn 1997, 1999; Kahn 2009)[17] or annual heating and cooling degree days (Roback 1982; Blomquist et al. 1988; Gyourko and Tracy 1991; Albouy 2012),[18] which are highly correlated with winter and summer temperatures. 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; Barreca et al. 2016). In the context of climate amenities, Fan et al. (2016) use the number of days below 32 degrees and the number of days above 80 degrees, while controlling for mean annual temperature. Albouy et al. (2016) use binned data to examine the impact of temperatures above and below 65 degrees F.

Our hedonic and discrete choice models use mean winter (December–February) and mean summer (June–August) temperatures, measured as climate normals for the period 1970–2000. The advantage of mean winter and summer temperatures is that they capture seasonality, which annual heating and cooling degree days and temperature bins do not. Also, with the MSA as the unit of observation, it is asking a lot of the data to estimate the impact of temperature when measured as the number of days in fine temperature bins.[19]

In interpreting temperature coefficients, we note that correlation between winter and summer temperatures and temperatures during other seasons of the year implies that winter and summer temperatures 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.

In the discussion that follows, we focus primarily on results for winter and summer temperatures; however, the hedonic and discrete choice models also include annual snowfall, mean summer precipitation, and July relative humidity. The climate variables in the models are summarized in Table 2. All variables are climate normals: the arithmetic mean of a climate variable computed for a 30-year period.[20] Following the literature, we also include the

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17 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.

18 A mean daily temperature greater than 65 degrees F results in (average temperature − 65) cooling degree days. A mean daily temperature less than 65 degrees results in (65 − average temperature) heating degree days.

19 Moreover, the number of days per year exceeding 80 degrees—based on climate normal for 1970–2000—is very small.

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

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.

4.4. Nonclimate Amenities

The nonclimate amenity variables used in both the discrete choice and hedonic models are also summarized in Table 2. These include amenity measures typically used in QOL studies as well as variables that are likely to be correlated with climate, such as elevation, visibility, and measures of parks and recreation opportunities. Because both sets of models are estimated using a single cross section of data, we attempt to avoid problems of omitted variable bias by including a variety of location-specific amenities in our models.

Many QOL 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 that are not adequately captured by other variables (e.g., better public transportation, restaurants, and live sporting events). We also estimate models with population density omitted.[21]

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.

4.5. Empirical Specification

The hedonic wage and price equations we estimate are semilog functions, a form commonly used in the hedonic literature and used by Albouy et al. (2016) in constructing

[21] We recognize that ideally we would want to instrument for population density. Although we do not instrument for population density, we conduct sensitivity analysis by replacing population density with other variables. The results indicate that the MWTP estimates are robust to these alternative specifications. See Sinha et al. (forthcoming) for details.

location-specific wage and housing price indices. When estimating equations (7) and (16), amenities enter the right-hand side of each equation in linear or logarithmic form, although we consider quadratic functions of winter and summer temperatures as a sensitivity analysis.

To examine heterogeneity in tastes for climate, we focus on winter and summer temperatures. In hedonic models, the residuals obtained by estimating equation (7) excluding winter and summer temperatures are used to estimate local linear regressions (equation 8), which allow MWTP for summer and winter temperatures to vary by city. In estimating discrete choice models, we allow the coefficients on winter and summer temperatures to be random. Specifically, we assume that the coefficients are jointly normally distributed with variance-covariance matrix Σ.[22] We compute the distribution of these coefficients for each sample household, conditional on its chosen MSA, and then average the means of these location-specific coefficients for all households in a city to compute MSA-specific MWTP for winter and summer temperatures.[23]

5. Estimation Results

In the spirit of Cragg and Kahn (1997) and Bayer et al. (2009), we compare estimates of mean MWTP from the discrete choice and hedonic models to see whether the discrete choice approach yields similar mean 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 on a household's current location.

5.1. Hedonic Results

We begin by examining how climate amenities are capitalized into wages and housing prices, based on national hedonic price functions. Columns 1 and 2 of Table 3 present climate coefficients from the hedonic wage and housing price regressions estimated when the MSA wage and housing price indices from equations (4′) and (5′) are each regressed on the vector of city-

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[22] In Sinha et al. (forthcoming), we allow other climate variables to have random coefficients, as well as the coefficients on moving costs and the Hicksian bundle. These alternative specifications have virtually no impact on mean MWTP for winter or summer temperature. The sorting patterns we observe for winter and summer temperatures are qualitatively similar to those we report below.

[23] Mean MWTP for winter temperature in an MSA is computed by averaging the means of the winter temperature distributions for all households in the MSA and dividing by α, the coefficient on the Hicksian bundle.

specific amenities.[24] The last two columns of the table show the climate amenity coefficients obtained when the QOL indices formed from the MSA wage and housing price indices are regressed on the vector of amenities.

Table 3 suggests that winter temperature is an amenity that is capitalized primarily into wages (i.e., wages are lower in MSAs with warmer winters) and summer temperature is a disamenity that is capitalized primarily into housing prices (i.e., housing prices are lower in MSAs with hotter summers). Housing prices are higher in MSAs with more sunshine but lower in areas with more snowfall. At the same time, wages are lower in MSAs with more snowfall. The wage and housing prices indices from equations (4′) and (5′) are combined into QOL indices using traditional (Roback) weights (column 3) and adjusted (Albouy) weights (column 4), and the impact of climate amenities on the QOL index differs depending on the weights used. The Albouy weights, which assign more importance to housing prices, suggest that summer temperature is more of a disamenity than winter temperature; traditional weights, which assign more weight to wages, assign a higher amenity value to winter temperature.

Table 4 displays MWTP for climate amenities implied by the QOL models, using, alternately, traditional and adjusted weights.[25] Each model controls for all the amenities listed in Table 2.[26] Models H.1 and H.2 allow winter and summer temperatures to enter in linear and quadratic forms. In model H.2, 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. When adjusted weights are used, 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 for winter temperature and –$358 for summer temperature in model H.1a). In contrast, the two values are approximately equal in magnitude when traditional weights are used (e.g., $207 and –$228 in model H.1t).[27]

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[24] The coefficients of nonclimate amenities are presented in Appendix Table A.3.

[25] Appendix Table A.4 displays MWTP for nonclimate amenities for the four models presented in Table 4. Appendix Table A.5 presents the MWTP for climate amenities when results are population-weighted.

[26] MWTP in Table 4 is calculated by multiplying the relevant coefficient by the mean income of prime-aged households.

[27] There are other differences in the values 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.

Table 4 assumes homogeneous tastes for climate amenities. We also use the QOL indices from each hedonic model to estimate flexible, local linear regressions that allow the coefficients on summer and winter temperatures to vary by MSA. Specifically, we regress the QOL index on all amenities except for winter and summer temperatures, and then use the residuals from this equation in a local linear regression with the kernel weights described in equation (8). Following Bajari and Benkard (2004) and Bajari and Kahn (2005), we enter winter and summer temperatures in linear form. With only 284 observations, results are 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. In Table 5, we present summary statistics of MWTP from the local linear regressions using bandwidths between 0.4 and 0.9. The MWTP for winter and summer temperatures for each city are plotted in Figures 1–4 using a bandwidth of 0.7 and in Appendix Figures A.1–A.4 using bandwidths between 0.4 and 0.9.

When preferences for temperature are allowed to vary across cities, both hedonic models suggest that summer temperature is a greater disamenity than winter temperature is an amenity: the MWTP for warmer winters averaged across all cities is less than half of the mean MWTP for cooler summers, using either set of weights. At a bandwidth of 0.5 (0.7), mean MWTP for winter temperature is \$95 (\$77) using traditional weights and \$76 (\$63) using adjusted weights. Mean MWTP to reduce summer temperature by 1 degree is \$231 (\$186) using traditional weights and \$246 (\$194) using adjusted weights.

The sorting patterns implied by the two sets of weights are, however, very different. Figures 1 and 2 display MWTP for winter temperature by city, plotted against winter temperature using traditional (Figure 1) and adjusted (Figure 2) weights. The use of traditional weights (Figure 1) suggests that households that live in cold cities have the greatest MWTP for warmer winters. The highest MWTP is in Duluth, Minnesota. Households along the Pacific coast would actually prefer cooler winters. This sorting pattern suggests that households in northern latitudes—in the East and West North Central and New England census divisions—would be willing pay the most for the beneficial portion of climate change. Using Albouy weights (Figure 2) suggests that households that enjoy warm winters (households in the West South Central and South Atlantic divisions) have the highest MWTP for warmer winters, although three MSAs in the northern United States also have high MWTP. Simply put, the two sets of weights have sorting patterns that are opposites of one another, which the correlations between winter temperature and MWTP for winter temperature in Table 5 confirm.

The two sets of weights also yield different sorting patterns for summer temperature (Figures 3 and 4). With traditional weights (Figure 3), the relationship between MWTP for warmer summers and summer temperature is upward-sloping: people with the highest MWTP to reduce summer temperature (the largest negative MWTP) are those who live in MSAs with cooler summer temperatures. The relationship between MWTP and temperature turns down at higher temperatures, although the extent of this negative relationship depends on bandwidth—the MWTP for cooler summers is higher for households living in the South with smaller bandwidths (see Appendix Figure A.3). The sorting pattern using adjusted weights (Figure 4) is the opposite of the pattern in Figure 3. The relationship between MWTP for cooler summers and summer temperature is fairly flat until 80 degrees and then turns sharply downward. Households in the South Atlantic and West South Central divisions—which are willing to pay the most for warmer winters (Figure 2)—are willing to pay the most to avoid warmer summers. As shown in Table 5 and in Appendix Figure A.4, this sorting pattern is robust to choice of bandwidth and agrees with Albouy et al. (2016, Figure 6, Panel C), who describe residents of areas with warmer summers as being more heat-averse on the margin.

In comparing hedonic results to the discrete choice results reported below, we focus on results obtained using adjusted (Albouy) weights. The sorting patterns shown in Figures 2 and 4 (and in Appendix Figures A.2 and A.4) using adjusted weights generally agree with the results reported by Albouy et al. (2016) even though we use different temperature measures.[28] The results are also more robust to choice of bandwidth than results based on traditional weights. We also report discrete choice models based on after-tax income to facilitate comparison with hedonic results based on Albouy weights.

5.2. 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).[29] 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, a point we return to below.

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[28] In the case of summer temperature, Panels C and D of Figure 6 in Albouy et al. (2016) show MWTP to avoid a day at 80 degrees (versus 65 degrees) to be roughly constant for households experiencing between 1,000 and 3,000 cooling degree days per year. This agrees with the flat portion of Figure 4. The upward-sloping portion of Figure 2, which shows households in warmer MSAs having higher MWTP for warmer winters, is consistent with Panel B of Figure 6 in Albouy et al. (2016) at low values of heating degree days.

[29] These results are reported in Table 9, discussed below.

Table 6 describes the results of estimating our base model for prime-aged households, controlling for all attributes in Table 2 and assuming homogeneous preferences. Model C.1 is the base model with income measured before taxes, model C.2 is the same model but with income measured after taxes, model C.3 is model C.1 with moving costs removed, and model C.4 is model C.2 with moving costs removed. The base model coefficients have been converted to MWTP by dividing by the coefficient on the Hicksian bundle. Standard errors are reported for all MWTP estimates.

Table 6 suggests that estimates produced by the discrete choice approach are two to four times as large as estimates produced by the hedonic approach, assuming homogeneous preferences. This is certainly true when the estimates from model C.1 are compared with those from the hedonic model with traditional weights (H.1t) and when estimates from model C.2 are compared with those from the hedonic model with adjusted weights (H.1a). Does this difference disappear when moving costs are removed from the discrete choice models? Model C.4 shows that removing moving costs from the model in which income is measured net of taxes brings MWTP to reduce summer temperature very close to what is estimated using the adjusted hedonic model but still leaves MWTP for winter temperature about three times what is estimated using the adjusted hedonic model.[30]

Table 7 presents estimates of MWTP for winter and summer temperatures and other climate amenities based on four mixed logit models.[31] Our base model (model M.1) controls for all the amenities in Table 2, as well as moving costs, and allows the coefficients on winter and summer temperatures to be jointly normally distributed. Model M.2 is identical to model M.1, except that income is measured as after-tax income. Both models suggest that on average, higher winter temperature is an amenity and warmer summer temperature a disamenity. Mean MWTP to reduce summer temperature by 1 degree is higher than mean MWTP to increase winter temperature by 1 degree ($627 versus $518 in model M.1; $522 versus $382 in model M.2). There is, however, considerable variation in tastes. Interestingly, the coefficients on winter and summer temperatures are negatively correlated: most (but not all) households that prefer milder winters also prefer milder summers, while those that favor colder winters like hotter summers.[32]

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[30] As a sensitivity analysis, Appendix Table A.6 shows how the results of Table 6 are altered when population density is dropped from the list of nonclimate amenities. Results are robust to the omission of population density.

[31] Table 7 in the text reports MWTP for climate variables only. MWTPs for nonclimate amenities are reported in Appendix Table A.7.

[32] Appendix Table A.8 explores the sensitivity of the discrete choice model to the Hicksian bundle entering equation (11) in quadratic form and to the use of the Cobb-Douglas utility function (equation 11′). Results are robust to these sensitivity analyses.

To examine how households sort across locations in relation to their taste for winter and summer temperatures, we calculate the joint distribution of the coefficients of winter and summer temperatures for each household, conditional on the household's choice of location. The means of these conditional distributions are averaged across all households in each city, divided by the coefficient on the Hicksian bundle, and plotted against city temperature in Figures 5 and 6.[33]

The pattern of taste sorting is similar whether we base location decisions on income before or after taxes.[34] Households with higher MWTP for warmer winters tend to locate in warmer cities: the correlation coefficient between winter temperature and mean MSA MWTP is 0.92 in model M.1 (Figure 5A) and 0.91 in model M.2 (Figure 5B). There is, however, some variation in mean MWTP across cities at a given temperature. For example, at a mean winter temperature of 40 degrees, households in the states of Oregon and Washington have a willingness to pay for a warmer winter that is much higher than the MWTP of households in Texas. At a mean winter temperature of 50 degrees, households on the Pacific coast are willing to pay more for warmer winter temperature than households in the East South Central division. Preferences for summer temperature (Figures 6A and 6B) 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 5 and 6 suggest that, holding temperature constant, MWTP for winter and summer temperatures varies by region: households in the East North Central census division appear to find hotter summers less of a disamenity than households that 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 climate variables other than 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.

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

[34] Figures 5A and 6A plot results based on model M.1, while Figures 5B and 6B plot results from model M.2, which is based on net-of-tax income.

Failure to control for moving costs has a large effect on the estimated value of climate amenities, as well as on the spatial distribution of MWTP for winter and summer temperatures. Model M.3 (M.4) shows the impact of dropping moving costs from the discrete choice model when income is measured before (after) taxes. While the mean of the distribution of MWTP for winter temperature remains positive, its magnitude drops by about 5 percent (15 percent). The mean of the distribution on the coefficient of summer temperature is even more sensitive: its magnitude drops by about 38 percent (35 percent) when moving costs are omitted. Table 7 also indicates the role that moving costs play in taste sorting: when moving costs are omitted from the base models, the standard deviations on the winter temperature coefficients are no longer statistically significant. In model M.3, the correlation coefficient between the winter and summer temperature coefficients switches from negative to positive in sign. Simply put, patterns of taste sorting are no longer identified when moving costs are removed from the discrete choice model.

This is borne out in Figure 7, which contrasts the sorting patterns from model M.3 when moving costs are removed with the patterns shown in Figures 5A and 6A. The top right panel of Figure 7 still shows a positive correlation between mean MWTP for winter temperature and mean winter temperature; however, the variation is small, and all MSAs have mean MWTP within about $20 of each other. The bottom right panel suggests that MWTP for warmer summers is positively associated with summer temperature. Similar results obtain when using income net of taxes (see Appendix Figure A.5). 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.

5.3. Comparison of Hedonic and Discrete Choice Results

The preceding results make clear that the mean values attached to winter and summer temperatures using the discrete choice approach are much larger than the values obtained from the hedonic models we have estimated. Under the assumption of homogeneous tastes (Table 6), mean MWTP for a 1 degree increase in winter temperature using the base discrete choice model (model C.1) is three times the estimate obtained from hedonic model using traditional weights (model H.1t). Mean MWTP for a 1 degree decrease in summer temperature is approximately 3.5 times larger using the discrete choice model. When location choices are based on after-tax income (Model C.2), mean MWTP for winter temperature is four times the estimate obtained using the hedonic model with adjusted weights (Model H.1a). The corresponding estimates for summer temperature are $595 (Model C.2) and $358 (Model H.1a).

The differences in mean MWTP persist when estimated tastes for climate vary across cities: mean estimates of MWTP for winter temperature vary with the bandwidth used in the hedonic models but are below $115 for all the bandwidths reported in Table 5, for both sets of weights. Mean MWTP is $382 (s.e. = $104) when the discrete choice model is estimated using after-tax income. The corresponding mean MWTP for a 1 degree decrease in summer temperature is $522 (s.e. = $180), twice as large as mean MWTP obtained from the hedonic model for all bandwidths ≥0.5 using either set of hedonic weights.[35]

The hedonic and discrete choice approaches also produce very different taste sorting patterns. The discrete choice models suggest that households sort across locations based on preferences for winter temperature: there is a strong positive correlation between winter temperature and MWTP for winter temperature in Figures 5A and 5B. The relationship between MWTP for winter temperature and MSA temperature resulting from the traditionally weighted local linear hedonic model (Figure 1) is the reverse: it suggests that households with the highest MWTP for winter temperature live in the coldest cities.

The sorting pattern produced by the hedonic model with adjusted weights (Figure 2) is closer to the sorting pattern produced by the discrete choice model: both models project that households living in Florida and Texas have the highest MWTP for warmer winters, but there are important differences. In the hedonic model, households in the West North Central division have an MWTP for winter temperature that is as high as that of households living in the South. In general, the correlation between MWTP for winter temperature and winter temperature is much weaker than in the discrete choice model.

The value placed on avoiding hotter summers also differs between the discrete choice and hedonic approaches. A key result from the discrete choice model is that preferences for warmer summers and warmer winters are negatively correlated. This leads to the inverted-U sorting pattern shown in Figures 6A and 6B. Households on the Pacific coast, which have high MWTP for warmer winters, also have a high MWTP for warmer summers. The same is true of households that live in the South Atlantic division. In contrast, the sorting pattern produced by the hedonic model with traditional weights shows a much stronger upward slope: according to this model, households on the Pacific coast have the lowest MWTP for milder summers of all US households. The sorting pattern produced by the hedonic model with adjusted weights differs from both the traditional hedonic sorting pattern and the discrete choice model: it displays a negative correlation between MWTP for an increase in summer temperature and mean summer temperature. It projects, as does the discrete choice model, that households in Texas and Florida

[35] Although we focus on winter and summer temperatures, the discrete choice model generally produces larger estimates of MWTP for other climate amenities; see Table 6.

have the highest MWTP to avoid hotter summers, but it also projects that households on the Pacific coast have the lowest MWTP for cooler summers.

5.4. What Accounts for the Differences?

Why do estimates of the amenity value of temperature differ between the two approaches? The discrete choice and hedonic models we have estimated differ in three ways: (1) the discrete choice model incorporates the psychological costs of moving from one's birthplace, which the hedonic models do not; (2) the discrete choice model allows for city-specific labor and housing markets, rather than assuming a national market; (3) the discrete choice model uses information on market shares (i.e., population), which the hedonic model does not.[36]

If moving costs prevent amenity values from being fully capitalized into wages and housing prices, then failure to account for moving costs in the hedonic model should reduce MWTP estimates compared with those produced by the discrete choice model. Equivalently, removing moving costs from the discrete choice model should cause discrete choice estimates of MWTP to fall. This is indeed what happens in both the conditional and mixed logit models. In Table 6, MWTP for summer temperature in model C.4 (discrete choice model based on after-tax income, no moving costs) is approximately equal to MWTP in the hedonic model with adjusted weights (see also columns 2 and 4 of Table 8). The two models still differ, however, in MWTP for winter temperature. In the mixed logit models, dropping moving costs reduces estimates of mean MWTP for winter and summer temperatures, but they do not coincide with means produced by the hedonic model with heterogeneous tastes (compare Tables 5 and 7). Moving costs therefore do not explain all the differences in mean MWTP between the hedonic and discrete choice approaches.

To investigate the impact of national versus city-specific labor markets, we estimate the discrete choice model derived from a Cobb-Douglas utility function (equation 9´), including only moving costs and city-specific fixed effects (δ_j) in the first stage. The second stage of estimation entails regressing city fixed effects on wages, housing prices, and amenities,

$$\delta_j = \alpha_Y \ln Y_j - \alpha_H \ln \rho_j + \boldsymbol{A}_j \boldsymbol{\beta} \quad + \xi_j \tag{20}$$

[36] The two approaches also differ in their underlying econometric assumptions. The discrete choice approach adds a product-specific shock to the consumer's utility function (ε_{ij}). This "taste for product," which is absent from the hedonic model, leads the discrete choice approach to have undesirable properties in the context of models of product choice (Ackerberg and Rysman 2005; Bajari and Benkard 2003, 2004; Berry and Pakes 2001). For example, in standard random utility models, the demand for each product is strictly positive at every price (Bajari and Benkard 2003, 2004). This can lead to very large values of consumer surplus associated with a product and overstate the welfare loss when a product is eliminated from the market. This is not, however, an issue in the current context.

which we assume vary only by city. In estimating equation (20), we replace $\ln Y_j$ by $(1 - \tau)\, \lambda_j^W$ and $\ln \rho_j$ by λ_j^P, the same wage and housing price indices that are used in estimating the hedonic model. This imposes the assumption of national labor and housing markets on the discrete choice model. The resulting MWTP estimates, in column (3) of Table 8, show that the assumption of national labor and housing markets reduces MWTP for both winter and summer temperatures compared with the base discrete choice model, which assumes city-specific labor and housing markets. It brings MWTP for a decrease in summer temperature in line with estimates from the hedonic model (column 4 of Table 8); however, MWTP to increase winter temperature is still three times what the hedonic model projects.

A third difference between the two approaches arises from the fact that the discrete choice model uses information on market shares in estimating model parameters, which the hedonic model does not. This can be seen by rewriting the equation for the second-stage of the discrete choice model (equation 20), following Bayer et al. (2007), as

$$\delta_j/\alpha_Y + (\frac{\alpha_H}{\alpha_Y})\ln\rho_j - \ln Y_j = \boldsymbol{A}_j \frac{\boldsymbol{\beta}}{\alpha_Y} + \xi_j/\alpha_Y \qquad (21)$$

where $\frac{\alpha_H}{\alpha_Y}$ is the share of income spent on housing. Equation (21) is similar to the hedonic equation, with the QOL index on the left-hand side adjusted by the city-specific fixed effect δ_j. Given this adjustment, there is no reason why the discrete choice model should yield the same estimates of MWTP as the hedonic approach, provided δ_j varies across cities. Maximization of the likelihood function of the conditional logit model guarantees that each δ_j equates the sum of the probabilities that each household chooses city *j* to the number of households in the sample that actually choose that city. Although δ_j will also be influenced by other variables that enter the first stage of estimation, δ_j will reflect the number of households living city *j*; under random sampling, this will be proportional to city population.[37] The use of quantity (share) information should therefore cause discrete choice estimates of MWTP to differ from hedonic estimates.

Equation (21) helps explain why mean MWTP for winter temperature is higher under the discrete choice than the hedonic approach. The city-specific fixed effects from the first stage of the conditional logit model with moving costs (the model in column 3 of Table 8) are more highly positively correlated with winter than with summer temperature. This raises MWTP for winter temperature in the discrete choice model compared with MWTP from the hedonic model.

[37] In the model of column (3) of Table 8, the correlation between δ_j and city population is 0.71.

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 temperatures. While previous comparisons of the two methods have focused on comparing mean MWTP (Cragg and Kahn 1997; Bayer et al. 2009) we have focused on comparing how MWTP for small changes in winter and summer temperatures vary 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.

Simply put, the patterns of taste sorting produced by the two approaches are quite different. The discrete location choice model suggests that households that 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: MWTP for an increase in winter temperature is higher for people living in North Dakota than for those in Florida. The hedonic results with adjusted weights 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 adjusted weights suggest that MWTP for cooler 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 hotter summers under climate change (Karl et al. 2009). The hedonic local linear regressions with traditional hedonic weights suggest 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, while the discrete choice model estimates that MWTP to avoid warmer summers is highest, for prime-aged households, in the Pacific, Mountain, and South Atlantic 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: when taste sorting is allowed, mean MWTP for a 1 degree increase in winter temperature is less than $100 using either hedonic model (Table 5), whereas it is approximately $400 in the discrete choice model (model M.2 of Table 7). Mean MWTP to avoid warmer summers is lower in both hedonic models (approximately $170 to $250, depending on bandwidth) than in the discrete choice model, where MWTP is over $500.[38]

These findings raise an obvious question: Why do results differ across models? Bayer et al. (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. Omitting moving costs reduces estimates of mean MWTP for winter and summer temperatures in our discrete choice models and brings the discrete choice estimates closer to estimates from the hedonic models, but it does not account for all the differences between the hedonic and discrete choice estimates.

The hedonic and discrete choice approaches differ in other ways. The construction of hedonic QOL indices is based on national labor and housing market equations that assume that the returns to human capital and the marginal cost of housing characteristics are everywhere equal. The discrete choice approach, in contrast, treats each city as a separate market and allows variation in the returns to human capital and in the marginal price of dwelling characteristics across cities to identify household preferences. As shown in Table 8, assuming national labor and housing markets in the context of the discrete choice model (but including moving costs) lowers mean MWTP for an increase in winter and a decrease in summer temperature, compared with the model with city-specific markets.

The discrete choice and hedonic models also use information on location choices differently. The city-specific fixed effects estimated in the first stage of the discrete choice model equate the sum of the probabilities of choosing a city to the number of persons in the sample who choose the city. In a random sample, this will be proportional to city population. When city fixed effects are regressed on amenities in the second stage of estimation of the discrete choice model, population is implicitly used to estimate preferences. This is not the case for the hedonic model. We show, following Bayer et al. (2007), that the second stage of estimation of the discrete choice model, assuming national labor and housing markets, is similar to that of the hedonic model, with hedonic prices adjusted for city-specific fixed effects. There is therefore no reason why the two approaches should produce identical estimates of mean MWTP for city-specific amenities.

This raises another question: If the hedonic and discrete choice approaches yield different results, which approach yields the more reliable estimates of the value of climate amenities for use in evaluating climate policy? We believe that several considerations argue in favor of the

[38] The mean estimate for the discrete choice model depends on whether income is after tax or before tax: mean MWTP for winter temperature is $382 (s.e. = $104) using after-tax income and $518 (s.e. = $144) using before-tax income. The corresponding estimates for reducing summer temperature are $522 (s.e. = $180) using after-tax income and $627 (s.e. = $249) using before-tax income.

discrete choice approach. As noted above, the discrete choice approach captures the stylized fact that the majority of households in the United States live in the same state in which the head of household was born. Informational and psychological frictions make households less than perfectly mobile. The discrete choice approach also makes use of spatial differences in labor and housing markets to identify household preferences, rather than assuming a national labor and housing market.

Finally, the discrete choice approach is more easily able to measure the impact of urban amenities on all household groups. The hedonic approach typically focuses on the preferences of prime-aged households, since a significant fraction of older households have no wage income. But climate benefits accrue to all households. Table 9 presents estimates of the discrete choice model for households headed by prime-aged adults, adults over 55, and all households with heads 16 years and older. Estimates of MWTP based on all households are approximately 40 percent greater than those based on the prime-aged sample. Older households place a higher value on warmer winters and cooler summers, and it is important to estimate these benefits.

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Table 1. Descriptive Statistics of Household Characteristics

Variable	Description	Full sample (*N*: 54,008) Mean	Full sample Std. dev.	Prime-aged (*N*: 33,180) Mean	Prime-aged Std. dev.	Greater than 55 (*N*: 17,643) Mean	Greater than 55 Std. dev.
Age of household head (mean)	Age	49.11	17.03	40.79	8.20	69.50	9.41
Gender of household head (proportion)	Male	63.93		67.02		60.60	
Marital status of household head (proportion)	Married	52.22		55.43		50.99	
Race of household head (proportions)	White	82.70		81.13		87.03	
	Black	13.11		13.97		10.98	
	Other	4.20		4.91		1.99	
Education of household head (proportions)	No high school	12.86		7.56		23.09	
	High school	25.96		24.06		29.71	
	Some college	30.89		33.73		23.65	
	College graduate	19.33		22.67		12.95	
	Postgraduate education	10.96		11.99		10.62	
Household head movement from place of birth (proportions)	Left state of birth	42.65		40.99		47.32	
	Left census division of birth	32.78		31.28		36.86	
	Left census region of birth	26.55		24.98		30.85	
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
Household wage earnings (proportion)	Households with zero wage earnings	16.75		2.23		46.94	
Total household income (mean)	Sum of wage, business, and farm incomes and income from other sources of all household members[a]	$63,312	$58,671	$69,161	$59,723	$57,294	$58,615

		Full sample (*N*: 54,008)		Prime-aged (*N*: 33,180)		Greater than 55 (*N*: 17,643)	
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	\$15,556	\$9,082	\$16,193	\$9,437	\$15,481	\$8,560
Size of household (proportions)	1 member	26.16		21.05		36.03	
	2 members	34.69		27.35		47.68	
	3 or more members	39.15		51.59		16.28	

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

Table 2. Descriptive Statistics of Amenity Variables

Variable	*N*	Mean	Std. dev.	Minimum	Maximum	Median
Avg. winter temperature (°F)	284	37.339	12.158	9.442	67.922	34.996
Avg. summer temperature (°F)	284	73.309	5.817	60.848	89.733	72.517
Annual snowfall (inches)	284	20.360	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 $PM_{2.5}$ (micrograms/cubic meter)	284	12.829	2.884	5.382	19.535	12.818
Population density (persons per square mile)	284	471.767	983.041	5.400	13,043.600	259.050
Violent crime rate (number of violent crimes per 1,000 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. Hedonic Wage, Housing Cost, and Quality of Life Regressions

	Wage reg.	Housing cost reg.	QOL reg. Traditional weights	QOL reg. Adjusted weights
Variable	Coef. (Std. err.)	Coef. (Std. err.)	Coef. (Std. err.)	Coef. (Std. err.)
Avg. winter temperature	–0.0030	–0.0001	0.0030	0.0015
	(0.0008)	(0.0020)	(0.0006)	(0.0005)
Avg. summer temperature	–0.0010	–0.0172	–0.0033	–0.0052
	(0.0015)	(0.0040)	(0.0010)	(0.0009)
July humidity	–0.0007	0.0020	0.0012	0.0010
	(0.0007)	(0.0016)	(0.0005)	(0.0003)
Annual snowfall	–0.0010	–0.0022	0.0004	–0.0002
	(0.0003)	(0.0007)	(0.0002)	(0.0002)
Ln(summer precipitation)	–0.0247	–0.0475	0.0128	–0.0031
	(0.0111)	(0.0283)	(0.0080)	(0.0067)
Annual sunshine	0.0004	0.0089	0.0019	0.0028
	(0.0009)	(0.0022)	(0.0006)	(0.0005)
No. of obs. (MSAs)	284	284	284	284
Adjusted R-squared	0.71	0.74	0.50	0.59

Note: All other amenities in Table 2 are included in the models reported in this table.

Table 4. Marginal Willingness to Pay for Climate Amenities: Hedonic Models, Homogeneous Tastes

	Traditional hedonic weights				Adjusted hedonic weights			
	Model H1.t		Model H2.t		Model H1.a		Model H2.a	
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	0.0030	\$207	0.0043	\$186	0.0015	\$104	0.0031	\$110
	(0.0006)	(\$42)	(0.0019)	(\$46)	(0.0005)	(\$33)	(0.0014)	(\$41)
Avg. summer temperature	–0.0033	–\$228	–0.0228	–\$228	–0.0052	–\$358	–0.0048	–\$355
	(0.0010)	(\$68)	(0.0131)	(\$68)	(0.0009)	(\$64)	(0.0158)	(\$65)
July humidity	0.0012	\$84	0.0012	\$84	0.0010	\$71	0.0010	\$71
	(0.0005)	(\$35)	(0.0005)	(\$35)	(0.0003)	(\$24)	(0.0003)	(\$23)
Annual snowfall	0.0004	\$29	0.0005	\$33	–0.0002	–\$16	–0.0001	–\$10
	(0.0002)	(\$16)	(0.0002)	(\$16)	(0.0002)	(\$11)	(0.0002)	(\$11)
Ln(summer precipitation)	0.0128	\$81	0.0157	\$99	–0.0031	–\$19	–0.0014	–\$9
	(0.0080)	(\$50)	(0.0087)	(\$55)	(0.0067)	(\$42)	(0.0069)	(\$44)
Annual sunshine	0.0019	\$129	0.0025	\$172	0.0028	\$191	0.0030	\$205
	(0.0006)	(\$44)	(0.0008)	(\$57)	(0.0005)	(\$35)	(0.0007)	(\$45)
No. of obs. (MSAs)	284		284		284		284	
Adjusted *R*-squared	0.50		0.50		0.59		0.59	

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

Table 5. Marginal Willingness to Pay for Climate Amenities: Hedonic Models, Heterogeneous Tastes

		Winter temperature				Summer temperature				Correlations		
Weights	Bandwidth	Mean	Std. dev.	10th pctile	90th pctile	Mean	Std. dev.	10th pctile	90th pctile	WT MWTP, ST MWTP	WT, WT MWTP	ST, ST MWTP
Traditional	0.4	$113	$81	–$4	$188	–$248	$273	–$622	$44	–0.05	–0.31	0.03
Traditional	0.5	$95	$58	$23	$146	–$231	$181	–$494	–$69	–0.23	–0.44	0.22
Traditional	0.6	$84	$47	$32	$132	–$209	$135	–$414	–$85	–0.36	–0.52	0.37
Traditional	0.7	$77	$39	$46	$123	–$186	$109	–$345	–$81	–0.46	–0.59	0.49
Traditional	0.8	$72	$32	$46	$110	–$165	$93	–$301	–$76	–0.54	–0.64	0.58
Traditional	0.9	$68	$27	$46	$101	–$148	$81	–$265	–$71	–0.61	–0.69	0.65
Adjusted	0.4	$90	$87	$2	$173	–$276	$305	–$530	–$42	–0.51	0.07	–0.53
Adjusted	0.5	$76	$58	$19	$115	–$245	$233	–$424	–$88	–0.58	0.03	–0.53
Adjusted	0.6	$68	$40	$29	$94	–$216	$169	–$358	–$107	–0.61	0.00	–0.56
Adjusted	0.7	$63	$29	$34	$80	–$194	$122	–$314	–$117	–0.60	–0.03	–0.61
Adjusted	0.8	$60	$22	$38	$76	–$179	$90	–$281	–$122	–0.55	–0.07	–0.67
Adjusted	0.9	$57	$17	$42	$72	–$169	$69	–$254	–$123	–0.49	–0.10	–0.72

Note: The mean MWTP across the 284 MSA regressions is weighted by MSA population.

Table 6. Comparison of Hedonic and Discrete Choice Models, Homogeneous Tastes

	Model C.1	Model C.2	Model C.3	Model C.4	Model H1.t	Model H1.a
Variable	MWTP	MWTP	MWTP	MWTP	MWTP	MWTP
	(Std. err.)	(Std. err.)	(Std. err.)	(Std. err.)	(Std. err.)	(Std. err.)
Avg. winter temperature	\$599	\$406	\$540	\$358	\$207	\$104
	(\$147)	(\$97)	(\$147)	(\$96)	(\$42)	(\$33)
Avg. summer temperature	–\$791	–\$595	–\$382	–\$322	–\$228	–\$358
	(\$246)	(\$163)	(\$278)	(\$178)	(\$68)	(\$64)
July humidity	–\$465	–\$295	–\$445	–\$271	\$84	\$71
	(\$139)	(\$90)	(\$125)	(\$80)	(\$35)	(\$24)
Annual snowfall	–\$377	–\$266	–\$122	–\$90	\$29	–\$16
	(\$65)	(\$44)	(\$67)	(\$43)	(\$16)	(\$11)
Ln(summer precipitation)	\$525	\$321	\$163	\$76	\$81	–\$19
	(\$188)	(\$124)	(\$184)	(\$118)	(\$50)	(\$42)
Annual sunshine	–\$151	–\$65	–\$267	–\$133	\$129	\$191
	(\$153)	(\$100)	(\$161)	(\$103)	(\$44)	(\$35)

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

Model C.1: Base conditional logit model
Model C.2: Base conditional logit model with income net of taxes
Model C.3: Base conditional logit model with moving costs removed
Model C.4: Base conditional logit model with income net of taxes and moving costs removed
Model H1.t: Hedonic model with traditional weights
Model H1.a: Hedonic model with adjusted weights

Table 7. Marginal Willingness to Pay for Climate Amenities: Mixed Logit Models

	M.1: Base model		**M.2:** Net of taxes		**M.3:** Omit moving costs		**M.4:** Net of taxes + omit moving costs	
Panel A: 1st stage estimates								
Variable	Coef. (Std. err.)		Coef. (Std. err.)		Coef. (Std. err.)		Coef. (Std. err.)	
Std. dev.: avg. winter temperature	0.0588		0.0592		0.0011		0.0032	
	(0.0026)		(0.0026)		(0.0128)		(0.0097)	
Std. dev.: avg. summer temperature	0.0592		0.0612		0.0352		0.0525	
	(0.0068)		(0.0066)		(0.0215)		(0.0174)	
Correlation coefficient	–0.6893		–0.6993		0.8614		–0.9433	
	(0.0827)		(0.0776)		(0.2756)		(0.1297)	
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	0.0209	$518	0.0210	$382	0.0184	$491	0.0171	$326
	(0.0058)	($144)	(0.0057)	($104)	(0.0055)	($146)	(0.0055)	($104)
Mean: avg. summer temperature	–0.0253	–$627	–0.0286	–$522	–0.0145	–$386	–0.0178	–$339
	(0.0100)	($249)	(0.0098)	($180)	(0.0108)	($288)	(0.0110)	($209)
July humidity	–0.0208	–$514	–0.0198	–$360	–0.0165	–$440	–0.0156	–$296
	(0.0054)	($135)	(0.0052)	($95)	(0.0046)	($124)	(0.0045)	($85)
Annual snowfall	–0.0170	–$422	–0.0176	–$321	–0.0047	–$126	–0.0052	–$99
	(0.0026)	($66)	(0.0026)	($49)	(0.0025)	($67)	(0.0025)	($48)
Ln(summer precipitation)	0.1708	$403	0.1517	$264	0.0678	$172	0.0593	$107
	(0.0768)	($181)	(0.0752)	($131)	(0.0732)	($186)	(0.0727)	($132)
Annual sunshine	–0.0149	–$368	–0.0125	–$229	–0.0082	–$219	–0.0040	–$75
	(0.0060)	($149)	(0.0059)	($108)	(0.0060)	($159)	(0.0059)	($111)

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

Table 8. Comparison of Hedonic and Discrete Choice Models, Homogeneous Tastes

	Base discrete choice model with taxes	**Discrete choice model with taxes, no moving costs**	**Discrete choice model, national labor and housing markets**	**Hedonic model, adjusted weights**
Variable	MWTP (Std. err.)	MWTP (Std. err.)	MWTP (Std. err.)	MWTP (Std. err.)
Avg. winter temperature	$406	$358	$344	$104
	($97)	($96)	($72)	($33)
Avg. summer temperature	–$595	–$322	–$423	–$358
	($163)	($178)	($125)	($64)
July humidity	–$295	–$271	–$207	$71
	($90)	($80)	($62)	($24)
Annual snowfall	–$266	–$90	–$167	–$16
	($44)	($43)	($28)	($11)
Ln(summer precipitation)	$321	$76	$241	–$19
	($124)	($118)	($84)	($42)
Annual sunshine	–$65	–$133	–$30	$191
	($100)	($103)	($72)	($35)

Note: For the models in columns (3) and (4), MWTP is computed at mean household income for the prime-aged sample ($69,188). When entering the regressions nonlinearly, amenity variables are evaluated at population-weighted means in order to compute MWTP. Nonlinear covariates are as follows: population density, summer precipitation, and elevation enter in log form, while distance to the coast enters the model quadratically.

Table 9. Marginal Willingness to Pay for Climate Amenities: Mixed Logit Results, Various Subsamples

	All ages (base model)		Prime-aged		Over 55 years	
Panel A: 1st stage estimates						
Variable	Coef. (Std. err.)		Coef. (Std. err.)		Coef. (Std. err.)	
Std. dev.: avg. winter temperature	0.0666		0.0588		0.0742	
	(0.0020)		(0.0026)		(0.0039)	
Std. dev.: avg. summer temperature	0.0522		0.0592		0.0331	
	(0.0060)		(0.0068)		(0.0091)	
Correlation coefficient	–0.8332		–0.6893		–0.9936	
	(0.0731)		(0.0827)		(0.1077)	
Panel B: 2nd stage estimates						
Variable	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
	(0.0056)	($160)	(0.0058)	($144)	(0.0070)	($199)
Mean: avg. summer temperature	–0.0307	–$873	–0.0253	–$627	–0.0516	–$1,424
	(0.0091)	($260)	(0.0100)	($249)	(0.0106)	($301)
July humidity	–0.0269	–$764	–0.0208	–$514	–0.0325	–$896
	(0.0049)	($142)	(0.0054)	($135)	(0.0054)	($155)
Annual snowfall	–0.0166	–$471	–0.0170	–$422	–0.0154	–$425
	(0.0024)	($70)	(0.0026)	($66)	(0.0026)	($75)
Ln(summer precipitation)	0.1408	$376	0.1708	$403	0.0926	$232
	(0.0720)	($192)	(0.0768)	($181)	(0.0823)	($206)
Annual sunshine	–0.0155	–$441	–0.0149	–$368	–0.0111	–$307
	(0.0057)	($162)	(0.0060)	($149)	(0.0067)	($185)

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

Figure 1. Marginal Willingness to Pay for Winter Temperature by Metropolitan Area, Local Linear Hedonic Model, Traditional Weights (bandwidth = 0.7)

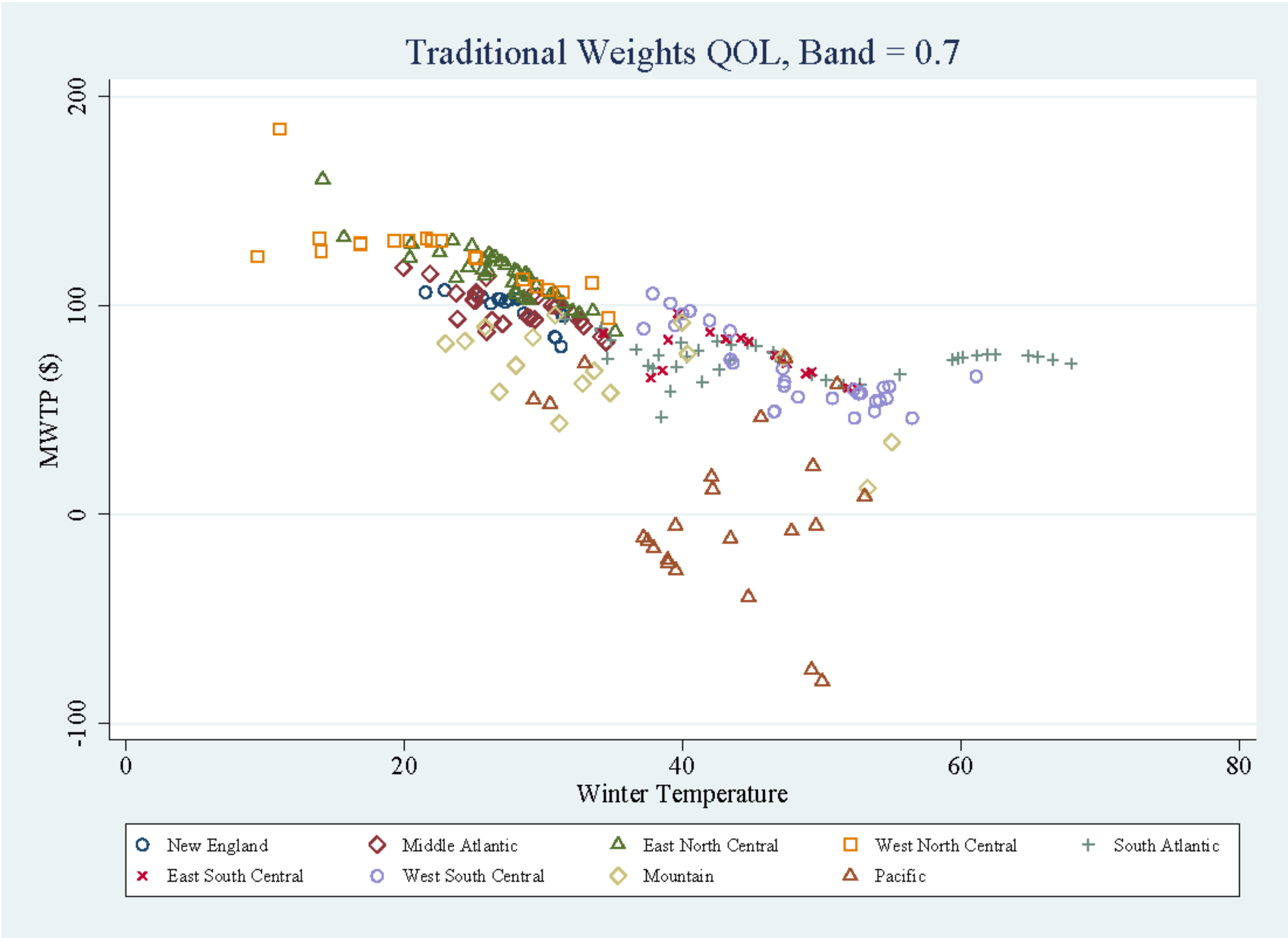


Figure 2. Marginal Willingness to Pay for Winter Temperature by Metropolitan Area, Local Linear Hedonic Model, Adjusted Weights (bandwidth = 0.7)

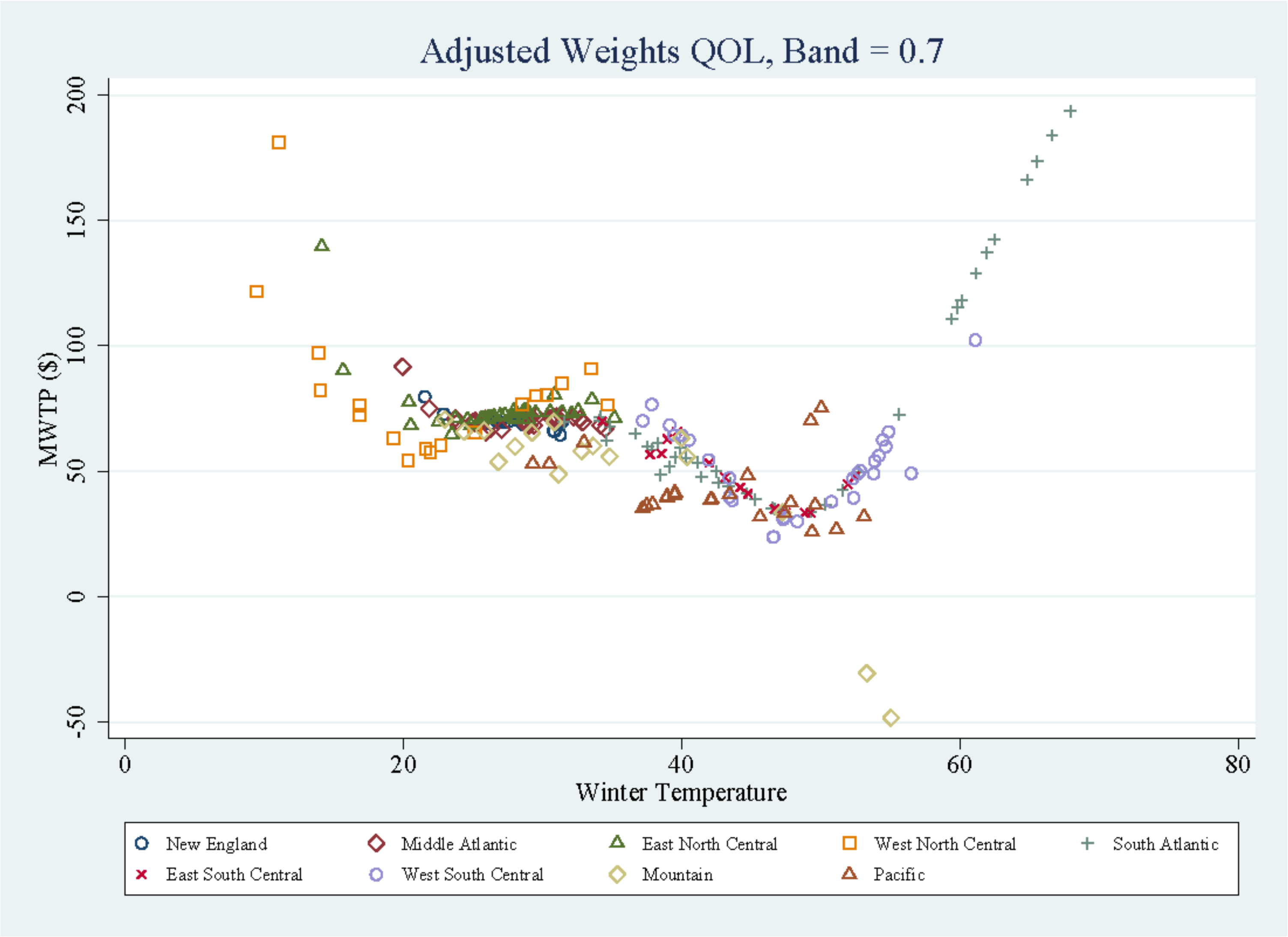


Figure 3. Marginal Willingness to Pay for Summer Temperature by Metropolitan Area, Local Linear Hedonic Model, Traditional Weights (bandwidth = 0.7)

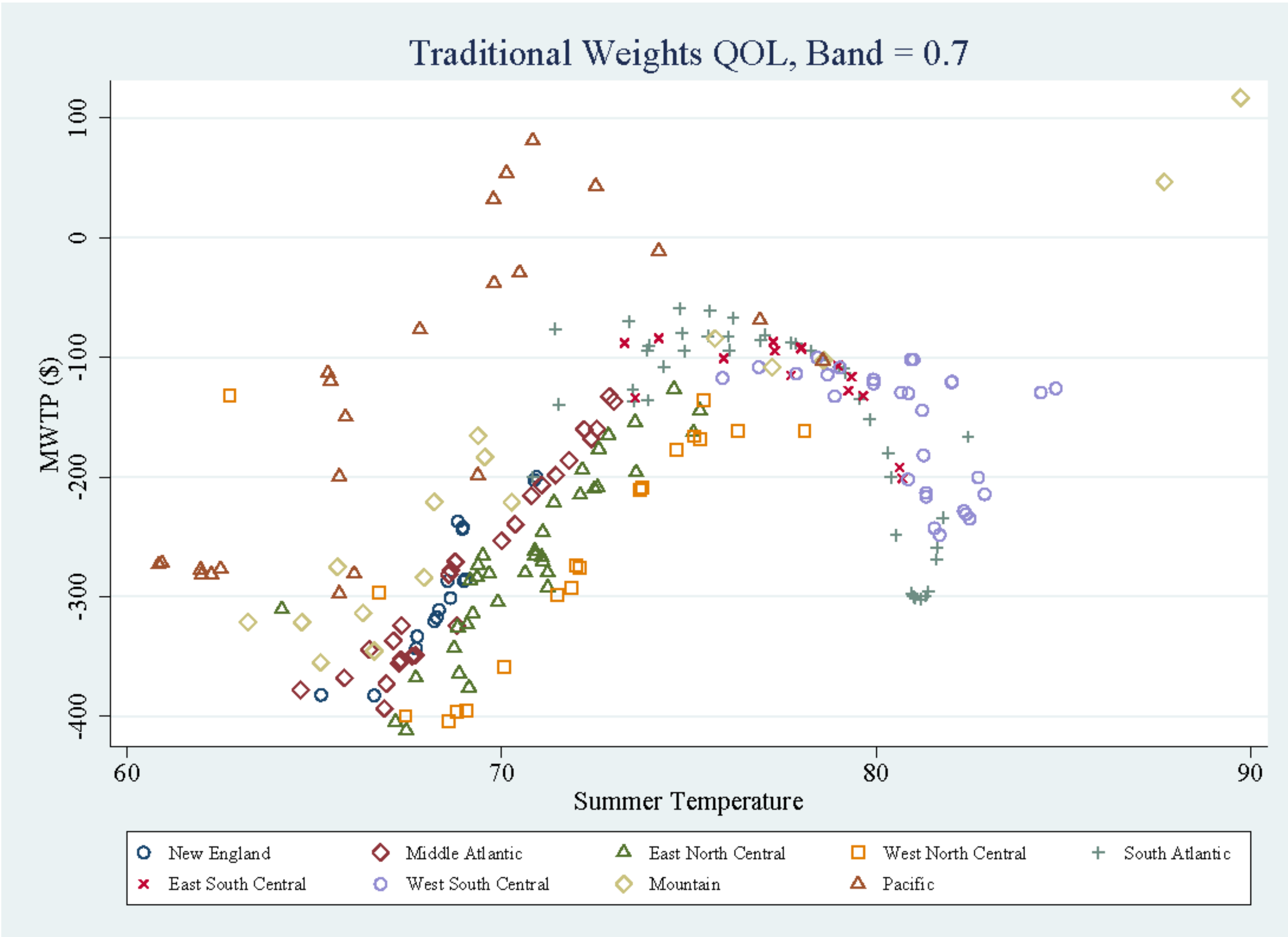


Figure 4. Marginal Willingness to Pay for Summer Temperature by Metropolitan Area, Local Linear Hedonic Model, Adjusted Weights (bandwidth = 0.7)

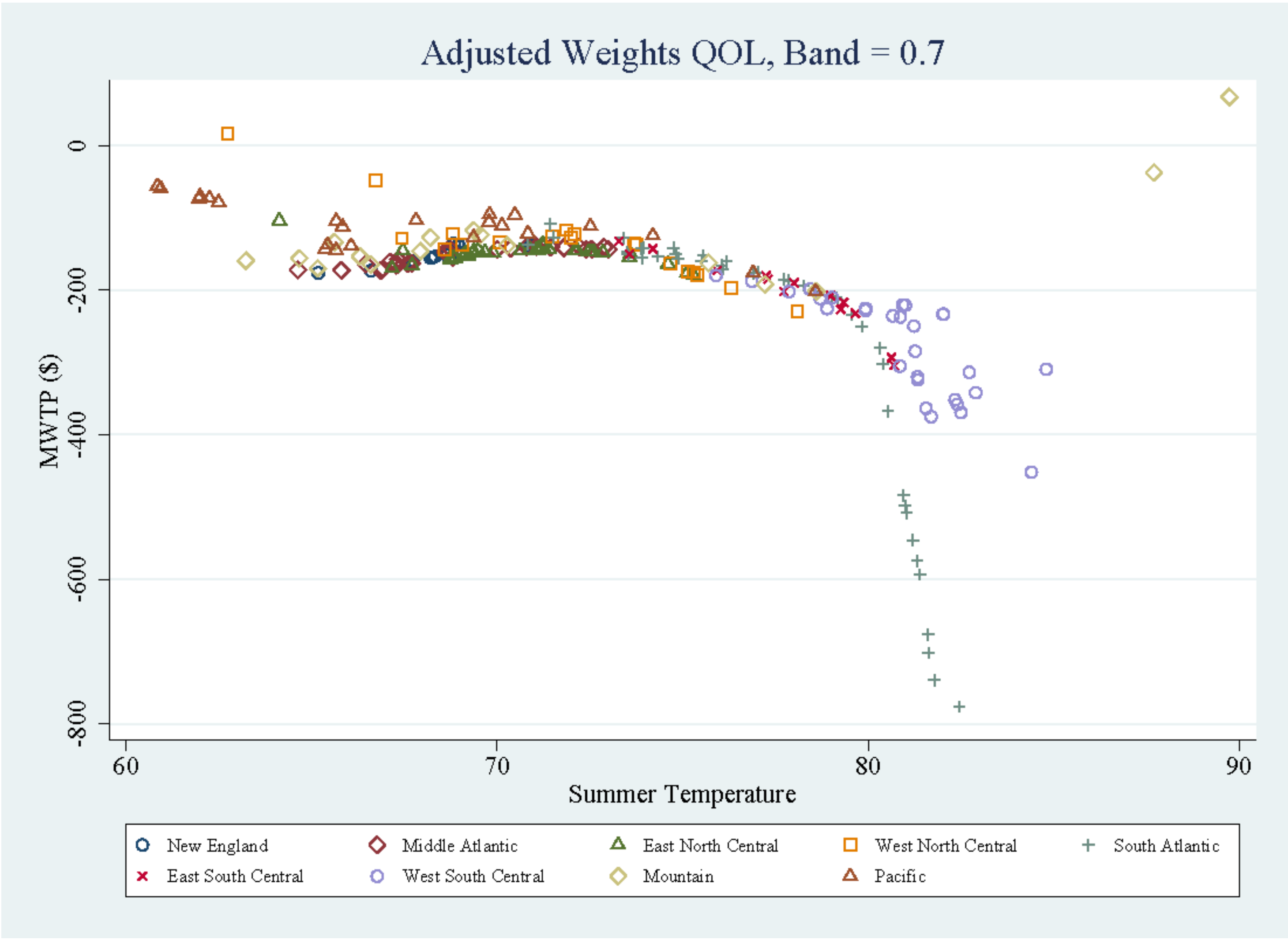


Figure 5A. Marginal Willingness to Pay for Winter Temperature by Metropolitan Area, Base Discrete Choice Model

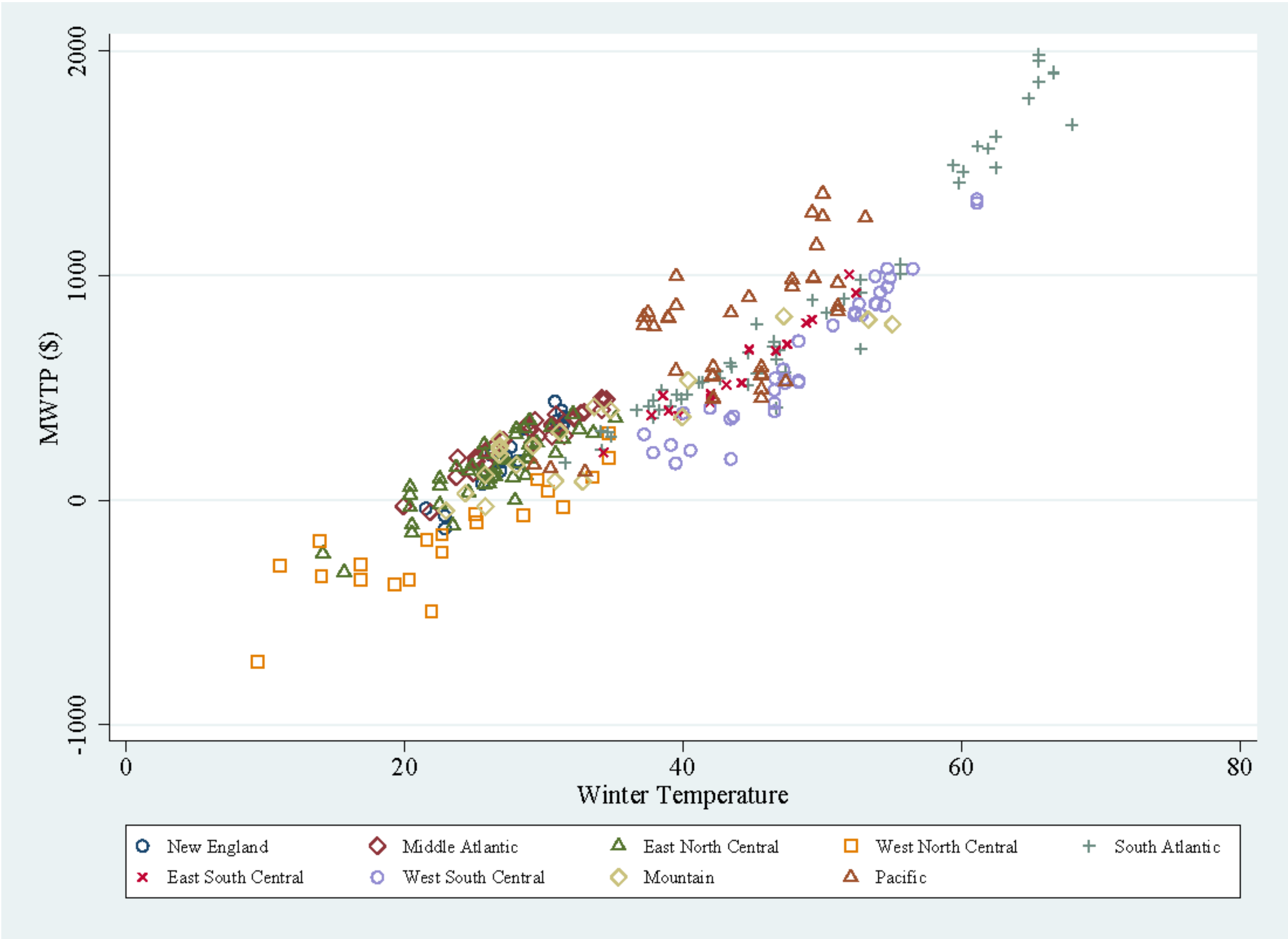


Figure 5B. Marginal Willingness to Pay for Winter Temperature by Metropolitan Area, Discrete Choice Model, Income Net of Taxes

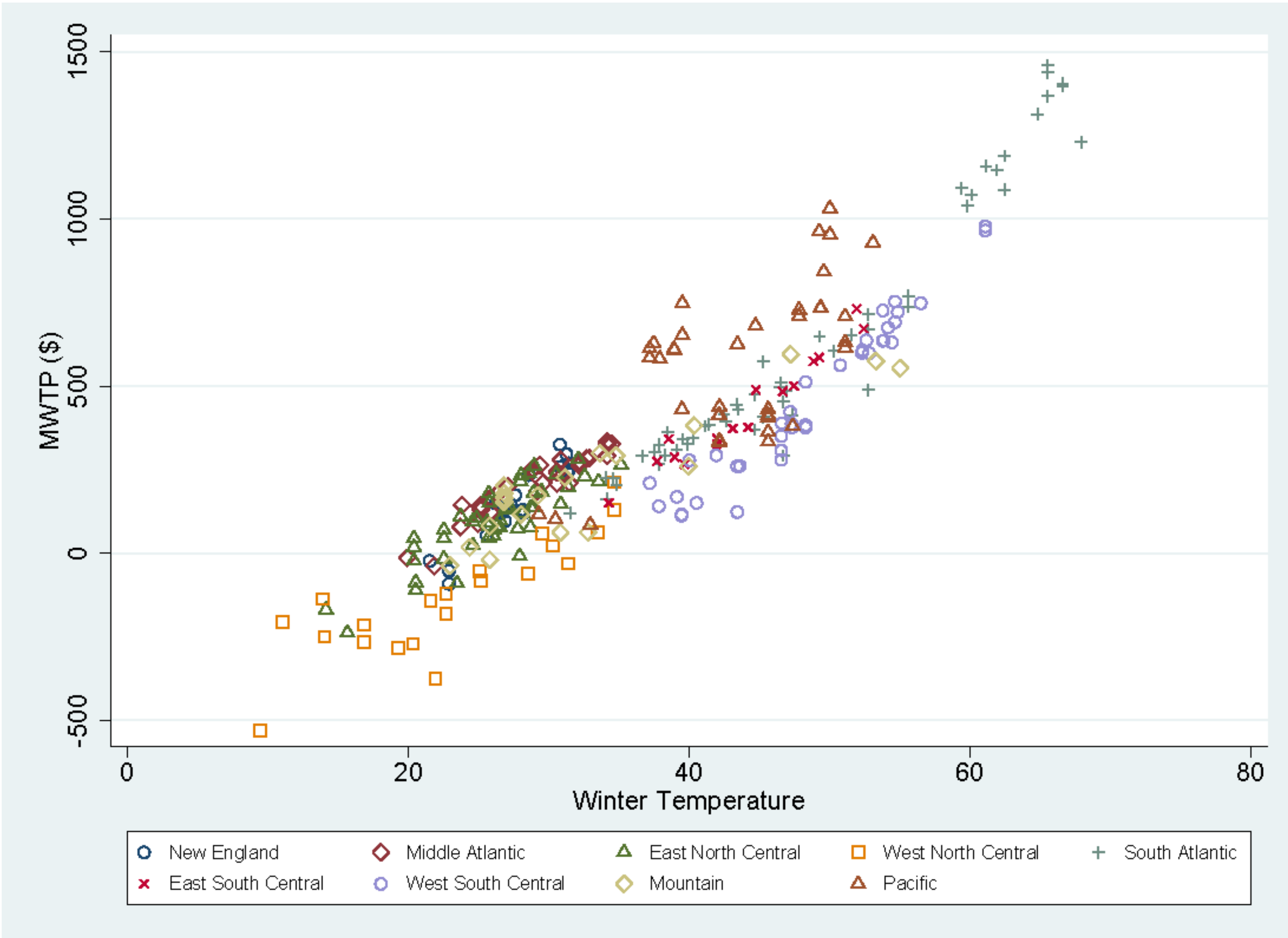


Figure 6A. Marginal Willingness to Pay for Summer Temperature by Metropolitan Area, Base Discrete Choice Model

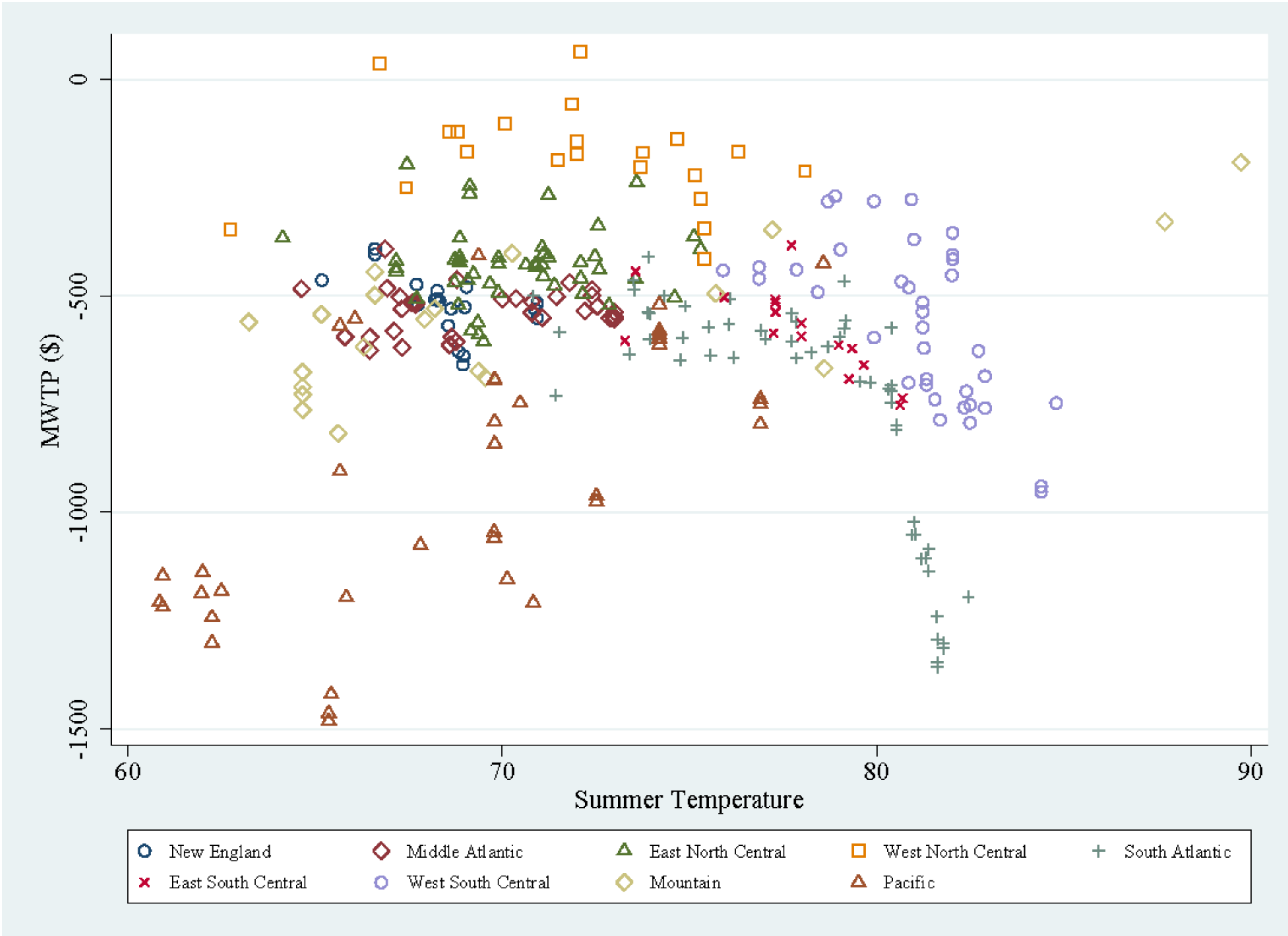


Figure 6B. Marginal Willingness to Pay for Summer Temperature by Metropolitan Area, Discrete Choice Model, Income Net of Taxes

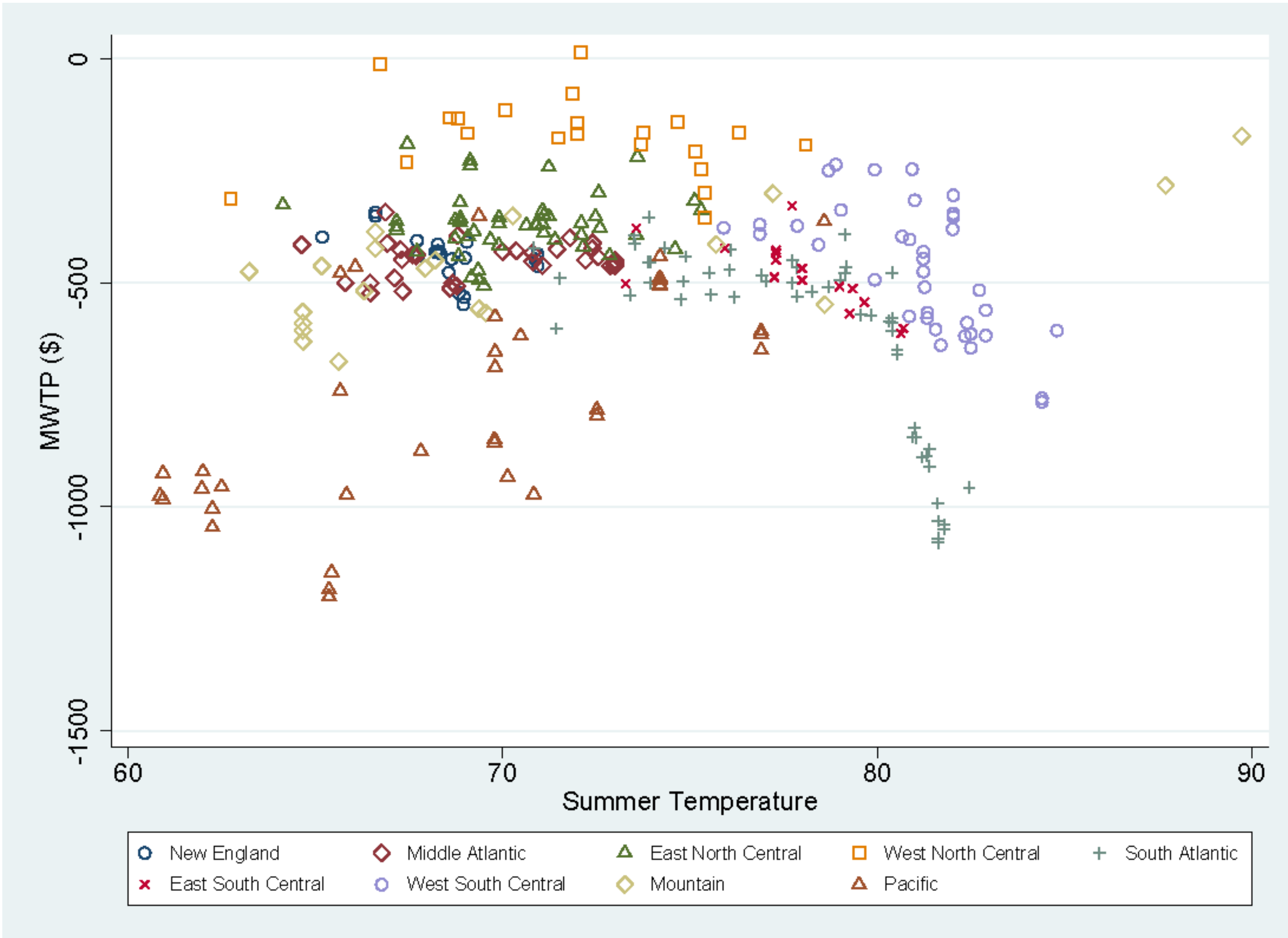
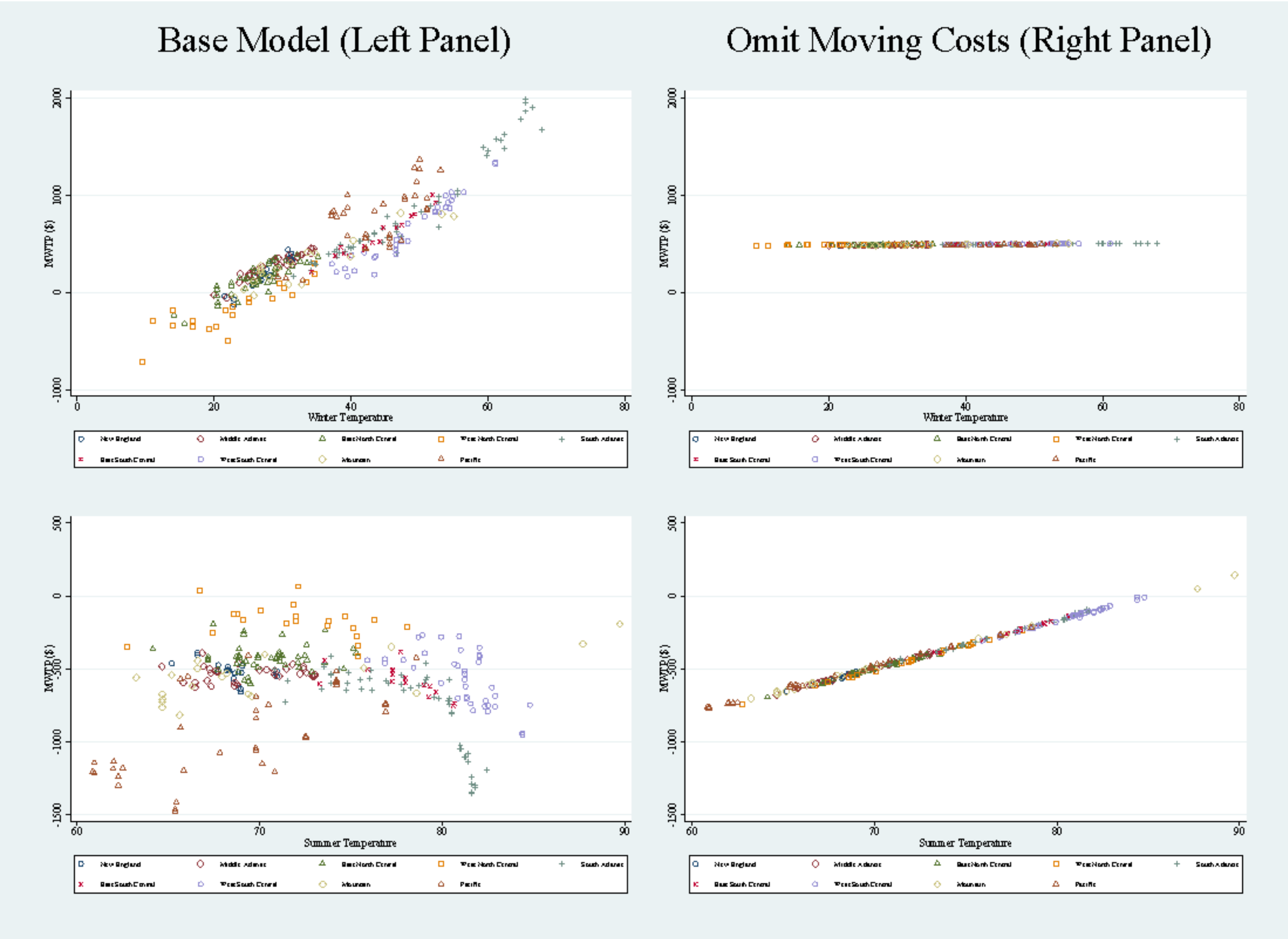


Figure 7. Impact of Removing Moving Costs on Marginal Willingness to Pay for Temperature by Metropolitan Area



Appendix

Table A.1. Summary of Hedonic Wage Coefficients

	National equation	MSA-specific equations (284)	
(Dependent variable: log(wage rate))	Coef.	Mean(Coef.)	Std.dev.(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 (left-out category is management occupation)	–0.120	–0.122	0.067
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, and 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, and 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 and 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

(Dependent variable: log(wage rate))	National equation	MSA-specific equations (284)	
	Coef.	Mean(Coef.)	Std.dev.(Coef.)
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 and 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
No. of obs.[b]	**2,916,211**	**10,268**	**16,223**
***R*-squared**[b]	**0.41**	**0.40**	**0.03**

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

[b] For the MSA-specific regressions, the value in the first column presents the average number of observations and average *R*-squared value across the 284 MSA regressions, while the second column presents the standard deviation of the relevant statistic across those regressions.

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.)	Std.dev.(Coef.)
House is owned	0.504	0.464	0.144
3 bedrooms (left-out category is less than 3 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 2 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	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 (left-out category is over 61 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
No. of obs.[a]	**3,255,748**	**11,464**	**18,376**
***R*-squared**[a]	**0.57**	**0.54**	**0.07**

[a] For the MSA-specific regressions, the value in the first column presents the average number of observations and average *R*-squared value across the 284 MSA regressions, while the second column presents the standard deviation of the relevant statistic across those regressions.

Table A.3. Hedonic Wage, Housing Cost, and Quality of Life Regressions (all coefficients)

	Wage reg.	Housing cost reg.	QOL reg. traditional weights	QOL reg. adjusted weights
Variable	Coef. (Std. err.)	Coef. (Std. err.)	Coef. (Std. err.)	Coef. (Std. err.)
Avg. winter temperature	–0.0030	–0.0001	0.0030	0.0015
	(0.0008)	(0.0020)	(0.0006)	(0.0005)
Avg. summer temperature	–0.0010	–0.0172	–0.0033	–0.0052
	(0.0015)	(0.0040)	(0.0010)	(0.0009)
July humidity	–0.0007	0.0020	0.0012	0.0010
	(0.0007)	(0.0016)	(0.0005)	(0.0003)
Annual snowfall	–0.0010	–0.0022	0.0004	–0.0002
	(0.0003)	(0.0007)	(0.0002)	(0.0002)
Ln(summer precipitation)	–0.0247	–0.0475	0.0128	–0.0031
	(0.0111)	(0.0283)	(0.0080)	(0.0067)
Annual sunshine	0.0004	0.0089	0.0019	0.0028
	(0.0009)	(0.0022)	(0.0006)	(0.0005)
Ln(population density)	0.0504	0.1302	–0.0179	0.0173
	(0.0069)	(0.0168)	(0.0049)	(0.0039)
Mean $PM_{2.5}$	0.0036	–0.0076	–0.0056	–0.0044
	(0.0018)	(0.0042)	(0.0014)	(0.0011)
Violent crime rate	0.0019	–0.0096	–0.0043	–0.0042
	(0.0019)	(0.0043)	(0.0017)	(0.0013)
Transportation score	–0.0007	–0.0015	0.0003	–0.0001
	(0.0002)	(0.0005)	(0.0001)	(0.0001)
Education score	0.0000	0.0000	0.0000	0.0000
	(0.0002)	(0.0006)	(0.0001)	(0.0001)

	Wage reg.	Housing cost reg.	QOL reg. traditional weights	QOL reg. adjusted weights
Variable	Coef. (Std. err.)	Coef. (Std. err.)	Coef. (Std. err.)	Coef. (Std. err.)
Arts score	0.0007	0.0013	–0.0004	0.0001
	(0.0003)	(0.0006)	(0.0002)	(0.0001)
Healthcare score	0.0002	0.0013	0.0002	0.0003
	(0.0002)	(0.0004)	(0.0001)	(0.0001)
Recreation score	0.0005	0.0009	–0.0002	0.0001
	(0.0002)	(0.0005)	(0.0002)	(0.0001)
Park area	0.0000	0.0000	0.0000	0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Visibility > 10 miles	0.0016	0.0024	–0.0010	0.0000
	(0.0004)	(0.0009)	(0.0003)	(0.0002)
Ln(elevation)	–0.0019	0.0035	0.0027	0.0021
	(0.0056)	(0.0125)	(0.0043)	(0.0032)
Distance to coast	–0.0006	–0.0011	0.0003	–0.0001
	(0.0001)	(0.0002)	(0.0001)	(0.0001)
(Distance to coast)^2	0.0000	0.0000	0.0000	0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
No. of obs. (MSAs)	284	284	284	284
Adjusted *R*-squared	0.71	0.74	0.50	0.59

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

Table A.4. MWTP for All Location-Specific Amenities, Hedonic Models

	Traditional hedonic weights				Adjusted hedonic weights			
	Model H1.t		**Model H2.t**		**Model H1.a**		**Model H2.a**	
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	0.0030	$207	0.0043	$186	0.0015	$104	0.0031	$110
	(0.0006)	($42)	(0.0019)	($46)	(0.0005)	($33)	(0.0014)	($41)
Avg. summer temperature	–0.0033	–$228	–0.0228	–$228	–0.0052	–$358	–0.0048	–$355
	(0.0010)	($68)	(0.0131)	($68)	(0.0009)	($64)	(0.0158)	($65)
July humidity	0.0012	$84	0.0012	$84	0.0010	$71	0.0010	$71
	(0.0005)	($35)	(0.0005)	($35)	(0.0003)	($24)	(0.0003)	($23)
Annual snowfall	0.0004	$29	0.0005	$33	–0.0002	–$16	–0.0001	–$10
	(0.0002)	($16)	(0.0002)	($16)	(0.0002)	($11)	(0.0002)	($11)
Ln(summer precipitation)	0.0128	$81	0.0157	$99	–0.0031	–$19	–0.0014	–$9
	(0.0080)	($50)	(0.0087)	($55)	(0.0067)	($42)	(0.0069)	($44)
Annual sunshine	0.0019	$129	0.0025	$172	0.0028	$191	0.0030	$205
	(0.0006)	($44)	(0.0008)	($57)	(0.0005)	($35)	(0.0007)	($45)
Ln(population density)	–0.0179	–$3	–0.0165	–$2	0.0173	$2	0.0173	$2
	(0.0049)	($1)	(0.0051)	($1)	(0.0039)	($1)	(0.0038)	($1)
Mean $PM_{2.5}$	–0.0056	–$384	–0.0056	–$387	–0.0044	–$303	–0.0051	–$350
	(0.0014)	($95)	(0.0016)	($110)	(0.0011)	($75)	(0.0012)	($84)
Violent crime rate	–0.0043	–$301	–0.0045	–$312	–0.0042	–$288	–0.0044	–$307
	(0.0017)	($116)	(0.0017)	($120)	(0.0013)	($87)	(0.0013)	($89)
Transportation score	0.0003	$23	0.0003	$23	–0.0001	–$9	–0.0001	–$8
	(0.0001)	($10)	(0.0001)	($10)	(0.0001)	($8)	(0.0001)	($8)
Education score	0.0000	$2	0.0000	$1	0.0000	$1	0.0000	$0
	(0.0001)	($10)	(0.0001)	($10)	(0.0001)	($9)	(0.0001)	($9)
Arts score	–0.0004	–$26	–0.0004	–$26	0.0001	$5	0.0001	$6
	(0.0002)	($12)	(0.0002)	($12)	(0.0001)	($9)	(0.0001)	($9)
Healthcare score	0.0002	$11	0.0002	$12	0.0003	$24	0.0003	$24
	(0.0001)	($8)	(0.0001)	($8)	(0.0001)	($7)	(0.0001)	($7)
Recreation score	–0.0002	–$17	–0.0002	–$16	0.0001	$4	0.0001	$4
	(0.0002)	($12)	(0.0002)	($12)	(0.0001)	($9)	(0.0001)	($9)
Park area	0.0000	–$1	0.0000	–$1	0.0000	$0	0.0000	$0

	Traditional hedonic weights				Adjusted hedonic weights			
	Model H1.t		**Model H2.t**		**Model H1.a**		**Model H2.a**	
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.)
	(0.0000)	($0)	(0.0000)	($0)	(0.0000)	($0)	(0.0000)	($0)
Visibility > 10 miles	–0.0010	–$68	–0.0011	–$78	0.0000	–$1	–0.0001	–$5
	(0.0003)	($21)	(0.0003)	($22)	(0.0002)	($16)	(0.0002)	($16)
Ln(elevation)	0.0027	$965	0.0021	$731	0.0021	$740	0.0017	$614
	(0.0043)	($1,531)	(0.0044)	($1,554)	(0.0032)	($1,126)	(0.0032)	($1,123)
Distance to coast	0.0003	$16	0.0003	$17	–0.0001	–$3	–0.0001	–$3
	(0.0001)	($3)	(0.0001)	($3)	(0.0001)	($3)	(0.0001)	($3)
(Distance to coast)^2	0.0000		0.0000		0.0000		0.0000	
	(0.0000)		(0.0000)		(0.0000)		(0.0000)	
No. of obs. (MSAs)	284		284		284		284	
Adjusted R-squared	0.50		0.50		0.59		0.59	

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

Table A.5. MWTP for Climate Amenities, Hedonic Models (population-weighted estimates)

	Traditional hedonic weights				Adjusted hedonic weights			
	Model H1.t		**Model H2.t**		**Model H1.a**		**Model H2.a**	
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	0.0025	$172	0.0006	$133	0.0012	$83	0.0001	$60
	(0.0005)	($38)	(0.0018)	($44)	(0.0004)	($29)	(0.0013)	($33)
Avg. summer temperature	–0.0006	–$43	–0.0189	–$45	–0.0035	–$245	–0.0149	–$246
	(0.0009)	($63)	(0.0149)	($63)	(0.0007)	($48)	(0.0114)	($48)
July humidity	0.0014	$96	0.0015	$104	0.0011	$74	0.0011	$79
	(0.0005)	($34)	(0.0005)	($34)	(0.0004)	($26)	(0.0004)	($26)
Annual snowfall	0.0007	$48	0.0006	$40	–0.0001	–$7	–0.0002	–$12
	(0.0002)	($16)	(0.0003)	($18)	(0.0002)	($12)	(0.0002)	($14)
Ln(summer precipitation)	–0.0139	–$88	–0.0139	–$88	–0.0178	–$113	–0.0178	–$112
	(0.0067)	($42)	(0.0070)	($44)	(0.0051)	($32)	(0.0054)	($34)
Annual sunshine	0.0004	$25	0.0006	$41	0.0018	$121	0.0019	$132
	(0.0006)	($42)	(0.0007)	($52)	(0.0005)	($32)	(0.0006)	($40)
No. of obs. (MSAs)	284		284		284		284	
Adjusted R-squared	0.51		0.51		0.74		0.74	

Note: MWTP is computed at mean household income for the prime-aged sample ($69,188). When entering the regressions nonlinearly, amenity variables are evaluated at population-weighted means in order to compute MWTP. Nonlinear covariates are as follows: population density, summer precipitation, and elevation enter in log form, while distance to the coast enters the model quadratically. Regressions are weighted by MSA populations.

Table A.6. Comparison of Hedonic and Discrete Choice Models, Homogeneous Tastes (sensitivity analysis)

	Discrete choice		Hedonic			
			Traditional weights		Adjusted weights	
	Base model	Omit ln(population density)	Base model	Omit ln(population density)	Base model	Omit ln(population density)
Variable	MWTP (Std. err.)	MWTP (Std. err.)	MWTP (Std. err.)	MWTP (Std. err.)	MWTP (Std. err.)	MWTP (Std. err.)
Avg. winter temperature	$599	$630	$207	$200	$104	$111
	($147)	($149)	($42)	($44)	($33)	($37)
Avg. summer temperature	–$791	–$771	–$228	–$233	–$358	–$353
	($246)	($271)	($68)	($72)	($64)	($62)
July humidity	–$465	–$414	$84	$72	$71	$82
	($139)	($151)	($35)	($34)	($24)	($24)
Annual snowfall	–$377	–$347	$29	$22	–$16	–$9
	($65)	($71)	($16)	($17)	($11)	($13)
Ln(summer precipitation)	$525	$428	$81	$103	–$19	–$40
	($188)	($204)	($50)	($49)	($42)	($42)
Annual sunshine	–$151	–$231	$129	$148	$191	$173
	($153)	($158)	($44)	($43)	($35)	($36)

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

Table A.7. MWTP for All Location-Specific Amenities, Mixed Logit Models

Panel A: 1st stage estimates

Variable	Base model Coef (Std. err.)	Net of taxes Coef (Std. err.)	Omit moving costs Coef (Std. err.)	Net of taxes + omit moving costs Coef (Std. err.)
Std. dev.: avg. winter temperature	0.0588	0.0592	0.0011	0.0032
	(0.0026)	(0.0026)	(0.0128)	(0.0097)
Std. dev.: avg. summer temperature	0.0592	0.0612	0.0352	0.0525
	(0.0068)	(0.0066)	(0.0215)	(0.0174)
Correlation coefficient	–0.6893	–0.6993	0.8614	–0.9433
	(0.0827)	(0.0776)	(0.2756)	(0.1297)

Panel B: 2nd stage estimates

	Base model		Net of taxes		Omit moving costs		Net of taxes + omit moving costs	
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	0.0209	$518	0.0210	$382	0.0184	$491	0.0171	$326
	(0.0058)	($144)	(0.0057)	($104)	(0.0055)	($146)	(0.0055)	($104)
Mean: avg. summer temperature	–0.0253	–$627	–0.0286	–$522	–0.0145	–$386	–0.0178	–$339
	(0.0100)	($249)	(0.0098)	($180)	(0.0108)	($288)	(0.0110)	($209)
July humidity	–0.0208	–$514	–0.0198	–$360	–0.0165	–$440	–0.0156	–$296
	(0.0054)	($135)	(0.0052)	($95)	(0.0046)	($124)	(0.0045)	($85)
Annual snowfall	–0.0170	–$422	–0.0176	–$321	–0.0047	–$126	–0.0052	–$99
	(0.0026)	($66)	(0.0026)	($49)	(0.0025)	($67)	(0.0025)	($48)
Ln(summer precipitation)	0.1708	$403	0.1517	$264	0.0678	$172	0.0593	$107
	(0.0768)	($181)	(0.0752)	($131)	(0.0732)	($186)	(0.0727)	($132)
Annual sunshine	–0.0149	–$368	–0.0125	–$229	–0.0082	–$219	–0.0040	–$75
	(0.0060)	($149)	(0.0059)	($108)	(0.0060)	($159)	(0.0059)	($111)

Ln(population density)	0.2094	$6	0.2559	$5	0.2891	$8	0.3361	$7
	(0.0494)	($1)	(0.0505)	($1)	(0.0441)	($1)	(0.0453)	($1)
Mean $PM_{2.5}$	0.0572	$1,416	0.0553	$1,009	0.0546	$1,454	0.0543	$1,032
	(0.0164)	($408)	(0.0164)	($301)	(0.0153)	($410)	(0.0153)	($291)
Violent crime rate	0.0006	$15	–0.0018	–$33	–0.0117	–$312	–0.0142	–$270
	(0.0142)	($352)	(0.0141)	($258)	(0.0150)	($400)	(0.0150)	($286)
Transportation score	0.0105	$259	0.0099	$180	0.0112	$298	0.0106	$202
	(0.0015)	($39)	(0.0015)	($28)	(0.0015)	($41)	(0.0015)	($29)
Education score	0.0043	$106	0.0041	$76	0.0035	$92	0.0033	$63
	(0.0016)	($41)	(0.0016)	($30)	(0.0016)	($43)	(0.0016)	($30)
Arts score	0.0043	$106	0.0047	$86	0.0034	$90	0.0037	$71
	(0.0018)	($46)	(0.0019)	($34)	(0.0016)	($42)	(0.0016)	($30)
Healthcare score	0.0002	$4	0.0008	$14	0.0002	$6	0.0008	$15
	(0.0012)	($31)	(0.0012)	($23)	(0.0012)	($32)	(0.0012)	($23)
Recreation score	0.0124	$307	0.0126	$229	0.0120	$320	0.0122	$232
	(0.0016)	($41)	(0.0016)	($30)	(0.0016)	($42)	(0.0016)	($30)
Park area	0.0001	$4	0.0002	$3	0.0001	$3	0.0001	$2
	(0.0001)	($1)	(0.0001)	($1)	(0.0000)	($1)	(0.0000)	($1)
Visibility > 10 miles	0.0073	$180	0.0081	$147	0.0009	$24	0.0011	$22
	(0.0033)	($82)	(0.0033)	($61)	(0.0035)	($92)	(0.0035)	($66)
Ln(elevation)	0.0895	$12,450	0.0935	$9,578	0.1145	$17,142	0.1166	$12,454
	(0.0481)	($6,706)	(0.0477)	($4,891)	(0.0415)	($6,234)	(0.0411)	($4,404)
Distance to coast	–0.0020	–$25	–0.0023	–$25	–0.0012	–$19	–0.0014	–$18
	(0.0007)	($14)	(0.0007)	($10)	(0.0008)	($15)	(0.0008)	($11)
(Distance to coast)^2	0.0000		0.0000		0.0000		0.0000	
	(0.0000)		(0.0000)		(0.0000)		(0.0000)	
No. of obs. (MSAs)	284		284		284		284	
Adjusted *R*-squared	0.82		0.83		0.82		0.83	

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

Table A.8. MWTP for Climate Amenities, Mixed Logit Models (sensitivity to specification of utility function)

	Base model		Quadratic Hicksian bundle		Cobb-Douglas utility Log(wage) in 1st stage with housing price index in 2nd stage	
Panel A: 1st stage estimates						
Variable	Coef (Std. err.)		Coef (Std. err.)		Coef (Std. err.)	
Std. dev.: avg. winter temperature	0.0588		0.0584		0.0603	
	(0.0026)		(0.0026)		(0.0025)	
Std. dev.: avg. summer temperature	0.0592		0.0572		0.0555	
	(0.0068)		(0.0069)		(0.0070)	
Correlation coefficient	–0.6893		–0.7007		–0.7624	
	(0.0827)		(0.0863)		(0.0851)	
Panel B: 2nd stage estimates						
Variable	Coef (Std. err.)	MWTP (Std. err.)	Coef (Std. err.)	MWTP (Std. err.)	Coef (Std. err.)	MWTP (Std. err.)
Mean: avg. winter temperature	0.0209	\$518	0.0218	\$463	0.0190	\$590
	(0.0058)	(\$144)	(0.0058)	(\$126)	(0.0059)	(\$184)
Mean: avg. summer temperature	–0.0253	–\$627	–0.0266	–\$566	–0.0208	–\$644
	(0.0100)	(\$249)	(0.0099)	(\$214)	(0.0102)	(\$317)

July humidity	–0.0208	–$514	–0.0201	–$428	–0.0236	–$733
	(0.0054)	($135)	(0.0054)	($118)	(0.0055)	($174)
Annual snowfall	–0.0170	–$422	–0.0170	–$363	–0.0174	–$539
	(0.0026)	($66)	(0.0026)	($60)	(0.0026)	($86)
Ln(summer precipitation)	0.1708	$403	0.1755	$356	0.1787	$527
	(0.0768)	($181)	(0.0762)	($156)	(0.0784)	($233)
Annual sunshine	–0.0149	–$368	–0.0140	–$297	–0.0177	–$549
	(0.0060)	($149)	(0.0059)	($128)	(0.0061)	($192)

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

Figure A.1. Marginal Willingness to Pay for Winter Temperature by Metropolitan Area, Local Linear Hedonic Model, Traditional Weights (various bandwidths)

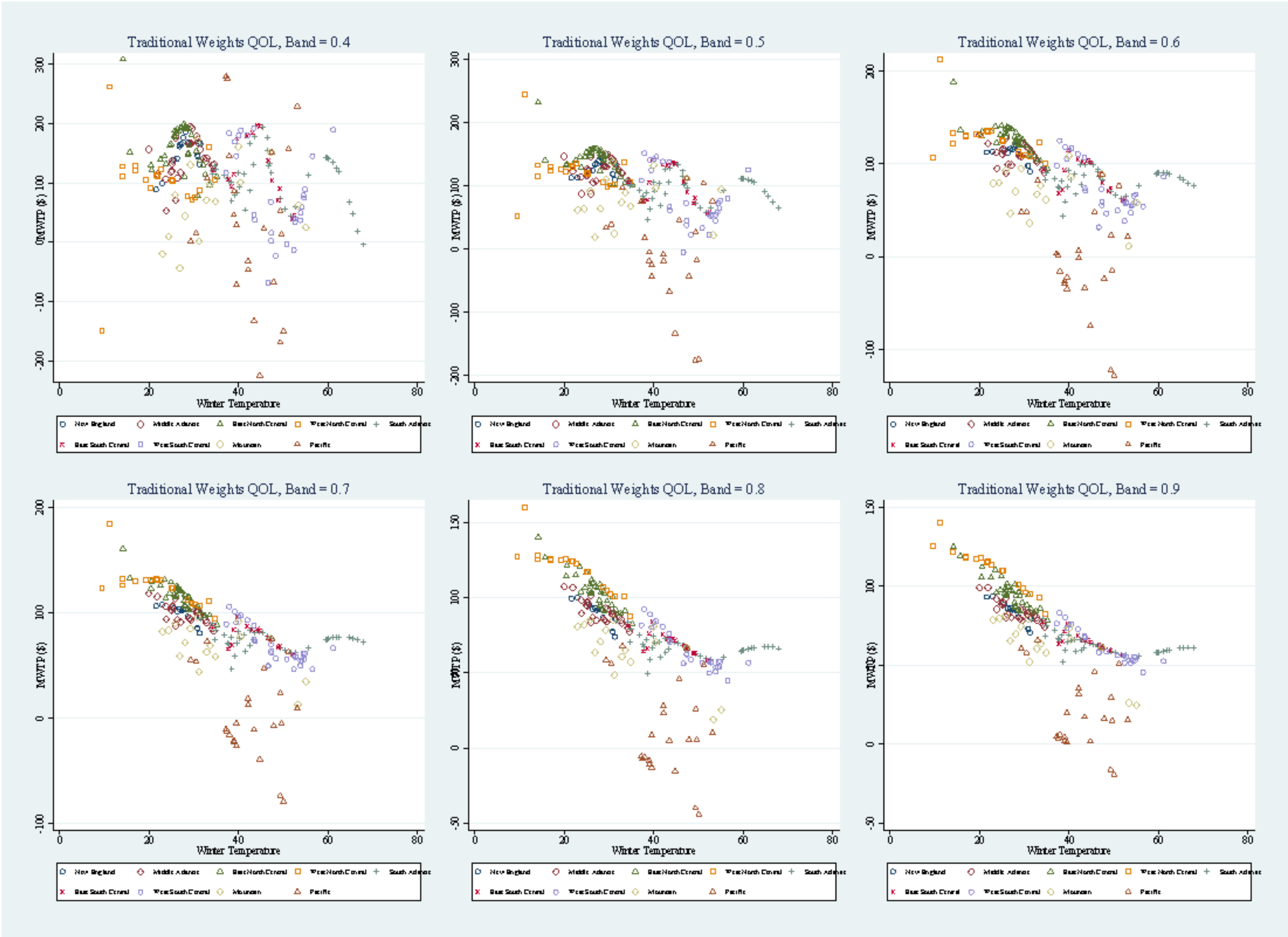


Figure A.2. Marginal Willingness to Pay for Winter Temperature by Metropolitan Area, Local Linear Hedonic Model, Adjusted Weights (various bandwidths)

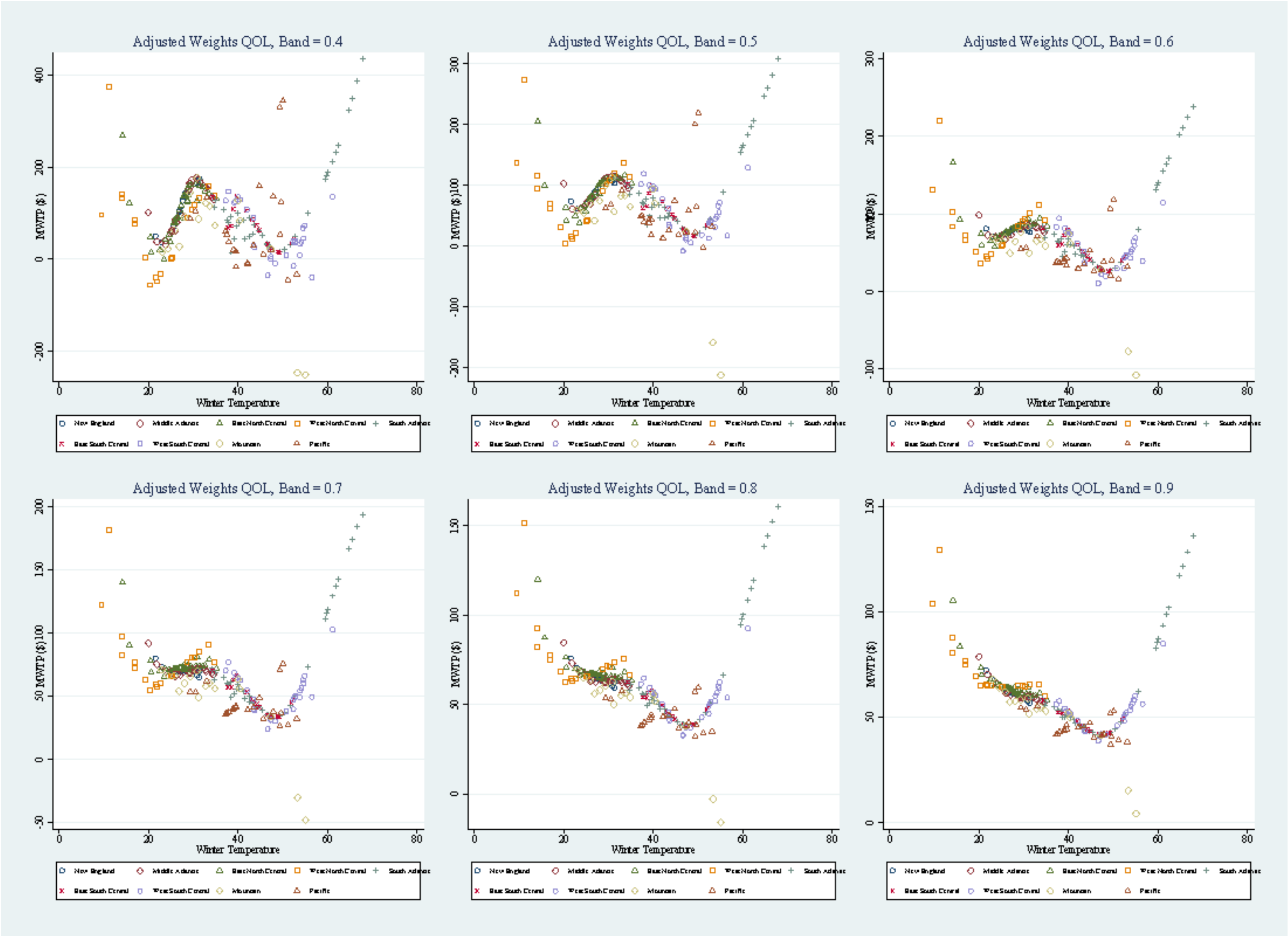


Figure A.3. Marginal Willingness to Pay for Summer Temperature by Metropolitan Area, Local Linear Hedonic Model, Traditional Weights (various bandwidths)

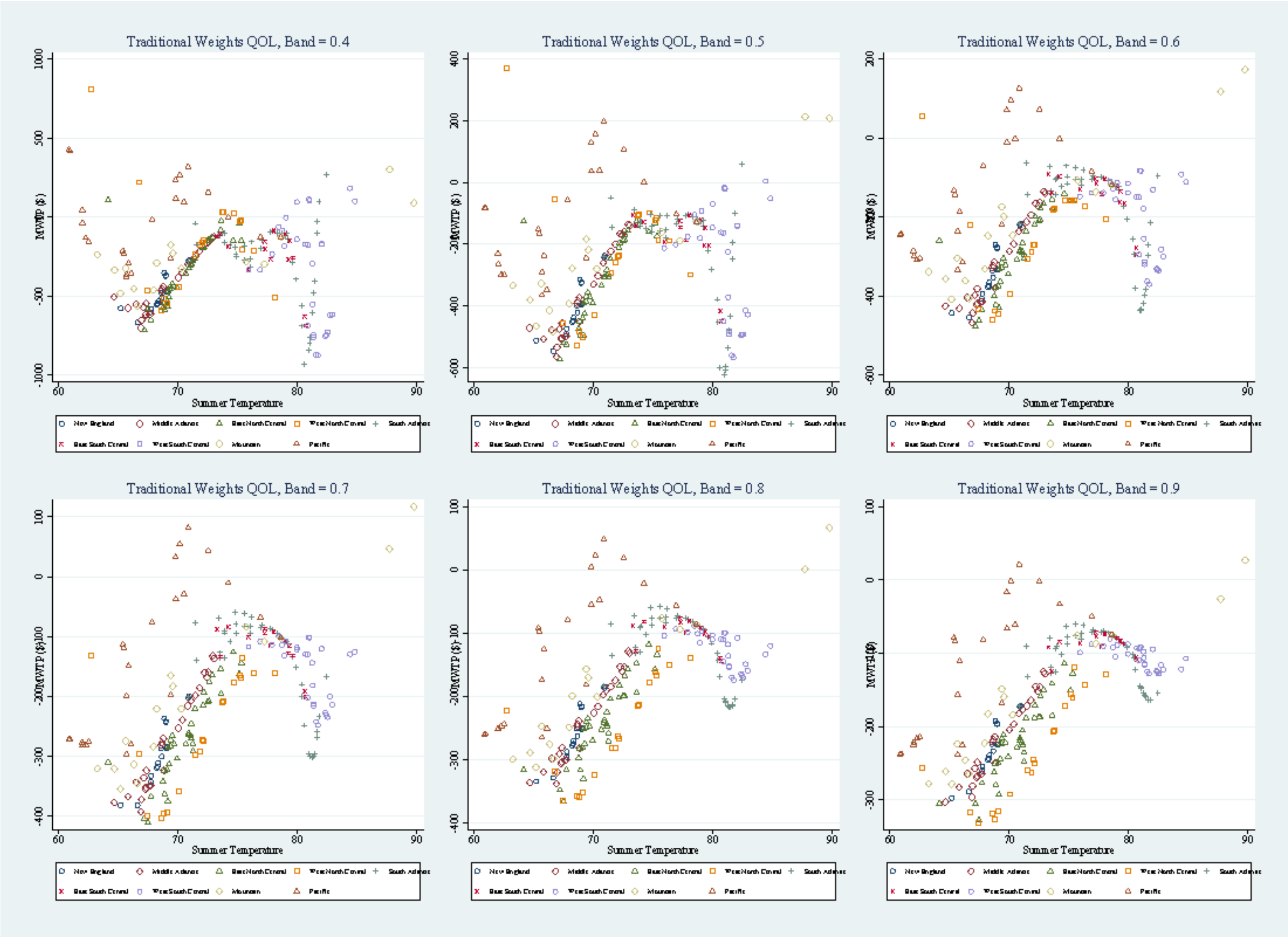


Figure A.4. Marginal Willingness to Pay for Summer Temperature by Metropolitan Area, Local Linear Hedonic Model, Adjusted Weights (various bandwidths)

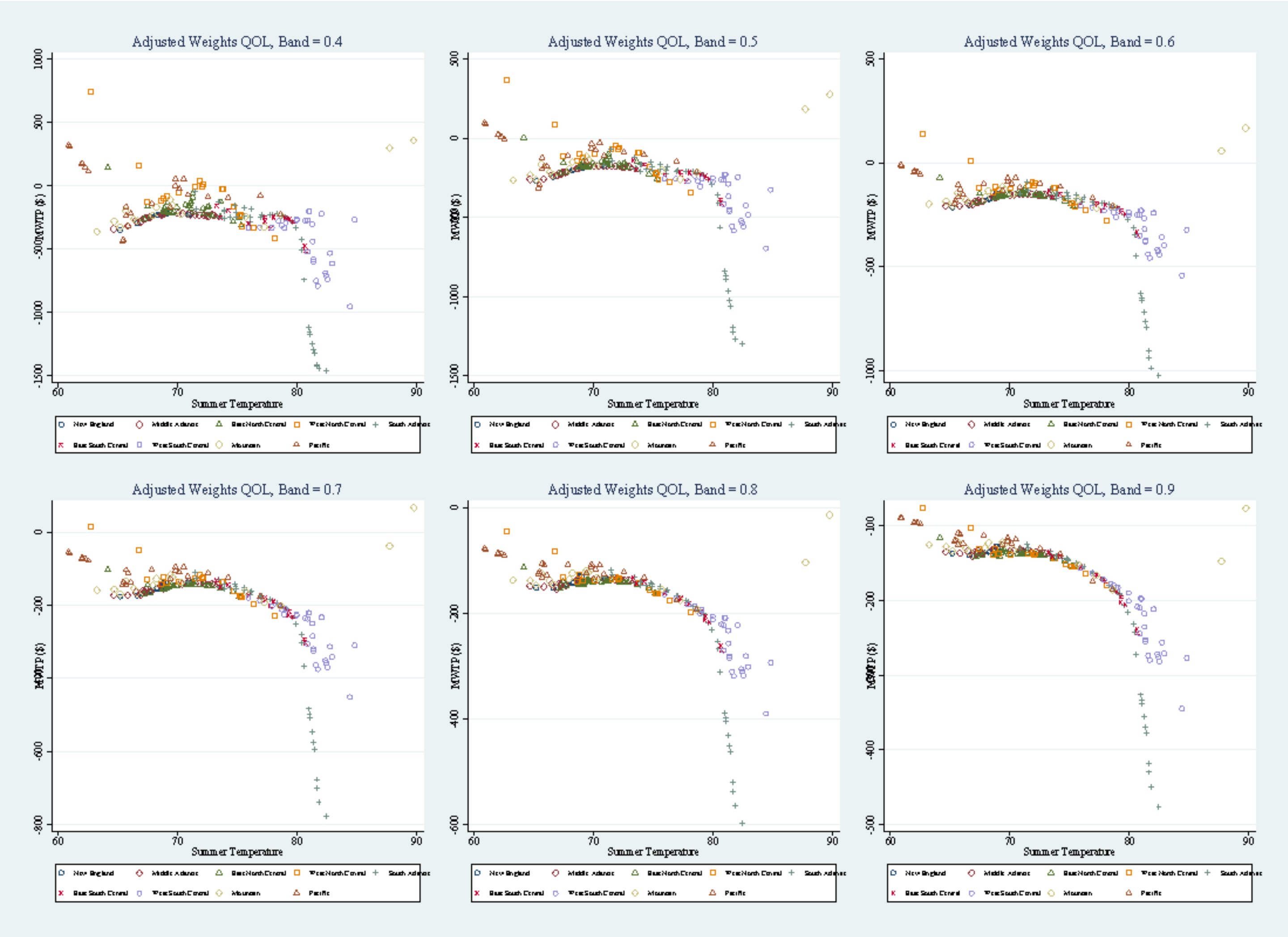


Figure A.5. Impact of Removing Moving Costs on Marginal Willingness to Pay for Temperature by Metropolitan Area Using Income Net of Taxes