Climate Amenities, Climate Change, and American Quality of Life

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PRELIMINARY DRAFT: DO NOT CITE OR DISTRIBUTE

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Abstract

This paper uses hedonic methods and variation in wages and housing costs to estimate households’ valuation of climate amenities. We find that, on the margin, households are willing to pay more to reduce heat than to reduce cold. The willingness to pay to avoid severe heat is not statistically different from the willingness to pay to avoid moderate heat, consistent with the fact that households can protect themselves by staying indoors. Finally, we find that northern households are less heat-tolerant than are southern households. Combining these preference estimates with “business as usual” climate forecasts for the United States, we find welfare losses in most areas by 2100 as the cost of hotter summers exceeds the gain from warmer winters. Northern households are projected to suffer greater losses in amenity value than southern households, both because they have stronger preferences and because the North is projected to experience a larger shift from days with comfortable temperatures towards days with moderate to extreme heat. These results are robust across numerous specifications and are not substantially attenuated by allowing for migration.
1. Introduction

There is a strong consensus in the scientific community that anthropogenic emissions of greenhouse gases are likely to substantially alter the earth’s climate over the next century. The most recent “business-as-usual” forecast from the United Nations’ International Panel on Climate Change (IPCC) predicts that the earth’s median surface temperature will increase by 6.5 degrees Fahrenheit (°F) between 2000 and 2100. The degree to which these changes should be mitigated through abatement of greenhouse gas emissions is now an active policy question. Because abatement is costly, the design of an optimal climate policy requires reliable estimates of the likely welfare losses under a business as usual scenario. Economists have begun to take a prominent role in assessing these losses, particularly in the vulnerable U.S. agricultural sector (see Schlenker and Roberts 2009 for a summary).

This paper is aimed at an area of damage assessment that has received comparatively little investigation: the impact of climate change on the amenity value of everyday life. Human beings are naturally averse to heat and cold, and particularly severe temperatures can even be fatal (Deschênes and Greenstone 2008). Projected climate change will reduce U.S. residents’ exposure to cold but increase exposure to heat; this fact is illustrated in figure 1, which maps present and future temperatures during January and July across the United States. It is therefore not clear a priori whether U.S. residents will find a warmer climate more amenable than the current one. Moreover, the substantial variation in present-day climate across the U.S. suggests that the household welfare impacts of climate change will be heterogeneous. While nearly all locations will experience an increase in exposure to hot weather, some areas, such as Michigan, will benefit from large reductions in cold while others, such as Texas, will not.

Our evaluation strategy uses hedonic methods to estimate U.S. households’ willingness to pay to reside in an area that has a mild climate. The intuition underlying this approach dates to Rosen (1974, 1979): local housing costs, taken relative to local wage levels, represent households’ valuation of a given area’s amenities. We denote this valuation as the local quality
of life (QOL) and infer households’ climate preferences through the cross-sectional covariance of QOL with climate. We then combine these estimated preferences with predictions of localized climate change from the IPCC to assess how QOL will change across the U.S. In using willingness to pay (WTP) estimates derived from the current distribution of prices, wages, and climate to forecast welfare impacts over a long time horizon, we hold preferences and technology fixed at their current levels. Should technological progress allow a wider range of climate adaptations than those used currently, or should preferences change such that households become accustomed to a warmer climate, then the realized welfare impact will be smaller than that estimated in this study. We also express our estimated welfare impacts in terms of the current levels of U.S. population and income, abstracting away from issues of discounting and long-run population and income growth.

We choose a cross-sectional hedonic estimation strategy, in the tradition of Mendelsohn et al. (1994), rather than a panel approach for several reasons. First, year-to-year changes in weather are unlikely to affect the WTP to locate in a given area because local QOL differences should reflect expectations of long-term climate. These expectations are better measured by a location’s climate in an average year rather than its weather in any given year. Second, secular climate changes over the past several decades have so far have been too slight to make inferences regarding climate valuation using long-run time series variation alone. Finally, because climate change is a long-term phenomenon, households will be able to mitigate potential damages through adaptation. For example, households may adapt to hotter summers by improving the insulation of their homes. The climate valuations that we estimate from our cross-sectional strategy inherently allow for such adaptation, given current technology.

The potential cost of our strategy is that identification requires unobserved location-specific factors that impact QOL to be uncorrelated with climate. This identification assumption is inherently untestable, nor do there exist viable instrumental variables to circumvent this issue. Our approach is therefore to assess the robustness of our estimated hedonic price schedule to an array of alternative specifications and the inclusion of various control variables, following the
cross-sectional literature on agricultural yields and farmland values (Schlenker et al. 2006, Fisher et al. 2009, and Schlenker and Roberts 2009).¹

Across numerous specifications, we consistently find that households are willing to pay more on the margin to avoid heat than they are to avoid cold. As a result, we find that most U.S. residents will be made worse off by large temperature increases. Under the business-as-usual A2 scenario from the IPCC’s fourth assessment report (2007), we project a statistically significant decrease in QOL of 1.5 to 2.0 percent of income per year by 2100. These results are robust to the inclusion of state fixed effects and to allowing for migration after climate change has taken effect (assuming that households stay within U.S. borders). Migration is unlikely to mitigate climate amenity losses because most locations will experience a QOL decrease following climate change. Over-crowding into areas that do benefit will cause the population to forego many of the benefits that their current locations have to offer.

Our analysis measures only the impact of climate on quality of life, meaning the value of amenities for which there are no explicit markets. These welfare impacts do not appear in national income accounts, as would impacts on urban or agricultural productivity (for a survey of the climate and productivity literature, see Tol 2002 and 2009). For data reasons, our cost of living data incorporate local utility costs, and as a result our welfare estimates exclude changes to heating and cooling expenditures. Instead, our estimates primarily reflect amenity values associated with outdoor exposure to uncomfortable temperatures and reflect indoor exposure only insofar as it is imperfectly controlled through heating and cooling.²

¹ This cross-sectional approach, in the context of agriculture, has been critiqued by Deschênes and Greenstone on the grounds that estimates are frequently not robust to seemingly minor changes in the econometric specification, presumably because of omitted variable bias. Fisher et al. (2009) and Schlenker and Roberts (2009), however, suggest that agricultural damage estimates are robust when the specification flexibly models damages over the temperature distribution—an approach we follow here—rather than relying on seasonal temperature averages or heating degree days and cooling degree days.

² Deschênes and Greenstone (2008), using panel data, find that a similar climate change scenario to that considered here will cause a 2% increase in the overall U.S. mortality rate by 2100, though this result is not statistically significant. They also estimate that climate change will cause energy expenditures to increase by 32% by 2100, equivalent to $48 billion annually at 2006 prices (0.3% of GDP).
In principle, our welfare measure accounts for the discomfort and health costs of climate change, including valuations of the increased mortality risk associated with extreme heat and cold as estimated in Deschênes and Greenstone (2008). Our measure also captures welfare changes related to individuals spending less time outdoors (Graff Zivin and Neidell 2010) and to increased expenditures on non-housing climate mitigation, such as automobile air conditioning. It does not capture many other important changes, such as the impact of rising sea levels. Extreme weather events are included only insofar as they are correlated with our climate variables. The same is true of other possible impacts, such as water availability.

Prior hedonic studies investigating U.S. households’ climate preferences have yielded disparate estimates, ranging from strongly positive WTP for incremental warming (Hoch and Drake 1974, Moore 1998) to indifference (Nordhaus 1996) to strongly negative WTP (Cragg and Kahn 1997 and 1999, Kahn 2009). Our approach has three substantial advantages relative to these studies. First, this is only paper of which we are aware that uses QOL estimates that appropriately account for local cost of living and wage differentials, taking into account housing costs, local and federal taxation, and local and traded services. Previous work that found net benefits from warming tended use measures of QOL that over-emphasized wage differentials relative to housing-cost differentials, either by ignoring housing-cost differentials entirely or by ignoring the impact of taxation. We find similar results when we over-emphasize wage differentials in our data. Second, we characterize local climates using the full distribution of realized daily temperatures rather than seasonal or monthly averages. Prior research into the impact of climate on agriculture (Schlenker et al. 2006, Schlenker and Roberts 2009) has shown

3 We do evaluate preferences for precipitation, humidity, and sunshine; however, these variables are only available at a monthly level (we ultimately aggregate further to annual or seasonal levels) and therefore do not capture extreme weather events.

that extreme temperatures are particularly harmful to crop yields. The issue of moderate versus extreme temperatures, however, has not been explored in the amenity valuation literature. We find, in contrast to the crop yield results, that extreme heat does not generate a greater disamenity than does moderate heat, nor does extreme cold generate a greater disamenity than moderate cold. This result is consistent with a model in which, once temperatures become sufficiently uncomfortable, households spend their time indoors so that further increases in heat or cold do not substantially affect welfare. The result also implies that the adverse effects of climate change on amenity values will be more severe in the North than in the South, since temperatures in the South are already uncomfortably hot in the summer.

Third, and finally, we allow for unobserved heterogeneity in households’ climate preferences so that households may sort into locations that best suit their tastes. We find that allowing for heterogeneity yields estimated welfare impacts that are particularly robust across specifications, and that northern households are more averse to heat than are southern households. This last result reinforces our finding that it may be northerners, not southerners, that suffer the greater amenity loss from climate change.

In what follows, we first discuss the hedonic model we use to derive location-specific QOL estimates from house price and wage data. Section 3 then describes the current and projected climate data, and section 4 presents estimates of preferences and climate change welfare impacts from a linear hedonic model with homogenous preferences. Section 5 then discusses and presents results from the estimation of a richer model that allows for preference heterogeneity. Section 6 discusses the importance of migration, and section 7 concludes.

2. Hedonic Estimates of Quality of Life

The intuition underlying our approach to climate valuation is that preferences for mild climates should be expressed through wage and housing-cost differentials across U.S. locations. This section first discusses a hedonic framework relating preferences for location-specific amenities to price and wage differentials and suggests how these differentials should be weighted
against one another in determining a single-index QOL measure for each location. We then discuss how we combine this framework with wage and cost data from the U.S. Census to derive location-specific estimates of QOL across the United States.

2.1 The relationship between QOL and cost of living and wage differentials

We relate households’ valuations of local amenities to wage and cost of living differentials across locations using the framework of Rosen (1974, 1979) and Roback (1982), expanded by Bajari and Benkard (2005) and Albouy (2008, 2009). The national economy contains many locations, indexed by $j$, which trade with each other and share a population of mobile, price-taking households, indexed by $i$. These households consume a quantity $x_i$ of a traded numeraire good and one unit of a non-traded "home" good $y$, with local price $p_j$ that can be thought of as the local cost of living. Households earn wage income $w_j$ that is location-dependent and own portfolios of land and capital that pay rental and interest income $R_i$ and $I_i$ respectively. Total household income $m_i$ is equal to $R_i + I_i + w_j$, out of which households pay a federal income tax of $\tau(m_i)$ that is redistributed in uniform lump-sum payments.\(^5\)

The location-dependence of wage income reflects the possibility that certain locations may have advantages, such as coastal access or agglomeration effects, that increase the marginal productivity of labor. To facilitate the construction of a QOL measure at each location $j$, we model each household $i$'s location-specific wage $w_j$ as $\phi_i w_j$, where $\phi_i$ denotes household-specific labor productivity and $w_j$ denotes the wage differential at $j$. To the extent that local wage differentials vary across households (due to occupation-specificity, for example), the $w_j$ can be thought of as the average wage differential at $j$ across all households. We return to this issue in the discussion below of our estimation of the $w_j$.

Each location is characterized by a $K$-dimensional observable vector of attributes $Z_j$ that includes climate, and by a scalar characteristic $\xi_j$ that is observable to households but not to the

\(^5\) Deductions and state taxes are discussed in Albouy (2008) and prove to be minor in practice.
econometrician. Following Rosen (1974), we assume that there is a continuum of locations \( j \) and that the set of available characteristics \((Z, \zeta)\) is a complete, compact subset of \( \mathbb{R}^{K+1} \).\(^6\) We allow households to have heterogeneous preferences over \((Z, \zeta)\), following Bajari and Benkard (2005), so that the utility of household \( i \) residing at location \( j \) is given by \( u_i^j = U^i(x^i, Z_j, \zeta_j) \), which we assume to be continuous and differentiable in all its arguments, and also strictly increasing in \( x^i \) and \( \zeta_j \). Households are assumed to be perfectly mobile, so that each chooses the location \( j \) that maximizes its utility subject to the budget constraint \( x^i = m^j_i (1 - \tau(m^j_i)) - p_j \).\(^7\)

Let \( p(Z_j, \zeta_j) \) denote the function relating cost of living \( p_j \) to \( j \)'s characteristics, and likewise for \( w(Z_j, \zeta_j) \) and \( w_j \). These functions are determined by an equilibrium between households’ demands for local amenities, firms’ location decisions, and local land supply.\(^8\) In this equilibrium, the following demand-side first order condition, in which \( \lambda \) denotes the marginal utility of money, must hold for all characteristics \( k \):

\[
\frac{1}{m_j^i} \frac{\partial U^i(x^i, Z_j, \zeta_j)}{\partial Z_k} = \frac{1}{m_j^i} \frac{\partial p(Z_j, \zeta_j)}{\partial Z_k} \left(1 - \tau(m_j^i)\right) \frac{\partial w(Z_j, \zeta_j)}{\partial Z_k} = \frac{p_j}{m_j^i} \frac{\partial \ln p(Z_j, \zeta_j)}{\partial Z_k} - \frac{w_j}{m_j^i} \left(1 - \tau(m_j^i)\right) \frac{\partial \ln w(Z_j, \zeta_j)}{\partial Z_k} \tag{1}
\]

Equation (1) relates, for household \( i \) living at location \( j \), the household’s marginal valuation of characteristic \( k \), expressed as a fraction of income, to the logarithms of the cost of

\(^6\) In our empirical implementation, this completeness assumption will be an approximation since we examine a finite, though large, number of U.S. PUMAs. Because of this finiteness, the heterogeneous climate preference estimates discussed in section 6 are, strictly speaking, set identified rather than point identified. However, the large number of PUMAs in our dataset suggests that these sets will be quite small. For further discussion of set versus point identification in hedonic models with heterogeneous preferences, see Bajari and Benkard (2005).

\(^7\) A few recent papers (Bayer, Keohane, and Timmins 2009 and Bishop 2009) suggest, using data on migrants, that preferences for local amenities may be under-estimated if mobility costs are not allowed for, raising the possibility that the welfare impacts estimated here are conservative.

\(^8\) The existence and differentiability of \( p(Z_j, \zeta_j) \) and \( w(Z_j, \zeta_j) \) hold under mild conditions. Rosen demonstrates the existence and differentiability of the quality of life function \( \hat{Q}(Z_j, \zeta_j) \) under the assumptions on demand given here and perfectly competitive land supply, while Bajari and Benkard (2005) show that a Lipshitz condition on \( U^i(x^i, Z_j, \zeta_j) \) is sufficient even under imperfect competition. Given this result, the separate existence and differentiability of \( p(Z_j, \zeta_j) \) and \( w(Z_j, \zeta_j) \) are given by the separate mobility conditions on households and firms and an assumption that local productivity differentials are continuous and differentiable in \( Z_j \) and \( \zeta_j \).
living and wage differentials at $j$. Let the U.S. average share of income spent on local goods be denoted by $s_y$, the average share of income derived from wages be denoted $s_w$, and the average marginal tax rate be denoted $\tau'$. These values in the year 2000 Census were 0.33, 0.75, and 0.32, respectively (for additional details, including the incorporation of local non-housing expenditures into $s_y$, see Albouy 2008). Let $\hat{p}_j$ denote the log housing cost differential at $j$, relative to the U.S. average, and likewise for $\hat{w}_j$. A natural quality of life measure at $j$, denoted $\hat{Q}_j$, is therefore the following weighted combination of $\hat{p}_j$ and $\hat{w}_j$.

$$\hat{Q}' = s_y \hat{p}_j - (1 - \tau')s_w \hat{w}_j$$

$$= 0.33 \hat{p}_j - 0.50 \hat{w}_j$$  \hspace{1cm} (2)

Let $\hat{Q}(Z_j, \xi_j)$ denote QOL as a function of local characteristics, per (2) and the functions $p(Z_j, \xi_j)$ and $w(Z_j, \xi_j)$. Then, by the first order condition (1), it must be that, for any household $i$ residing at $j$, the marginal willingness to pay (MWTP) for characteristic $k$, as a fraction of income, is equal to the derivative of the QOL function at $j$ with respect to characteristic $k$:

$$\frac{1}{m' \lambda} \frac{\partial U^i(x', Z_j, \xi_j)}{\partial Z_k} = \frac{\partial \hat{Q}(Z_j, \xi_j)}{\partial Z_k}$$  \hspace{1cm} (3)

The first order condition (3) is illustrated in figure 2 in the case of a model with a single characteristic, average summer temperature $T_s$. The bold line denotes a hypothetical QOL function $\hat{Q}(T_s)$ that is decreasing in $T_s$, indicating that milder weather must be “paid for” either through higher housing prices or lower wages. In this sense, $\hat{Q}(T_s)$ can be thought of as the hedonic “price” of a location with a summer average temperature of $T_s$. The slope of $\hat{Q}(T_s)$ at any given location is equal to households’ MWTP for $T_s$ at that location, as shown for locations A and B on the figure.

2.2 Estimates of wage and housing cost differentials, and QOL

We estimate wage and housing-cost differentials using the 5 percent sample of Census data from the 2000 Integrated Public Use Microdata Series (IPUMS). Geographic data are
available by Public Use Microdata Areas (PUMAs), which are census-defined geographic areas with a population between 100,000 and 200,000 people.

Inter-PUMA wage differentials $w_j$ are calculated from the logarithm of hourly wages for full-time workers, aged 25 to 55. These differentials control for observable skill and occupation differences across workers to provide an analogue to the $\varphi^i$ factors in the model. We therefore regress the log wage of worker $i$ in PUMA $j$ on PUMA-indicators $\mu^w_j$ and extensive controls $X^w_{ij}$ (each interacted with gender) for education, experience, race, occupation, and industry, as well as veteran, marital, and immigrant status, in an equation of the form $\ln w_{ij} = X^w_{ij} \beta^w + \mu^w_j + \varepsilon^w_{ij}$. The estimates $\mu^w_j$ are used as the PUMA wage differentials $w_j$ and are interpreted as the causal effect of a PUMA’s characteristics on a worker's wage. Identifying these differentials requires that workers do not sort across locations according to their unobserved skills.9

Both housing values and gross rents, including utilities, are used to calculate housing costs. Following previous studies, imputed rents are converted from housing values using a discount rate of 7.85 percent (Peiser and Smith 1985), with utility costs added, to make the imputed rents comparable to gross rents. To avoid measurement error from imperfect recall or rent control, the sample includes only units that were acquired in the last ten years. Housing-cost differentials are calculated in a manner similar to wage differentials, using a regression of housing costs on flexible controls $Y_{ij}$ (each interacted with renter status) for size, rooms, acreage, commercial use, kitchen and plumbing facilities, type and age of building, and the number of residents per room. This regression takes the form $\ln p_{ij} = Y_{ij} \beta^p + \mu^p_j + \varepsilon^p_{ij}$. The coefficients $\mu^p_j$ are used as PUMA-level housing cost differentials $p_j$. Proper identification of housing-cost differences requires that average unobserved housing quality does not vary systematically across locations.

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9 Glaeser and Mare (2001) argue that no more than one third of the urban-rural wage gap could be due to selection, suggesting that at least two thirds of wage differentials are valid, although this issue deserves greater investigation. At the same time, it is possible that the estimated differentials could be too small, as some control variables, such as occupation or industry, could depend on the worker’s location. As wages tend to be higher in areas with more temperate climates, an overstated wage differential will likely bias our estimate of the impact of climate change downwards.
We incorporate energy and insulation costs in our housing-cost measure since gross rents often include them.\(^{10}\) Our QOL differential therefore does not incorporate these costs and instead primarily reflects the disamenity value of adverse outdoor temperatures plus the disamenity value of adverse indoor temperatures insofar as they are not mitigated by insulation and energy use. If households choose to have their houses somewhat cold in the winter and somewhat warm in the summer, the discomfort from those changes will be capitalized into QOL estimates. When households heat and cool to their temperature bliss point, indoor temperatures are not capitalized; with no heating or cooling, indoor temperatures are completely capitalized. In addition, the QOL estimates incorporate any disamenity value from spending more time indoors to avoid uncomfortable outdoor temperatures.

Descriptive statistics for QOL and other PUMA-level control variables are given in table 1. Estimated QOL differentials across PUMAs for the year 2000 are mapped in figure 3. These estimates show that households find the amenities in areas along the coasts and in certain mountain areas to be quite desirable. Areas in the middle of the country, where seasons are more extreme, tend to be less desirable although there is considerable variation. As discussed in Albouy (2008), the QOL model correctly predicts the relationship between housing-costs and wages, controlling for observable amenities, and QOL estimates correlate well with other measures of overall amenities, such as the *Places Rated Almanac* (Savageau 1999).

3. Data

We estimate our main specifications at the PUMA-level using all 2,057 PUMAs in the contiguous 48 states as of the 2000 census.\(^{11}\) In this section we summarize our acquisition and

\(^{10}\) This approach follows the standard practice in the QOL literature from Blomquist *et al.* (1988) to Chen and Rosenthal (2008).

\(^{11}\) We have also mapped our data to the county-level and run some of our empirical specifications at a county-level resolution. Point estimates for preferences and climate change welfare impacts are similar to those discussed below, but are noisier across specifications and have larger standard errors. We believe that the county-level results are noisier because counties are frequently too large to capture important micro-climates, particularly in densely-populated coastal areas such as San Francisco.
treatment of present-day climate data, climate change projections, and control variables. Additional details are provided in an appendix (yet to be completed).

3.1 Present-day climate data

The most important set of climate variables in our analysis addresses the average yearly distribution of temperatures in each PUMA. We obtained daily temperature data over 1970-1999 from Schlenker and Roberts (2009) at a resolution of approximately 4 kilometer by 4 kilometer gridpoints. Schlenker and Roberts (2009) created these data by combining and interpolating monthly temperature data at this tight resolution from the Parameter-elevation Regressions on Independent Slopes Model (PRISM)\textsuperscript{12} climate mapping system with daily temperature data at weather stations from the National Climactic Data Center (NCDC).\textsuperscript{13} Schlenker and Roberts (2009) show that their interpolation is extremely accurate in a cross-validation exercise.

To transform the daily temperature data into temperature distribution data at each grid point, we created temperature bins with a width of 0.9 degrees Fahrenheit (0.9ºF, equivalent to 0.5 degrees Celsius). We then calculated, over 1970-1999, the average number of days at each gridpoint in which the average temperature (calculated as the mean of the daily high and low temperature) fell within each bin. Within each PUMA, we averaged the bin distributions at each gridpoint to yield a PUMA-level dataset of temperature distributions.\textsuperscript{14}

We also collected data on precipitation, humidity, and sunshine (percent of daylight hours for which the sun is not obscured by clouds). Precipitation and humidity data were obtained directly from PRISM at the PRISM grid points over 1970-1999 and averaged at the PUMA by month-of-year level. The PRISM group does not model sunshine; thus, we obtained sunshine data from the NCDC for the 156 weather stations that record sunshine information. These data

\textsuperscript{12}http://www.prism.oregonstate.edu
\textsuperscript{13}http://www.ncdc.noaa.gov/oa/ncdc.html
\textsuperscript{14}A handful of densely-populated PUMAs are so small that they do not contain any PRISM grid points. For these PUMAs, we used the average of the temperature distributions at nearby grid points. See the appendix for details.
take the form of average sunshine by month-of-year at each station. We calculated PUMA-level data on sunshine by month-of-year via interpolation from nearby weather stations. Because of this interpolation, our sunshine data are the least accurate of our climate variables.

3.2 Projected climate data

Predicted temperature changes are taken from the Intergovernmental Panel on Climate Change Assessment Report 4 (IPCC AR4) released in 2007. We use two “business as usual” scenarios in which no actions to reduce greenhouse gas emissions are taken: the A2 scenario from the Community Climate System Model (CCSM) and the A1F1 scenario from the Hadley Centre. The A2 scenario predicts average U.S. warming of 8.3°F from the baseline present day (1970-1999) to the end of the century (2090-2099), while the A1F1 scenario predicts warming of 9.6°F. Our analysis will tend to focus on the relatively conservative A2 scenario, though we will also provide results for A1F1.

Simulation data for both models are available at a resolution of 1.4 degrees longitude by 1.4 degrees latitude, covering 1970-2099 and including predicted daily temperatures, monthly precipitation, monthly humidity, and monthly sunshine. At each climate model gridpoint, we obtain decade by decade data on projected climate changes, through 2090-2099, by subtracting the 1970-1999 baseline simulation data from each future decade’s simulated climate. We then create a PUMA-level dataset of climate change projections by interpolating between the climate model grid points. PUMA-level future projected climates are obtained by adding these change projections to the PUMA-level present-day climate data discussed above.

Data for present and projected (A2 model) climate variables are given in the top half of table 1. Temperature distributions are summarized by heating degree days (HDD) and cooling degree days (CDD) statistics. HDD and CDD are measures of how frequently, and by how much, a PUMA’s temperatures are below (for HDD) or above (for CDD) a baseline temperature of
To calculate the heating degrees associated with a single day, the average temperature of the day is subtracted from 65°F. If this value is greater than zero, it represents the number of heating degrees for the day; if less than zero, the day has zero heating degrees. HDD is then the sum of each day’s heating degrees over an entire year. CDD is defined in a similar fashion for temperatures greater than 65°F.

Table 1 shows that, on average, the effects of climate change will be manifest primarily through changes in temperature. The average U.S. PUMA will experience a reduction in HDD of 36% and an increase in CDD of 113% under the A2 scenario. These temperature changes are also given in map form in figure 1, which shows substantial increases in both January and July temperatures across the United States. The interior South, in particular, is forecast to experience substantial gains in the number of extremely hot days for which the average temperature exceeds 90°F. Changes to precipitation, relative humidity, and sunshine will, however, be relatively minor on average, though some areas are expected to receive meaningful changes.\textsuperscript{16}

### 3.3 Control variables

Table 1 also presents data on the control variables that we will use when estimating preferences. The geographic controls are used in all estimates and include, for each PUMA, the minimum distances from the PUMA’s centroid to an ocean and Great Lakes coastline and the average slope of the land in each PUMA, a measure of mountainousness. Demographic data include measures of population density, educational attainment, age, and racial / ethnic composition. Table 1 also provides statistics on the distribution of population across PUMAs, which by definition must exceed 100,000 people, and on the QOL measure.\textsuperscript{17}

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\textsuperscript{15} Graves (1979) began the use of HDD and CDD as amenity variables.

\textsuperscript{16} We emphasize that our study captures only the amenity impact of changes in precipitation, not impacts on water supply.

\textsuperscript{17} The mean QOL differential is not exactly zero in table 1 because the table shows un-weighted data, while QOL differentials are defined so that the income-weighted mean is zero.
4. Estimation of a Linear Hedonic Model with Homogenous Preferences

We begin by estimating a simple hedonic model in which we assume that climate preferences are homogenous across the U.S. population and that factors (including climate) affecting quality of life (QOL) enter linearly. While this model is highly restrictive, it follows the previous literature and serves as an introduction to our approach, providing a benchmark against which our subsequent richer model can be evaluated. Moreover, under these assumptions, the estimated regression coefficients on the determinants of QOL can be interpreted directly as estimated willingness-to-pay (WTP).

We estimate the impact of marginal changes to climate on QOL using (3) below, an OLS regression of each PUMA $j$’s QOL differential $\hat{Q}_j$ on climate and other characteristics $Z_j$ of PUMA $j$.

$$\hat{Q}_j = \sum_k \pi_k Z_{jk} + \xi_j$$

The parameters $\pi_k$ represent the WTP of households for an additional unit of $Z_k$, measured as a fraction of income. The disturbance term $\xi_j$ is a vertical location characteristic that is observed by households but not by the econometrician. We face two substantial challenges in estimating (4). First, we must select a functional form through which the climate variables—the temperature distribution in particular—must enter. Second, consistent estimation of the $\pi_k$ requires that $\xi_j$ be orthogonal to the characteristics $Z_j$. In the absence of instruments, this orthogonality cannot be tested and must be assumed. We therefore assess the stability of our estimates of the $\pi_k$ to alternative specifications that “toggle” on and off the demographic control variables and state fixed effects. Our specifications always include the geographic variables, as these are clearly exogenous and strongly correlated with climate.18

18 The estimates of the disamenity of cold and heat increase substantially in magnitude when the geographic controls are excluded.
4.1 An empirical model based on HDD and CDD

We first estimate a particularly simple version of (4) in which temperatures enter only through the variables HDD and CDD. This specification is a natural starting point in light of the view that these variables are widely believed to determine indoor heating and cooling requirements. However, this functional form does imply strong restrictions on preferences: WTP is fixed to be greatest at 65°F, and utility must decrease linearly away from 65°F.

Right-hand-side variables in our initial model also include annual precipitation, humidity, and sunshine (henceforth collectively referred to as “other climate” variables), as well as geographic controls for coastal proximity and mountainousness. In section 5, we examine the importance of breaking out the other climate variables by season. Distances from the ocean and Great Lakes enter the specification as quadratics in inverse distance, and slope enters linearly.19

Estimated preferences for temperatures are given in panel A of figure 4 as the willingness to pay, as a fraction of income, for an additional day at each temperature relative to a day at 65°F. Also plotted are the present and future (2090-2099, A2 scenario) U.S. income-weighted average temperature distributions. Per the HDD/CDD specification, WTP is maximized as 65°F and decreases linearly with heat and cold. The WTP function slopes downward more steeply over hot temperatures than over cold temperatures, indicating a stronger estimated distaste for heat than for cold. This difference in slopes is statistically significant with a p-value less than 0.001.20

The result that heat is worse than cold on the margin is a central result of this paper and is robust across a number of specifications, as will be shown. It also seems intuitively reasonable. The second law of thermodynamics explains that it is more costly for physical and biological

19 The inclusion of higher order terms in either coastal distance or slope does not substantially affect our estimates of climate preferences or climate change welfare impacts.
20 All inference is conducted using standard errors that are clustered at the metropolitan statistical area (msa) level. PUMAs that are not part of an msa are clustered within each state. There are 287 clusters in the data.
systems to cool than to heat. In practical terms, individuals can easily wear additional clothing to protect from the cold, while little can be removed to provide relief from heat.

Column I of table 2 provides the estimated preferences for temperature and other variables for this specification. Estimated preferences for HDD and CDD are given by the fraction of income that households would be willing to pay for an additional day at 50°F or 80°F, respectively, relative to 65°F, scaled up by 365. These estimated WTPs are -3.5% and -12.7% of income, respectively, and can be interpreted, given the linear WTP assumption, as the WTP to move from an “ideal” climate in which every day is 65°F to a climate in which every day is 50°F or 80°F.

Regarding preferences for other characteristics, we find that households have a strong preference for sunshine, as well as a distaste for precipitation and (counterintuitively) a preference for humidity. These latter two effects become statistically insignificant in richer specifications. In general, it is difficult to disentangle preferences for these three “other weather” attributes as they are strongly correlated—locations with a lot of sunshine also tend to be non-humid and dry. When sunshine and precipitation are excluded, the estimated WTP for humidity becomes negative and statistically significant. We also estimate a strong preference for slope, a preference to be close to an ocean, and a distaste for closeness to a Great Lake.

Using climate change projections for 2090-2100, we calculate PUMA-level welfare impacts using these preference estimates and map them, for the A2 scenario, in figure 5. Given the assumptions of homogenous preferences and an HDD/CDD specification, and the result that aversion to heat is stronger than aversion to cold, the strongest amenity impacts of climate change are felt in the interior South, where the increase in extreme heat is most severe. Column I of table 3 presents the aggregate estimated welfare impacts for this model. Under the A2 scenario, we find that the average U.S. household will experience a loss in amenity value of 2.24% of income that is statistically significant at the 1% level.21 This welfare impact is

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21 All standard errors for welfare impacts are block bootstrapped, clustering on msa.
essentially driven entirely by projected temperature changes, since the projected changes for the other weather variables are small on average. Only about 3% of the U.S. population—primarily households located in the Pacific Northwest, upper peninsula of Michigan, and northern Maine—are actually estimated to experience welfare gains. Welfare losses are slightly larger—2.57% of income—under the A1F1 scenario.

We also estimate an HDD/CDD model in which we restrict the distaste for cold to equal the distaste for heat. Preference estimates from this model are given in panel B of figure 4 and column II of table 2; estimated welfare impacts are given in column II of table 3. This model does not fit the data well, as evidenced by the relatively low $R^2$ of the model and the fact that the unrestricted model in column I rejected the equality of WTP for heat and cold. Forcing this preference equality also substantially changes the estimated welfare impacts from climate change: the average impact under the A2 scenario is only -0.21% of income. Thus, the impact of climate change on the value of climate amenities depends strongly on the extent to which increases in heat are valued more strongly than decreases in cold.

4.2 An empirical model based on a flexible function of temperature

While still retaining (for now) our assumptions that preferences are linear and homogenous, we relax in this subsection the assumption that HDD and CDD are sufficient statistics for temperature preferences in the estimation of (4). Instead, we model the WTP for exposure to an additional day at temperature $t$, relative to a day at 65°F, as the unknown function $f(t)$. $f(t)$ is assumed to take a value of zero at 65°F, but may take any positive or negative value away from this point, thereby relaxing the assumption of the HDD and CDD model that the maximum WTP occurs at 65°F.\(^{22}\)

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\(^{22}\) The HDD and CDD specification of section 4.1 can be seen as a special case of $f(t)$ in which the function is two-piece linear, with a meeting of the two pieces at 65°F.
To understand the shape of \( f(t) \), we model it using cubic splines per (5) below, in which \( S_1(t) \) through \( S_5(t) \) are standard cubic B-spline basis functions defined over the support of all present-day temperatures observed in the data.\(^{23}\)

\[
f(t) = \sum_{s=1}^{S} \beta_s S_s(t) \tag{5}
\]

We estimate this spline using our binned climate data. Defining \( N_{jt} \) as the average number of days per year at location \( j \) for which the average temperature is between \( t \) and \( t + 0.9 \), we flexibly estimate climate preferences using (6):

\[
\hat{Q}_j = \sum_t N_{jt} f(t) + \alpha \cdot Z_j + \xi_j
= \sum_{s=1}^{S} \beta_s (\sum_t N_{jt} S_s(t)) + \alpha \cdot Z_j + \xi_j
\tag{6}
\]

Figure 6 presents estimated WTP curves for 4\(^{th}\), 6\(^{th}\), 8\(^{th}\), 10\(^{th}\), 12\(^{th}\), and 14\(^{th}\) degree splines (the empirical specification, as in section 4.1, includes the other weather variables and geographic controls). While the 4\(^{th}\) degree and 14\(^{th}\) degree splines appear too restrictive and too noisy, respectively, several regularities emerge from the set of 6 plots. First, at the far extremes of the temperature distribution, there are insufficient realizations to permit inference. The point estimates and standard errors explode below 20ºF and above 90ºF for all but the 4\(^{th}\) and 6\(^{th}\) degree splines. Second, the restriction from the HDD/CDD model that WTP is maximized at 65ºF appears justified: the WTP curves consistently have an interior maximum near 65ºF. Third, and finally, the restriction from the HDD/CDD model that WTP declines linearly away from 65ºF does not appear justified. The slopes of the WTP curves tend to be steep at temperatures near 65ºF (on both the hot and cold sides), but the curves then appear to “level off” once temperatures are sufficiently far from 65ºF (until the far extremes are reached and inference is lost).

\(^{23}\) The temperature range is -38.7ºF to 110.8 ºF.
The noisiness of the spline estimates at temperatures at the extremes of the present-day distribution preclude their direct use as estimates of temperature preferences and as a basis for estimating welfare impacts from climate change. However, it also appears that the HDD/CDD model may be unjustifiably restricting the shape of the WTP curves. We therefore examine three alternative specifications that are designed to allow for flexibility in WTP in the interior of the present-day temperature distribution while conservatively projecting WTP at the far extremes via functional form restrictions. First, we use a four-piece linear spline, with kink points at 65°F, 50°F, and 75°F. Second, we use a four-piece linear spline, with the same kink points, restricted so that WTP is flat at temperatures below 50°F and above 75°F. Finally, we use a 10th degree cubic spline but restrict the WTP curve to be flat outside the middle 90% of the income-weighted temperature distribution.

Preference estimates from these three models are given in figure 7 and columns III through VIII of table 2. Estimates for each model are given both with and without the demographic controls and state fixed effects. The unrestricted four-piece linear spline models confirm that WTP declines steeply in the neighborhood of 65°F but then becomes flat once temperatures are sufficiently hot or cold. This model rejects the restriction that the WTP specification is given by HDD/CDD (equivalent to constant slopes through the 50°F and 75°F kinks) with a p-value of 0.002. It fails, however, to reject the model in which the WTP curve is forced to be flat below 50°F and above 75°F with a p-value of 0.858 (0.251 when demographics and state fixed effects are included). We still find that the WTP to avoid heat is greater than (and statistically distinct from) the WTP to avoid cold. Overall, the estimated WTP curves are similar

24 We are not the first to confront the issue of how to conduct inference at temperatures near and beyond the limit of what is realized in present-day data. Prior work in the crop yield and health literatures has assumed that the damage function is constant beyond the point at which inference is no longer feasible (Deschénes and Greenstone 2007, 2008, Schlenker and Roberts 2009). The modeling approach that we will focus on—four-piece linear splines with a restriction that MWTP is constant at the extremes—accords with this prior practice.

25 The choices of 50°F and 75°F tend to yield the best fit to the data (per R²) over most specifications. Alternative choices, such as 55°F or 80°F do not substantially impact the preference or welfare estimates.

26 We impose these cutoffs after estimating the full 10th degree spline rather than beforehand, as reversing the order leads to unstable estimates at the cutoff points.
for all three functional forms, with or without the demographic controls and state fixed effects, and the three models yield very similar R² measures of fit.

The result that WTP declines less steeply over extreme temperatures than moderate temperatures is aligned with the intuition that households can protect themselves from extremes by taking shelter in climate-controlled indoor environments. Once temperatures become sufficiently uncomfortable that households no longer spend discretionary time outside, further increases in heat or cold are no longer important to amenity values. This result is consistent with recent research by Graff Zivin and Neidell (2010) that uses time diary data to show that households spend less time outside in cold or hot weather. It is also an interesting contrast to the Schlenker and Roberts (2009) result that crop yields are severely (non-linearly) reduced by extreme heat. While humans can take shelter inside, crops cannot.

Estimated climate change welfare impacts for these three functional forms are given in columns III through VIII of table 3. Losses are smaller than those estimated for the HDD/CDD model—generally 1.4% to 2.0% of income—consistent with the reduced importance of extreme heat in the estimated preferences. Figure 8 maps the distribution of estimated welfare impacts for the restricted four-piece linear spline model given by table 3, column V. This distribution contrasts sharply with that of the HDD/CDD model displayed in figure 5: welfare effects are estimated to be largest in magnitude in the mid-Atlantic states, upper Midwest, and along the coasts (except for the Pacific Northwest). This distributional shift occurs because summer temperatures in the interior South are typically sufficiently hot that households residing there are already in the flat portion of the WTP curve. Thus, contrary to conventional wisdom, it may be northern households that suffer more from projected temperature changes than southern households. An important caveat to this result, however, is that while the data indicate that the

27 Controlling for demographic variables and state fixed effects separately, rather than jointly, also has little impact on the estimated temperature preferences, with the exception of the restricted 10th degree cubic spline model. In this case, including demographic controls alone roughly halves the estimated aversion to heat and the aggregate welfare impact from climate change.
WTP curve is flatter between 75ºF and 90ºF than between 65ºF and 75ºF, inferences about temperatures beyond 90ºF come only from functional form projections because such temperatures are extremely rare in the present-day data. We cannot rule out the possibility that, at such extremely high temperatures, even brief moments of time spent outside (walking to and from one’s car, for example) become so difficult to tolerate that the WTP for such days falls sharply.

5. Estimation of a Hedonic Model with Heterogeneous Preferences

5.1 Empirical strategy

We now relax the assumption that all households in the U.S. share homogenous preferences for hot and cold weather. In addition, we allow households to sort themselves into those locations that best suit their preferences. Estimation of preferences under these more relaxed conditions is based on the framework developed by Bajari and Benkard (2005) and applied by Bajari and Kahn (2005). The intuition behind this approach lies in the first order condition given by equation (3) and is illustrated in figure 2, which depicts a hedonic equilibrium in which the only characteristic is average summer temperature, $T_s$. Given a nonlinear hedonic price function $\hat{Q}(Z_j, \xi_j)$, the MWTP of households located at $j$ for a given characteristic $k$ is simply given by $\partial \hat{Q}(Z_j, \xi_j) / \partial Z_k$. The equilibrium depicted in figure 2 is consistent with positive sorting, in which households with a high MWTP to avoid heat settle in areas with low summer temperatures. Flexible estimation of $\hat{Q}(Z_j, \xi_j)$ allows us to recover the distribution of MWTP for each characteristic $k$ across the population of households.

We emphasize that we are only able to identify the MWTP of each household given the climate at its location; we cannot identify the shape of households’ WTP curves away from the climate at their location. In figure 2, for example, the MWTP at locations A and B are identified, but the shapes of the indifference curves of households at A and B are otherwise not identified. Because the projected changes to climate are non-marginal, estimation of welfare impacts
requires a functional form assumption regarding the shape of the WTP function. In predicting welfare impacts, we assume that the WTP curve is linear with a slope equal to our estimated MWTP. We take this approach because it is both transparent and conservative; allowing for concavity would result in more negative predicted welfare effects than those reported here.28

To flexibly estimate $\hat{Q}(Z_j, \xi_j)$, we follow Bajari and Benkard (2005) and Bajari and Kahn (2005) by using local linear regression per Fan and Gijbels (1996). Suppose that, local to location $j^*$, $\hat{Q}(Z_j, \xi_j)$ satisfies (7) below:

$$\hat{Q}_j = \sum_k \beta_k^* Z_{jk} + \xi_j$$  (7)

In (7), the implicit prices $\beta$ are tagged with the superscript $j^*$ to denote the fact that we estimate a distinct set of prices at each location. We obtain the $\beta^{j^*}$ at each location via weighted least squares per (8) and (9):

$$\beta^{j^*} = \arg\min_\beta \left( \hat{Q} - Z \beta \right)^TW(\hat{Q} - Z \beta)$$  (8)

$$\hat{Q} = \begin{bmatrix} \hat{Q}_j \end{bmatrix}; \ Z = \begin{bmatrix} Z_j \end{bmatrix}; \ W = \text{diag}\left[ K_h(\ Z_j - Z_{j^*}) \right]$$  (9)

$W$ is a matrix of kernel weights defined so that, in the estimation of prices local to $j^*$, locations that are similar to $j^*$ in characteristics space receive the greatest weight.29 We use a normal kernel function with a bandwidth $h$ of 3, per (10) and (11) below. $\sigma_k$ denotes the standard deviation of characteristic $k$ across the sample.30

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28 Should the hedonic price function $\hat{Q}(Z_j, \xi_j)$ exhibit any concavities, the linear WTP assumption implies that at a concavity in $\hat{Q}(Z_j, \xi_j)$ a household satisfying the FOC will actually be locally minimizing utility rather than maximizing utility. For the estimated models discussed below, we have calculated the minimum amount of concavity required to satisfy households’ utility maximization over all locations, treating WTP as quadratic in characteristics. Allowing for concavity increases the estimated magnitude of climate change welfare losses by about 0.2 to 0.3 percentage points. Future versions of this paper will describe our concavity calculation in an appendix.

29 We exclude from $W$ the inverse distance and squared distance from the Great Lakes and the inverse squared distance from an ocean, as these variables generate near-perfect collinearity in the weighted covariate matrix. Specifications that include state fixed effects in the $Z$ matrix exclude them from the $W$ matrix, also for collinearity reasons.

30 The use of a normal kernel follows Bajari and Benkard (2005) and Bajari and Kahn (2005). We also follow these papers in choosing the kernel bandwidth by eye to yield smoothly varying MWTP estimates across the population. Future versions of this paper will also examine the use of the mean squared error minimizing bandwidth, which is likely smaller than that used here.
\[ K(Z) = \prod_k N(Z_k / \hat{\sigma}_k) \]  
\[ K_h(Z) = K(Z / h) / h \]

The local linear regression approach introduces considerable flexibility into how households in different locations can value heat and cold. For example, the MWTP for heat varies not just with the amount of heat experienced at a given location, but also with other characteristics. That is, the specification allows for the possibility that households in coastal areas may be relatively tolerant of heat or that households residing in locations in which there are a large number of days with cold temperatures may be relatively heat-tolerant (consistent with a preference for seasonality).

In our specification of the climate variables in \( Z \), we use the restricted four-piece linear spline function used to generate the homogenous preference results in columns V and VI of tables 2 and 3. While conservative, this specification is more stable in the local linear regressions (each of which only uses a fraction of the data) than are the unrestricted four-piece linear spline or the restricted 10th-degree cubic spline.

5.2 Estimation results

Panel A of figure 9 illustrates the estimated distribution of MWTP (scaled up by 365) for an additional day at 80°F, relative to a day at 65°F, as a function of CDD. The empirical model includes the other climate variables and geographic controls, but not the demographic controls or state fixed effects. The distribution has a clear positive slope, consistent with sorting of households with a strong aversion to heat to locations with few hot days. Panel B illustrates that households’ MWTP for an additional day at 50°F decreases slightly with HDD, consistent with modest concavity in households’ utility functions over the number of cold days experienced in their locations. On average, the MWTP to avoid heat exceeds that to avoid cold, consistent with the homogenous preference model results.
Panels C and D of figure 9 illustrate the same MWTP distributions for an empirical model that includes demographic variables and state fixed effects. These distributions are noisier than those given in panels A and B, indicating that the inclusion of these controls in $Z$ and $W$ hinders inference of clear sorting patterns in the data.

Table 4 presents preference and climate change welfare impact estimates for a variety of specifications, under both heterogeneous and homogenous preferences. Column I corresponds to a “reference case” model that includes the other weather and geographic controls (as do all models shown) but not demographic controls or state fixed effects. The average MWTP to avoid cold and heat from the heterogeneous preferences model is slightly larger than that estimated in the homogenous preference model, and the heterogeneous preferences model therefore predicts a slightly larger welfare impact from climate change (-1.64% of income vs. -1.40%). This difference is driven by the fact that households estimated to have the most intense dislike of heat tend to live in northern areas that are likely to experience the greatest shifts in the temperature distribution away from comfortable temperatures near 65°F towards moderate or severe heat.

Figure 10 maps the distribution of welfare impacts from the heterogeneous preferences model shown in table 4, column I. Relative to the homogenous preference results shown in figure 8, the most severe climate change impacts are shifted even further north, driven by northerners’ relatively low tolerance for heat. Impacts along the Gulf Coast and in Florida are lower when allowing for preference heterogeneity, consistent with the intuition that heat is more tolerable along a coastline. Overall, allowing for preference heterogeneity reinforces the result that the impact of climate change on climate amenities may be felt more by northern households than by southern ones.

The remaining columns of table 4 present preference and welfare estimates from alternative empirical specifications, across which the heterogeneous preferences results are robust (point estimates of the welfare effect associated with the A2 model range from -1.28% to -1.72% of income across the eight columns). Column II adds the demographic controls, column III adds state fixed effects, and column IV adds both. The inclusion of state fixed effects tends to
increase the estimated aversion to both heat and cold, potentially reflecting the fact that identification in these models relies on large states such as California that have substantial within-state climate variation. These increases in estimated MWTP are similar in magnitude for cold and heat; thus, the estimated climate change welfare impacts are not substantially affected.

Columns V and VI disaggregate the other weather variables by interacting them with winter (October-March) and summer (April-September) dummies. This change does not substantially impact the results. Columns VII and VIII explore the extent to which the estimation results are driven by California—a large and unique state that possesses very moderate coastal climates and many of the highest QOL areas in the country. Removing California from the sample has little impact on the results from the heterogeneous preferences model (with or without the demographic controls and state fixed effects), indicating that the preference and welfare results are not driven by any unobserved characteristics associated with that state. The homogenous preference model results, however, become attenuated and imprecise when California is dropped from the sample, demonstrating that the nonlinear hedonic price function permitted by allowing for preference heterogeneity yields a better fit to the data.

5.3 Alternative measures of QOL

Section 2 above emphasized the importance of correctly weighting housing price and wage differentials when calculating a QOL measure. We therefore conclude this section by examining climate preference and welfare estimates based on alternative weights. First, we consider weights of 0.25 on housing price differentials and 1.00 on wage differentials, rather than the 0.33 and 0.50 used thus far. These alternative weights correspond to those used in the earlier QOL literature and do not account for federal taxation or prices of local goods other than housing (see Albouy 2008 for a discussion). Preference and welfare estimates based on these weights are presented in column II of table 5 (estimates use the heterogeneous preferences model with the restricted four-piece linear spline specification for MWTP). This specification, in the absence of demographic controls and state fixed effects, actually estimates positive amenity
values associated with heat and cold and positive welfare impacts from climate change. This result is consistent with some estimates of climate preferences from earlier literature that also under-weighted housing price differentials and found either positive or insignificant WTP for heat (Hoch and Drake 1974, Nordhaus 1996, Moore 1998). Inclusion of demographic controls and state fixed effects in the specification returns the result that households have a distaste for heat and cold, though with greater magnitudes than in the reference case estimate of column I.

Columns III and IV of table 5 simply use price and negative wage differentials, respectively, as left-hand-side variables. Estimates without demographic controls or state fixed effects find that both house prices and wages decrease with heat and cold. It is these wage effects that generate estimates that households enjoy heat and cold in hedonic regressions that over-weight wage differentials.

6. Migration

The welfare impacts we have estimated thus far assume that households will remain in their current locations following changes to climate. If climate change is only marginal, then these welfare effects will be fully robust to migration via the envelope theorem. However, given the large climate changes currently projected, the second-order effect of migration may materially mitigate welfare damages.

This section assesses the potential importance of migration using a parsimonious, transparent model that is based on the homogenous preference assumptions of section 4.\textsuperscript{31} Intuitively, households will leave areas with worsening climates and migrate towards areas with improving climates. We model a benchmark case in which households have zero mobility costs, so that positively-sloped local housing supply functions provide the primary friction limiting migration of all households to the highest quality location. In addition, households can also

\footnote{Forecasting migration in a model with heterogeneous preferences requires simulation that is beyond the scope of the present paper.}
choose to crowd into existing housing, but may also face limited labor-market opportunities from diminishing returns due to local fixed factors. For tractability, we constrain households to remain within U.S. borders, ruling out migration to Canada.

We assume that the housing supply is given by a function with a constant elasticity \( \varepsilon_s \). Denote the climate-driven QOL change in PUMA \( j \) by \( \hat{\Delta Q}_j \) and the U.S. average QOL change by \( \hat{\Delta Q}_{avg} \). In the absence of impacts of overcrowding on QOL or firm productivity,\(^{32}\) the log change in population in PUMA \( j \), denoted \( \Delta N_j \), is given by:

\[
\Delta N_j = \varepsilon \left( \hat{\Delta Q}_j - \hat{\Delta Q}_{avg} \right)
\]

Equation (12), in combination with the PUMA-specific impacts of climate change on QOL from section 4, then yields estimates of PUMA-level migration.

We use an elasticity of 5 in our model to investigate the importance of a particularly large migration effect, so that a 2 percent reduction in the willingness-to-pay to live in an area results in a 10 percent population drop. Equation (12), in combination with the PUMA-specific impacts of climate change on QOL from section 4, then yields estimates of PUMA-level migration.

We focus on the model that uses the restricted four-piece linear spline for the MWTP specification, without demographic controls or state fixed effects. Allowing for migration only trivially changes the welfare impact of climate change (A2 scenario) from -1.40% to -1.38% of income (results are similar when demographic controls and state fixed effects are included). This small impact of migration results from several factors. First, very few locations, such as the Pacific Northwest, actually experience amenity improvements from climate change. Even with a supply elasticity of 5, migration to such areas is ultimately constrained by price increases associated with crowding. Thus, most migration will be from areas with large negative welfare impacts to areas with modest negative welfare impacts, limiting migration’s value in mitigating

\(^{32}\) Albouy (2009) models these crowding effects and outlines assumptions under which changes in population can be related to changes in QOL through a reduced form housing supply elasticity \( \varepsilon_Q \). In a model that is calibrated according to empirical estimates of parameters such as the substitutability of labor, land, and capital in production, the estimate of \( \varepsilon_Q \) is 1.90. Saiz (2008) has estimated local housing supply elasticities for 95 metropolitan areas in the U.S. The median estimated elasticity is 1.34 and the maximum is 5.16. In addition, in a medium run climate change scenario, worsening areas may only depopulate slowly as the supply of housing diminishes slowly over time due to depreciation, consistent with a small downside supply elasticity (Glaeser and Gyourko 2005). It is therefore likely that our use of a supply elasticity of 5 results in an overestimate of migration and an underestimated welfare impact.
climate amenity losses. Second, the amenity losses are small enough so that, even with a large housing supply elasticity of 5, there will be little migration driven by changes in climate amenities. We estimate that the average absolute value of the population change across all PUMAs is only 2.4%. Finally, we emphasize that these estimates assume that there are no mobility costs, so that the importance of mobility for welfare is likely to be even less than that estimated here.

7. Conclusions

This paper uses cross-sectional variation in housing prices, wages, and climate to estimate, using hedonic methods, the extent to which households value climate amenities. We combine these estimated valuations with climate change forecasts from the scientific literature to assess how climate change will impact household welfare through changes in quality of life, predicated on holding both technology and the estimated climate preferences fixed over time. We adopt a cross-sectional hedonic strategy rather than a panel approach (which would use time-series variation in weather) because differences in quality of life should reflect long-term climate rather than yearly weather fluctuations, and so that our estimates to reflect the potential for climate adaptation. This approach does raise concerns regarding omitted location-specific factors: we address this issue by verifying the robustness of our results to alternative specifications and controls, including models that include state fixed effects.

We have three central findings regarding U.S. households’ climate preferences: (1) the willingness to pay to avoid heat is greater than the willingness to pay to avoid cold; (2) households are not estimated to be significantly more averse to severe heat and cold than to moderate heat and cold; and (3) northern households are more averse to heat than are southern households. Result 1 is consistent with the second law of thermodynamics, result 2 is consistent

33 Implications of sea level rise for migration, barring damage mitigation efforts such as the construction of sea walls, may of course be more severe.
with the fact that humans can protect themselves from severe weather by taking shelter indoors, and result 3 is consistent with taste-based sorting. Together, these results suggest that the effect of climate change on climate amenity values will be negative on average (equivalent to a welfare loss of between 1.5% and 2.0% of income) and that northern households will suffer more than southern households.

The most important caveat to our results is that we have little statistical power to make inferences regarding households’ willingness to pay (WTP) to avoid temperatures at or beyond the limits of the present-day temperature distribution. While it does appear that WTP is roughly constant over moderately to severely hot temperatures realized in present-day, we cannot say for certain that this trend will hold over the extremely hot temperatures that are predicted to be realized in the future but are not yet reached currently. Should the WTP to avoid heat actually increase over this temperature range, then our estimates of the effect of climate change on climate amenity values will be conservative, particularly in the southern U.S.

References


Figure 1: Present and projected future January and July mean temperatures

Present-day temperatures are 1970-1999 average. Projections use the IPCC A2 scenario for 2090-2099.
Figure 2: Illustrative hedonic price function with demand-side equilibrium FOC’s satisfied

Figure 3: Quality of life (QOL) differentials in 2000
Figure 4: Estimated temperature willingness to pay (WTP) from homogenous preference HDD/CDD models

Panel A: HDD / CDD specification
Panel B: HDD / CDD specification with identical slope restriction
WTP for a day at each temperature is relative to 65°F, expressed as a fraction of income.
WTP estimates in both panels generated from models including other weather and geographic controls, but excluding demographic controls and state fixed effects.
Dashed lines around WTP estimates denote 95% confidence intervals.
Distributions at the bottom of each panel are income-weighted U.S. average present (1970-1999) and future (2090-2099, A2 scenario) temperature distributions.

Figure 5: Predicted changes in QOL as percent of income; linear homogenous preference HDD/CDD model (panel A of figure 4, column I of tables 2 and 3); A2 scenario 2090-2099
Figure 6: Estimated temperature willingness to pay (WTP) from homogenous preference cubic spline models

WTP for a day at each temperature is relative to 65°F, expressed as a fraction of income. WTP estimates in all panels generated from models including other weather and geographic controls, but excluding demographic controls and state fixed effects. Dashed lines around WTP estimates denote 95% confidence intervals. Distributions at the bottom of each panel are income-weighted U.S. average present (1970-1999) and future (2090-2099, A2 scenario) temperature distributions.
Figure 7: Estimated temperature willingness to pay (WTP), homogenous preference models

Panel A: four-piece linear spline WTP model, kink points at 50°F, 65°F, 75°F
Panel C: four-piece linear spline WTP model, kink points at 50°F, 65°F, 75°F, restriction that MWTP is constant below 50°F and above 75°F
Panel E: 10th degree cubic spline WTP model, restriction that WTP is constant over the bottom 5% and top 5% of the U.S. income-weighted temperature distribution
Panels B, D, and F add demographic controls and state fixed effects to panels A, C, and E. All models include other weather and geographic controls.
WTP for a day at each temperature is relative to 65°F, expressed as a fraction of income.
Dashed lines around WTP estimates denote 95% confidence intervals.
Distributions at the bottom of each panel are income-weighted U.S. average present (1970-1999) and future (2090-2099, A2 scenario) temperature distributions.
Figure 8: Predicted changes in QOL as percent of income; linear homogenous preferences model with temperature preferences specified as a restricted four-piece linear spline (per panel C of figure 7 and column V of tables 2 and 3); A2 scenario 2090-2099
Figure 9: Estimated marginal willingness to pay (MWTP) for heat and cold, heterogeneous preferences models

Panels show the distribution of MWTP (as a fraction of income, scaled up by 365) across PUMAs for an additional day at 80°F or 50°F, relative to a day at 65°F. MWTP functional form for temperatures is the restricted four-piece linear spline in all panels. Models used in all panels include other weather and geographic controls. Models used to generate estimates in panels C and D include demographic controls and state fixed effects. Models used for panels A and B do not.
Figure 10: Predicted changes in QOL as percent of income; heterogeneous preferences model with temperature preferences specified as a restricted four-piece linear spline (per panels A and B of figure 9 and column 1 of table 4); A2 scenario 2090-2099
<table>
<thead>
<tr>
<th>Table 1: Descriptive statistics for primary dataset.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sample consists of 2057 Public Use Microdata Areas (PUMAs)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>Std. Dev</th>
<th>10th percentile</th>
<th>90th percentile</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Temperature data, 1970-1999 average</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Average annual heating degree days (1000s)</td>
<td>4.384</td>
<td>2.204</td>
<td>1.326</td>
<td>7.009</td>
</tr>
<tr>
<td>Average annual cooling degree days (1000s)</td>
<td>1.290</td>
<td>0.929</td>
<td>0.374</td>
<td>2.762</td>
</tr>
<tr>
<td><strong>Temperature data, 2090-2099 projected (CCSM A2)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Projected avg. annual heating degree days (1000s)</td>
<td>2.821</td>
<td>1.698</td>
<td>0.425</td>
<td>4.845</td>
</tr>
<tr>
<td>Projected avg. annual cooling degree days (1000s)</td>
<td>2.747</td>
<td>1.234</td>
<td>1.447</td>
<td>4.719</td>
</tr>
<tr>
<td><strong>Other climate data, 1970-1999 average</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Average annual precipitation (inches)</td>
<td>39.26</td>
<td>14.09</td>
<td>16.25</td>
<td>53.85</td>
</tr>
<tr>
<td>Average annual relative humidity (%)</td>
<td>63.58</td>
<td>8.10</td>
<td>53.31</td>
<td>70.52</td>
</tr>
<tr>
<td>Average annual sunshine (% of available daylight)</td>
<td>60.14</td>
<td>7.85</td>
<td>51.88</td>
<td>72.67</td>
</tr>
<tr>
<td><strong>Other climate data, 2090-2099 projected (CCSM A2)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Projected avg. annual precipitation (inches)</td>
<td>41.60</td>
<td>15.56</td>
<td>14.68</td>
<td>56.91</td>
</tr>
<tr>
<td>Projected avg. annual relative humidity (%)</td>
<td>62.41</td>
<td>8.94</td>
<td>50.64</td>
<td>69.44</td>
</tr>
<tr>
<td>Projected avg. annual sunshine (% of available daylight)</td>
<td>61.52</td>
<td>7.86</td>
<td>53.36</td>
<td>71.76</td>
</tr>
<tr>
<td><strong>Geographic data</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Distance from centroid of puma to ocean (miles)</td>
<td>250.1</td>
<td>272.1</td>
<td>4.3</td>
<td>729.2</td>
</tr>
<tr>
<td>Distance from centroid of puma to Great Lake (miles)</td>
<td>763.2</td>
<td>715.4</td>
<td>54.0</td>
<td>2128.4</td>
</tr>
<tr>
<td>Average land slope (degrees)</td>
<td>1.677</td>
<td>2.131</td>
<td>0.191</td>
<td>4.270</td>
</tr>
<tr>
<td><strong>Demographic data (2000 census)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Weighted population density (people per sq. mile)</td>
<td>5,466</td>
<td>11,997</td>
<td>360</td>
<td>9,981</td>
</tr>
<tr>
<td>Percent high school graduates</td>
<td>80.1%</td>
<td>10.0%</td>
<td>67.2%</td>
<td>90.9%</td>
</tr>
<tr>
<td>Percent of population with bachelors degree</td>
<td>24.1%</td>
<td>12.4%</td>
<td>11.3%</td>
<td>41.0%</td>
</tr>
<tr>
<td>Percent of population with graduate degree</td>
<td>8.7%</td>
<td>5.6%</td>
<td>3.7%</td>
<td>20.3%</td>
</tr>
<tr>
<td>Average age</td>
<td>48.7</td>
<td>2.6</td>
<td>45.3</td>
<td>51.8</td>
</tr>
<tr>
<td>Percent hispanic</td>
<td>8.9%</td>
<td>13.6%</td>
<td>0.6%</td>
<td>81.6%</td>
</tr>
<tr>
<td>Percent black</td>
<td>12.3%</td>
<td>17.6%</td>
<td>0.5%</td>
<td>96.7%</td>
</tr>
<tr>
<td>Population (1000s)</td>
<td>135.9</td>
<td>32.9</td>
<td>103.8</td>
<td>182.2</td>
</tr>
<tr>
<td>Quality of life differential (in logs)</td>
<td>-0.002</td>
<td>0.055</td>
<td>-0.060</td>
<td>0.077</td>
</tr>
</tbody>
</table>
Table 2: Estimation results for the linear, homogenous preferences model
Dependent variable is quality of life (QOL) differential as fraction of income

<table>
<thead>
<tr>
<th>Temperature function</th>
<th>I</th>
<th>II</th>
<th>III</th>
<th>IV</th>
<th>V</th>
<th>VI</th>
<th>VII</th>
<th>VIII</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>HDD/CDD</td>
<td>HDD/CDD  equality</td>
<td>Linear spline</td>
<td>Linear spline</td>
<td>Restricted linear spline</td>
<td>Restricted linear spline</td>
<td>Restricted cubic spline</td>
<td>Restricted cubic spline</td>
</tr>
<tr>
<td>MWTP for a day at 50F (x365)</td>
<td>-0.035</td>
<td>(0.012)</td>
<td>-0.024</td>
<td>(0.012)</td>
<td>-0.185</td>
<td>(0.048)</td>
<td>-0.180</td>
<td>(0.047)</td>
</tr>
<tr>
<td>MWTP for a day at 80F (x365)</td>
<td>-0.127</td>
<td>(0.030)</td>
<td>-0.024</td>
<td>(0.012)</td>
<td>-0.233</td>
<td>(0.045)</td>
<td>-0.252</td>
<td>(0.046)</td>
</tr>
<tr>
<td>Average annual precipitation (inches)</td>
<td>-0.049</td>
<td>(0.018)</td>
<td>-0.107</td>
<td>(0.020)</td>
<td>-0.007</td>
<td>(0.023)</td>
<td>0.017</td>
<td>(0.029)</td>
</tr>
<tr>
<td>Average annual relative humidity (percent)</td>
<td>0.132</td>
<td>(0.048)</td>
<td>0.147</td>
<td>(0.049)</td>
<td>0.071</td>
<td>(0.057)</td>
<td>0.066</td>
<td>(0.050)</td>
</tr>
<tr>
<td>Average annual sunshine (percent of all daytime hours)</td>
<td>0.235</td>
<td>(0.061)</td>
<td>0.115</td>
<td>(0.053)</td>
<td>0.208</td>
<td>(0.060)</td>
<td>0.121</td>
<td>(0.063)</td>
</tr>
<tr>
<td>Average land slope (degrees)</td>
<td>0.006</td>
<td>(0.001)</td>
<td>0.009</td>
<td>(0.001)</td>
<td>0.006</td>
<td>(0.001)</td>
<td>0.004</td>
<td>(0.001)</td>
</tr>
<tr>
<td>Inverse distance to ocean (miles)</td>
<td>0.281</td>
<td>(0.044)</td>
<td>0.308</td>
<td>(0.040)</td>
<td>0.277</td>
<td>(0.043)</td>
<td>0.152</td>
<td>(0.041)</td>
</tr>
<tr>
<td>Squared inverse distance to ocean (miles)</td>
<td>0.014</td>
<td>(0.120)</td>
<td>0.010</td>
<td>(0.123)</td>
<td>0.016</td>
<td>(0.121)</td>
<td>-0.008</td>
<td>(0.050)</td>
</tr>
<tr>
<td>Inverse distance to Great Lakes (miles)</td>
<td>-0.252</td>
<td>(0.048)</td>
<td>-0.274</td>
<td>(0.045)</td>
<td>-0.245</td>
<td>(0.045)</td>
<td>-0.172</td>
<td>(0.031)</td>
</tr>
<tr>
<td>Squared inverse distance to Great Lakes (miles)</td>
<td>0.099</td>
<td>(0.139)</td>
<td>0.105</td>
<td>(0.143)</td>
<td>0.101</td>
<td>(0.140)</td>
<td>0.052</td>
<td>(0.059)</td>
</tr>
<tr>
<td>Log of weighted population density</td>
<td>0.013</td>
<td>(0.003)</td>
<td>0.013</td>
<td>(0.003)</td>
<td>0.013</td>
<td>(0.003)</td>
<td>0.013</td>
<td>(0.003)</td>
</tr>
<tr>
<td>Fraction high school graduates</td>
<td>-0.038</td>
<td>(0.038)</td>
<td>-0.038</td>
<td>(0.038)</td>
<td>-0.041</td>
<td>(0.038)</td>
<td>-0.041</td>
<td>(0.038)</td>
</tr>
<tr>
<td>Fraction bachelors degrees</td>
<td>-0.021</td>
<td>(0.056)</td>
<td>-0.021</td>
<td>(0.056)</td>
<td>-0.018</td>
<td>(0.055)</td>
<td>-0.025</td>
<td>(0.056)</td>
</tr>
<tr>
<td>Fraction graduate degrees</td>
<td>0.351</td>
<td>(0.095)</td>
<td>0.349</td>
<td>(0.095)</td>
<td>0.349</td>
<td>(0.095)</td>
<td>0.359</td>
<td>(0.096)</td>
</tr>
<tr>
<td>Average age (x100)</td>
<td>0.229</td>
<td>(0.065)</td>
<td>0.233</td>
<td>(0.065)</td>
<td>0.233</td>
<td>(0.065)</td>
<td>0.235</td>
<td>(0.068)</td>
</tr>
<tr>
<td>Fraction hispanic</td>
<td>0.005</td>
<td>(0.031)</td>
<td>0.003</td>
<td>(0.032)</td>
<td>0.003</td>
<td>(0.032)</td>
<td>0.003</td>
<td>(0.032)</td>
</tr>
<tr>
<td>Fraction black</td>
<td>-0.071</td>
<td>(0.015)</td>
<td>-0.071</td>
<td>(0.015)</td>
<td>-0.071</td>
<td>(0.015)</td>
<td>-0.069</td>
<td>(0.015)</td>
</tr>
<tr>
<td>State fixed effects</td>
<td>N</td>
<td>N</td>
<td>N</td>
<td>Y</td>
<td>N</td>
<td>Y</td>
<td>N</td>
<td>Y</td>
</tr>
<tr>
<td>Number of observations</td>
<td>2057</td>
<td>2057</td>
<td>2057</td>
<td>2057</td>
<td>2057</td>
<td>2057</td>
<td>2057</td>
<td>2057</td>
</tr>
<tr>
<td>R²</td>
<td>0.428</td>
<td>0.398</td>
<td>0.437</td>
<td>0.693</td>
<td>0.436</td>
<td>0.692</td>
<td>0.438</td>
<td>0.692</td>
</tr>
</tbody>
</table>

Unit of observation is a puma. All regressions are weighted by population in each puma.
MWTP (marginal willingness to pay) is relative to 65F and expressed as a fraction of income.
Linear splines are four-piece with breakpoints at 50F, 65F, and 75F. Cubic spline is 10th degree.
Restricted linear spline forces constant MWTP below 50F and above 75F.
Restricted cubic spline forces constant MWTP over the highest and lowest 5% of the population-weighted U.S. average temperature distribution.
Parenthetical values indicate standard errors clustered on metropolitan statistical area (msa). Non-msa areas are clustered at the state level.
<table>
<thead>
<tr>
<th>Component driven by temperature change</th>
<th>CCSM A2 Scenario</th>
<th>Hadley A1F1 Scenario</th>
</tr>
</thead>
<tbody>
<tr>
<td>Change in welfare as percent of income</td>
<td>-2.4% -0.2% -1.65% -1.4% -1.42% -1.69% -1.98%</td>
<td>-2.57% -0.12% -1.79% -1.48% -1.65% -1.90% -2.36%</td>
</tr>
<tr>
<td>(0.51%) (0.08%) (0.77%) (1.11%) (0.37%) (0.49%) (0.63%)</td>
<td>(0.64%) (0.01%) (0.97%) (1.41%) (0.43%) (0.56%) (0.75%)</td>
<td></td>
</tr>
<tr>
<td>Component driven by other weather changes</td>
<td>-2.28% 0.06% -1.82% -1.76% -1.55% -1.58% -1.83% -2.09%</td>
<td>-2.84% 0.01% -2.17% -2.16% -2.18% -2.23% -2.51%</td>
</tr>
<tr>
<td>(0.56%) (0.04%) (0.81%) (1.13%) (0.37%) (0.48%) (0.71%)</td>
<td>(0.70%) (0.01%) (1.03%) (1.41%) (0.44%) (0.56%) (0.84%)</td>
<td></td>
</tr>
<tr>
<td>($64) ($10) ($95) ($137) ($61) ($78) ($113)</td>
<td>($79) ($2) ($120) ($175) ($54) ($70) ($93) ($131)</td>
<td></td>
</tr>
<tr>
<td>Percent of population losing</td>
<td>96.6% 81.3% 97.4% 96.8% 97.2% 97.5% 97.2%</td>
<td>97.0% 67.8% 98.0% 97.1% 95.9% 94.9% 97.3%</td>
</tr>
<tr>
<td>(0.6%) (6.2%) (12.8%) (27.3%) (1.6%) (9.0%) (7.9%)</td>
<td>(0.8%) (13.2%) (14.9%) (28.1%) (3.2%) (7.4%) (11.2%)</td>
<td></td>
</tr>
</tbody>
</table>

Parenthetical values indicate standard errors obtained via block bootstrap on msa. Non-msa areas are clustered at the state level.
### Table 4: Preference estimates and projected U.S. average welfare impacts from climate change for 2090-2100

<table>
<thead>
<tr>
<th></th>
<th>I</th>
<th>II</th>
<th>III</th>
<th>IV</th>
<th>V</th>
<th>VI</th>
<th>VII</th>
<th>VIII</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Heterogeneous preferences model</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Average MWTP for a day at 50F (x365)</td>
<td>-0.178</td>
<td>-0.164</td>
<td>-0.257</td>
<td>-0.223</td>
<td>-0.162</td>
<td>-0.155</td>
<td>-0.165</td>
<td>-0.221</td>
</tr>
<tr>
<td></td>
<td>(0.048)</td>
<td>(0.038)</td>
<td>(0.063)</td>
<td>(0.048)</td>
<td>(0.057)</td>
<td>(0.079)</td>
<td>(0.142)</td>
<td>(0.126)</td>
</tr>
<tr>
<td>Average MWTP for a day at 80F (x365)</td>
<td>-0.254</td>
<td>-0.228</td>
<td>-0.281</td>
<td>-0.284</td>
<td>-0.224</td>
<td>-0.216</td>
<td>-0.241</td>
<td>-0.262</td>
</tr>
<tr>
<td></td>
<td>(0.052)</td>
<td>(0.040)</td>
<td>(0.056)</td>
<td>(0.046)</td>
<td>(0.058)</td>
<td>(0.074)</td>
<td>(0.155)</td>
<td>(0.115)</td>
</tr>
<tr>
<td>CCSM A2 change in welfare as percent of income</td>
<td>-1.64%</td>
<td>-1.31%</td>
<td>-1.28%</td>
<td>-1.59%</td>
<td>-1.72%</td>
<td>-1.33%</td>
<td>-1.55%</td>
<td>-1.51%</td>
</tr>
<tr>
<td></td>
<td>(0.36%)</td>
<td>(0.27%)</td>
<td>(0.65%)</td>
<td>(0.53%)</td>
<td>(0.35%)</td>
<td>(0.62%)</td>
<td>(0.85%)</td>
<td>(0.60%)</td>
</tr>
<tr>
<td>Hadley A1F1 change in welfare as percent of income</td>
<td>-1.76%</td>
<td>-1.38%</td>
<td>-1.51%</td>
<td>-1.81%</td>
<td>-1.73%</td>
<td>-1.47%</td>
<td>-1.64%</td>
<td>-1.74%</td>
</tr>
<tr>
<td></td>
<td>(0.42%)</td>
<td>(0.32%)</td>
<td>(0.78%)</td>
<td>(0.62%)</td>
<td>(0.43%)</td>
<td>(0.78%)</td>
<td>(1.02%)</td>
<td>(0.71%)</td>
</tr>
<tr>
<td><strong>Homogenous preferences model</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>MWTP for a day at 50F (x365)</td>
<td>-0.165</td>
<td>-0.153</td>
<td>-0.262</td>
<td>-0.207</td>
<td>-0.157</td>
<td>-0.099</td>
<td>-0.063</td>
<td>0.012</td>
</tr>
<tr>
<td></td>
<td>(0.040)</td>
<td>(0.037)</td>
<td>(0.037)</td>
<td>(0.043)</td>
<td>(0.048)</td>
<td>(0.070)</td>
<td>(0.139)</td>
<td>(0.096)</td>
</tr>
<tr>
<td>MWTP for a day at 80F (x365)</td>
<td>-0.226</td>
<td>-0.209</td>
<td>-0.275</td>
<td>-0.260</td>
<td>-0.209</td>
<td>-0.165</td>
<td>-0.120</td>
<td>-0.048</td>
</tr>
<tr>
<td></td>
<td>(0.047)</td>
<td>(0.038)</td>
<td>(0.038)</td>
<td>(0.044)</td>
<td>(0.054)</td>
<td>(0.070)</td>
<td>(0.149)</td>
<td>(0.094)</td>
</tr>
<tr>
<td>CCSM A2 change in welfare as percent of income</td>
<td>-1.40%</td>
<td>-1.14%</td>
<td>-1.07%</td>
<td>-1.42%</td>
<td>-1.65%</td>
<td>-1.24%</td>
<td>-0.93%</td>
<td>-0.79%</td>
</tr>
<tr>
<td></td>
<td>(0.37%)</td>
<td>(0.28%)</td>
<td>(0.66%)</td>
<td>(0.52%)</td>
<td>(0.34%)</td>
<td>(0.59%)</td>
<td>(0.83%)</td>
<td>(0.66%)</td>
</tr>
<tr>
<td>Hadley A1F1 change in welfare as percent of income</td>
<td>-1.48%</td>
<td>-1.21%</td>
<td>-1.27%</td>
<td>-1.65%</td>
<td>-1.67%</td>
<td>-1.35%</td>
<td>-0.86%</td>
<td>-0.87%</td>
</tr>
<tr>
<td></td>
<td>(0.43%)</td>
<td>(0.32%)</td>
<td>(0.77%)</td>
<td>(0.62%)</td>
<td>(0.43%)</td>
<td>(0.75%)</td>
<td>(1.01%)</td>
<td>(0.81%)</td>
</tr>
<tr>
<td><strong>Demographic controls</strong></td>
<td>N</td>
<td>Y</td>
<td>N</td>
<td>Y</td>
<td>N</td>
<td>Y</td>
<td>N</td>
<td>Y</td>
</tr>
<tr>
<td><strong>State fixed effects</strong></td>
<td>N</td>
<td>N</td>
<td>Y</td>
<td>Y</td>
<td>N</td>
<td>Y</td>
<td>N</td>
<td>Y</td>
</tr>
<tr>
<td><strong>Seasonal precip, humid, sun</strong></td>
<td>N</td>
<td>N</td>
<td>N</td>
<td>N</td>
<td>N</td>
<td>Y</td>
<td>Y</td>
<td>N</td>
</tr>
<tr>
<td><strong>California dropped</strong></td>
<td>N</td>
<td>N</td>
<td>N</td>
<td>N</td>
<td>N</td>
<td>N</td>
<td>Y</td>
<td>Y</td>
</tr>
</tbody>
</table>

Unit of observation is a puma. All regressions are weighted by population in each puma.

MWTP (marginal willingness to pay) is relative to 65F and expressed as a fraction of income.

MWTP shown for the heterogeneous preferences model is the income-weighted average MWTP across all PUMAs.

All specifications use a restricted four-piece linear spline for MWTP, with constant MWTP below 50F and above 80F.

Parenthetical values indicate standard errors clustered on msa. Non-msa areas are clustered at the state level.

Homogenous MWTP standard errors are analytic. All other standard errors are block bootstrapped.
Table 5: Preference estimates and projected U.S. average welfare impacts from climate change for 2090-2100. Heterogeneous preferences model with alternative quality of life (QOL) measures

<table>
<thead>
<tr>
<th>QOL measure</th>
<th>Reference case (0.33p - 0.50w)</th>
<th>Underweight prices (0.25p - 1.00w)</th>
<th>Housing prices only (1.00p)</th>
<th>Wages only (-1.00w)</th>
</tr>
</thead>
<tbody>
<tr>
<td>No demographics, no state FE</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Average MWTP for a day at 50F</td>
<td>-0.178 (0.048)</td>
<td>0.134 (0.112)</td>
<td>-1.369 (0.301)</td>
<td>0.476 (0.170)</td>
</tr>
<tr>
<td>(x365)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Average MWTP for a day at 80F</td>
<td>-0.254 (0.052)</td>
<td>0.182 (0.105)</td>
<td>-1.930 (0.344)</td>
<td>0.664 (0.170)</td>
</tr>
<tr>
<td>(x365)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CCSM A2 change in welfare as percent of income</td>
<td>-1.64% (0.36%)</td>
<td>1.25% (0.60%)</td>
<td>-12.62% (2.60%)</td>
<td>4.40% (1.13%)</td>
</tr>
<tr>
<td>Hadley A1F1 change in welfare as percent of income</td>
<td>-1.76% (0.42%)</td>
<td>1.67% (0.70%)</td>
<td>-14.50% (3.01%)</td>
<td>5.29% (1.31%)</td>
</tr>
</tbody>
</table>

Demographics, state FE

| Average MWTP for a day at 50F | -0.223 (0.048) | -0.261 (0.108) | -0.514 (0.282) | -0.133 (0.160) |
| (x365) | | | | |
| Average MWTP for a day at 80F | -0.284 (0.046) | -0.326 (0.083) | -0.672 (0.261) | -0.158 (0.127) |
| (x365) | | | | |
| CCSM A2 change in welfare as percent of income | -1.59% (0.53%) | -2.43% (0.78%) | -2.10% (2.01%) | -1.90% (0.92%) |
| Hadley A1F1 change in welfare as percent of income | -1.81% (0.62%) | -2.59% (0.90%) | -2.86% (2.50%) | -1.88% (1.12%) |

Unit of observation is a puma. All regressions are weighted by population in each puma. MWTP (marginal willingness to pay) is relative to 65F and expressed as a fraction of income. MWTP shown for the heterogeneous preferences model is the income-weighted average MWTP across all PUMAs. All specifications use a restricted four-piece linear spline for MWTP, with constant MWTP below 50F and above 75. Parenthetical values indicate standard errors clustered on msa. Non-msa areas are clustered at the state level. Homogenous MWTP standard errors are analytic. All other standard errors are block bootstrapped.