Aversion to Extreme Temperatures, Climate Change, and Quality of Life

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David Albouy, University of Michigan and NBER

Walter Graf, University of Michigan

Ryan Kellogg, University of Michigan and NBER

Hendrik Wolff, University of Washington

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 extreme heat than to reduce extreme cold. Combining these estimates with "business as usual" climate forecasts for the United States, we find welfare losses in most areas by 2100, with particularly large effects in California, southern states, and urban centers. On average, the cost of hotter summers exceeds the gain from warmer winters by 2 to 3 percent of income per year. These results account for taste heterogeneity and sorting; moreover, they 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 to 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. A more recent climate model developed at MIT (Sokolov *et al.* 2009), predicts even more dramatic warming of 9.4°F under a similar scenario. 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 extreme heat and extreme 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 plots current and projected temperature distributions for four U.S. cities. 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 current 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 Ann Arbor, will benefit from large reductions in cold while others, such as Houston, 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 find that households are willing to pay more on the margin to avoid heat than they are to avoid cold, particularly at the extremes. As a result, we find that most U.S. residents will be made worse off by large temperature increases. We use the business-as-usual A2 scenario from the IPCC's fourth assessment report (2007), which forecasts population-weighted average U.S. warming of 8.3°F by 2100. Under this scenario, we project a significant decrease in QOL of 2 to 3 percent of income per year by 2100. These results are robust to the inclusion of state fixed effects and to allowing for preference heterogeneity and mobility. Under the moderate warming projected by 2050 (3.4°F), we find damage estimates that are only about 0.5 percent of income and statistically insignificant, suggesting that the marginal damages of greenhouse gas emissions rise with the quantity emitted.

We also consider the role that migration may play in mitigating the damage from climate change. Even allowing for large migration responses—enough enough to depopulate half of Los Angeles in some scenarios—we find that at a minimum two-thirds, and in most cases 90 percent, of the estimated welfare costs will still be incurred, assuming that households stay within U.S. borders. Most locations will experience a QOL decrease following climate change, and increased 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 extreme temperatures on quality of life, meaning the value of amenities for which there are no explicit markets. These welfare impacts do

[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 carefully accounts for the incidence of extreme temperatures—an approach we follow here—rather than relying on seasonal averages or heating degree days and cooling degree days.

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 extreme temperatures and reflect indoor exposure only insofar as it is imperfectly controlled through heating and cooling.[2]

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 (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 temperature 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).[3] 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

[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).

[3] Hedonic studies focusing on countries other than the U.S. include Maddison and Bigano (2003) in Italy, Rehdanz (2006) in Great Britain, Rehdanz and Maddison (2009) in Germany, and Timmins (2007) in Brazil. In addition, alternative non-hedonic approaches have been used to estimate the impact of climate change on amenities. Shapiro and Smith (1981) and Maddison (2003) use a household production function approach, Fritjers and Van Praag (1998) use hypothetical equivalence scales, and Rehdanz and Maddison (2005) link a panel of self-reported happiness across 67 countries with temperature and precipitation.

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 (Deschênes and Greenstone 2007, Schlenker and Roberts 2009) and health (Deschênes and Greenstone 2008) has shown that extreme temperatures can be important determinants of welfare impacts; however, this issue has not been explored in the amenity valuation literature using housing prices and wages. 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 also substantially affects the distribution of these impacts across the U.S.

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 welfare impacts from a simple 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 mobility, 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 counties, 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^i 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_j^i is equal to $R^i + I^i + w_j^i$, out of which households pay a federal income tax of $\tau\left(m_j^i\right)$ that is redistributed in uniform lump-sum payments.[4]

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^i as $\varphi^i w_j$, where φ^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 $\boldsymbol{Z_j}$ that includes climate, and by a scalar characteristic ξ_j that is observable to households but not to the

[4] 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 ($\boldsymbol{Z}$, ξ) is a complete, compact subset of $\mathbb{R}^{K+1}$.[5] We allow households to have heterogeneous preferences over ($\boldsymbol{Z}$, ξ), following Bajari and Benkard (2005), so that the utility of household *i* residing at location *j* is given by $u_j^i = U^i(x^i, \boldsymbol{Z}_j, \xi_j)$, which we assume to be continuous and differentiable in all its arguments, and also strictly increasing in x^i and ξ_j. Households are assumed to be perfectly mobile, so that each chooses the location *j* that maximizes its utility subject to the budget constraint $x^i = m_j^i(1 - \tau\left(m_j^i\right)) - p_j$.[6]

Let $\boldsymbol{p}(\boldsymbol{Z}_j, \xi_j)$ denote the function relating cost of living p_j to *j*'s characteristics, and likewise for $\boldsymbol{w}(\boldsymbol{Z}_j, \xi_j)$ and w_j. These functions are determined by an equilibrium between households' demands for local amenities, firms' location decisions, and local land supply.[7] In this equilibrium, the following demand-side first order condition, in which λ denotes the marginal utility of money, must hold for all characteristics *k*:

$$\begin{aligned}\frac{1}{m_j^i\lambda}\frac{\partial U^i(x^i,\boldsymbol{Z}_j,\xi_j)}{\partial Z_k} &= \frac{1}{m_j^i}\frac{\partial \boldsymbol{p}(\boldsymbol{Z}_j,\xi_j)}{\partial Z_k} - \frac{(1-\tau(m_j^i))\varphi^i}{m_j^i}\frac{\partial \boldsymbol{w}(\boldsymbol{Z}_j,\xi_j)}{\partial Z_k} \\ &= \frac{p_j}{m_j^i}\frac{\partial \ln \boldsymbol{p}(\boldsymbol{Z}_j,\xi_j)}{\partial Z_k} - \frac{w_j^i(1-\tau(m_j^i))}{m_j^i}\frac{\partial \ln \boldsymbol{w}(\boldsymbol{Z}_j,\xi_j)}{\partial Z_k}\end{aligned} \tag{1}$$

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

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[5] In our empirical implementation, this completeness assumption will be an approximation since we examine a finite, though large, number of U.S. counties. 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 counties 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).

[6] 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.

[7] The existence and differentiability of $\boldsymbol{p}(\boldsymbol{Z}_j, \xi_j)$ and $\boldsymbol{w}(\boldsymbol{Z}_j, \xi_j)$ hold under mild conditions. Rosen demonstrates the existence and differentiability of the quality of life function $\hat{\boldsymbol{Q}}(\boldsymbol{Z}_j, \xi_j)$ under the assumptions on demand given here and perfectly competitive land supply, while Bajari and Benkard (2005) show that a Lipshitz condition on $U^i(x^i, \boldsymbol{Z}_j, \xi_j)$ is sufficient even under imperfect competition. Given this result, the separate existence and differentiability of $\boldsymbol{p}(\boldsymbol{Z}_j, \xi_j)$ and $\boldsymbol{w}(\boldsymbol{Z}_j, \xi_j)$ are given by the separate mobility conditions on households and firms and an assumption that local productivity differentials are continuous and differentiable in $\boldsymbol{Z}_j$ and ξ_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 τ'. 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 $\hat{w}_j$.

$$\begin{aligned}\hat{Q}^j &= s_y \hat{p}_j - (1-\tau')s_w \hat{w}_j \\ &= 0.33\hat{p}_j - 0.50\hat{w}_j\end{aligned} \tag{2}$$

Let $\hat{\boldsymbol{Q}}(\boldsymbol{Z}_j, \xi_j)$ denote QOL as a function of local characteristics, per (2) and the functions $\boldsymbol{p}(\boldsymbol{Z}_j, \xi_j)$ and $\boldsymbol{w}(\boldsymbol{Z}_j, \xi_j)$. 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*:

$$\frac{1}{m_j^i \lambda} \frac{\partial U^i(x^i, \boldsymbol{Z}_j, \xi_j)}{\partial Z_k} = \frac{\partial \hat{\boldsymbol{Q}}(\boldsymbol{Z}_j, \xi_j)}{\partial Z_k} \tag{3}$$

The first order condition (3) is illustrated in figure 2 in the case of a model with a single characteristic, summer average temperature T_s. The bold line denotes a hypothetical QOL function $\hat{\boldsymbol{Q}}(T_s)$ 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, $\hat{\boldsymbol{Q}}(T_s)$ can be thought of as the hedonic "price" of a location with a summer average temperature of T_s. The slope of $\hat{\boldsymbol{Q}}(T_s)$ 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 matched to counties using the GeoCorr2 engine from the University of Missouri Census Data Center. As a result, less populous counties share the same data.

Inter-county 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 φ^i factors in the model. We therefore regress the log wage of worker i in county j on county-indicators μ_j^w and extensive controls X_{ij}^w (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 $\ln w_{ij} = X_{ij}^w \beta^w + \mu_j^w + \varepsilon_{ij}^w$. The estimates μ_j^w are used as the county wage differentials w_j and are interpreted as the causal effect of a county's characteristics on a worker's wage. Identifying these differentials requires that workers do not sort across locations according to their unobserved skills.[8]

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 $\ln p_{ij} = Y_{ij} \beta^p + \mu_j^p + \varepsilon_{ij}^p$. The coefficients μ_j^p are used as housing cost differentials p_j. Proper identification of housing-cost differences requires that average unobserved housing quality does not vary systematically across locations.

[8] This assumption may not hold completely: Glaeser and Mare (2001) argue that up to 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.[9] Our QOL differential therefore does not incorporate these costs and instead primarily reflects the disamenity value of extreme outdoor temperatures plus the disamenity value of extreme 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 extreme temperatures.

Descriptive statistics for QOL and other county-level control variables are given in table 1. Estimated QOL differentials across counties 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. Temperature Data and Predicted Climate Changes

We conduct our analysis at the county-level using 3,105 counties in the contiguous 48 states. In our initial empirical specifications, the two variables by which we measure the climate prevalent in any given county are its heating degree days (HDD) and cooling degree days (CDD). HDD and CDD are measures of how frequently, and how far, a county's temperatures

[9] This approach follows the standard practice in the QOL literature from Blomquist *et al.* (1988) to Chen and Rosenthal (2008).

are below (for HDD) or above (for CDD) a baseline temperature of 65°F.[10] 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. The number of HDD for a given location is equal to the sum of the heating degrees for every day of an average year. CDD are defined in a similar fashion for temperatures greater than 65°F. HDD and CDD data were generously provided by Deschênes and Greenstone (2008), who derived their HDD and CDD variables from the National Climactic Data Center's daily weather data from 1961-1990.

In richer specifications, we make use of "binned" county-level climate data. These data indicate, for an average year between 1961 and 1990, the number of days in which a given county's residents would experience an average temperature within a given one-degree wide bin. These data were also provided by Deschênes and Greenstone (2008).

Predicted temperature changes are taken from the Intergovernmental Panel on Climate Change Assessment Report 4 (IPCC AR4), which presents four climate change scenarios. We focus on the A2 "business as usual" scenario under which the global average surface temperature will increase by about 6.5°F by the year 2100.

Figure 1 plots, for four selected U.S. locations, the projected future distribution of temperatures per the A2 scenario against the present distribution. At all four locations, there is a substantial predicted increase in exposure to days in which the average temperature is greater than 80°F by 2100. This increase in extreme heat is offset by reductions in extreme cold in some, but not all, locations. Table 1 summarizes the projected temperature changes in terms of HDD and CDD: the average U.S. county will experience a reduction in HDD of 33% and an increase in CDD of 116%. Figures 4 and 5 map the present and projected distributions of HDD and CDD across the U.S. The increases are CDD are widespread and substantial in all but the coldest regions of the U.S.

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[10] Graves (1979) began the use of HDD and CDD as amenity variables, now common in the QOL literature.

4. Results from 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 county j's QOL differential $\hat{Q}_j$ on climate and other characteristics $\boldsymbol{Z_j}$ of county j.

$$\hat{Q}_j = \sum\nolimits_k \pi_k Z_{jk} + \xi_j \tag{4}$$

The parameters π_k represent the WTP of households for an additional unit of Z_k, measured as a fraction of income. The disturbance term ξ_j is a vertical location characteristic that is observed by households but not by the econometrician. Consistent estimation of the π_k requires that ξ_j be orthogonal to the characteristics $\boldsymbol{Z_j}$. In the absence of instruments, this orthogonality cannot be tested and must be assumed. We therefore assess the stability of our estimates of the π_k to alternative specifications.

4.1 An empirical model based on HDD and CDD

We first estimate a particularly simple version of (4) in which climate enters only through the variables HDD and CDD. Such a specification is a natural starting point in light of the view that these variables 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 can decrease only linearly away from 65°F.

The results from estimating (4) using HDD and CDD are presented in table 2. Column I reports the estimates of a model in which HDD and CDD constitute the only columns of $\boldsymbol{Z}$. The estimates suggest that households have a strong willingness to pay to avoid extreme temperatures, and very hot weather in particular. The WTP to avoid an additional 1000 HDD is 2.5% of income and the WTP to avoid an additional 1000 CDD is 5.3% of income. Both of these estimates are statistically significant at the 1% level using standard errors that are clustered on metropolitan statistical area (msa), of which there are 321 in the data.[11]

Column II adds a set of variables to (4) to control for four natural county-level characteristics: precipitation, mountainousness (measured by the average slope in the county), an ocean coastline, and a Great Lakes coastline. Inclusion of these variables substantially attenuates the WTP for HDD and CDD relative to column I; these WTP are now -0.8% and -1.9% of income, respectively. The estimated WTP coefficient for each characteristic has the expected sign: precipitation decreases WTP, while coastlines and mountains increase it. The decrease in WTP for CDD upon inclusion of the natural controls can be attributed to a positive correlation between CDD and precipitation (due to the hot and rainy South), a negative correlation between CDD and mountainousness, and a negative correlation between CDD and a coastline.

Column III controls for demographic characteristics of each county: population density and the average education level. The percentage of a county's population that has earned at least a bachelors' degree is estimated to have a particularly strong impact on QOL: the WTP for a one percentage point increase in bachelors' degree attainment is 0.26% of income. In this specification, the estimated coefficient on HDD is essentially unchanged, and that on CDD is lower in magnitude than was the case in column II, though still greater in magnitude than that on HDD.

[11] Rural counties that do not belong to an msa are clustered together at the state level. Some counties belong to multiple msas; we treat these counties as part of the msa with the largest population.

In column IV, we control for unobserved state-specific factors (regulations, for example) by including a set of state fixed effects in the specification. This regression therefore only uses within-state variation in climate to identify the WTP for additional HDD and CDD. In this specification, the magnitudes of the estimated WTP for HDD and CDD both increase, and the estimated WTP to avoid extreme heat is still greater than that to avoid extreme cold.

The central result that heat is worse than cold on the margin makes a great deal of intuitive sense. The second law of thermodynamics explains that it is more costly for physical and biological 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.

Using climate change projections for 2090-2100, we calculate welfare impacts for each specification I through IV reported in table 2 and present these impacts in table 3. In specification I, without controls, the overall estimated impact on QOL is quite large in aggregate—3.6% of national income—and statistically significant at the 1% level. This estimate is, however, somewhat sensitive to alternative specifications, and while always negative is below 1.0% of income for specification III (and is no longer statistically significant at conventional levels). Figure 6 presents a map of the county-specific changes in QOL predicted by specification IV. The negative welfare impact of climate change is concentrated in the South, where the increase in CDD substantially outweighs the decrease in HDD. Some northern and mountainous areas are predicted to benefit from climate change due to milder winters.

Overall, while these results from the simple linear, homogenous preference model based on HDD and CDD suggest that climate change may significantly impact welfare through a reduction in QOL, the noisiness of the point estimates precludes a more precise conclusion at this point.

4.2 An empirical model based on a flexible function of climate

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 climate 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.[12]

We model $f(t)$ using a 4th degree cubic spline per (5) below, in which $S_1(t)$ through $S_4(t)$ are standard cubic B-spline basis functions defined over the support of all temperatures observed in the data.[13]

$$f(t) = \beta_1 S_1(t) + \beta_2 S_2(t) + \beta_3 S_3(t) + \beta_4 S_4(t) \tag{5}$$

We estimate this spline using the climate data that are "binned" into one-degree intervals. Defining N_{jt} as the average number of days per year at location j for which the average temperature is between t and $t+1$, we flexibly estimate climate preferences using (6):

$$\begin{aligned} \hat{Q}_j &= \sum_t N_{jt} f(t) + \alpha \cdot Controls_j + \xi_j \\ &= \sum_{s=1}^{4} \beta_k \left(\sum_t N_{jt} S_s(t)\right) + \alpha \cdot Controls_j + \xi_j \end{aligned} \tag{6}$$

The shape of the estimated WTP curve $f(t)$ is dictated by the estimates of β_1 through β_4. Estimated WTP curves are presented in figure (7); panel (A) presents the case in which all controls are included in the specification, and panel (B) includes all controls and state fixed effects. In both cases, WTP is maximized very near 65°F, in agreement with the HDD and CDD

[12] 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.

[13] The results discussed below (including those of section 6) are qualitatively unchanged when we use a 5th degree rather than 4th degree cubic spline.

specifications. The flexible WTP curves shown in figure 7 also agree with the HDD and CDD specifications in that there is greater disutility from hot weather than from cold weather; however, this disparity is accentuated with the flexible functional form. WTP decreases with an increasing rate as the temperature increases above 65°F but flattens at extremely cold temperatures. In addition, the WTP to avoid heat and cold is estimated to be greater when state fixed effects are included in the specification.

Using these estimates to project welfare losses from climate change requires, in some counties, extrapolation of the WTP curve beyond the support of the observed present-day temperature data. Rather than extrapolate the spline curves beyond the support of the data used to estimate them, we conservatively assume that the WTP for extremely hot days beyond the support is constant and equal to the WTP at the hottest temperature observed in the present-day data.

The particularly strong aversion to extreme heat shown in figure 7 is manifest in larger estimates of welfare losses from this flexible specification than from the HDD and CDD specification. Estimates of welfare losses due to climate change through 2090-2100 are presented in the upper section of table 4 for specifications with different sets of controls and fixed effects. Across these specifications, the smallest point estimate of welfare losses is 2% of income, and losses are statistically distinct from zero at the 10% level in all but specification I (natural controls, no state fixed effects). As with the HDD and CDD-based model, the welfare estimates vary across specifications, with specifications including state fixed effects yielding welfare impacts that are approximately 80% larger than those without them.

The lower section of table 4 presents welfare estimates that use climate change projections for 2040-2050. These estimated near-term welfare losses are approximately five times smaller than those estimated for 2090-2100 and are generally not statistically distinct from zero at conventional significance levels. These results suggest that moderate levels of climate change may not be very costly in terms of lost amenity values.

5. A Hedonic Model with Heterogeneous Preferences and Sorting

5.1 Empirical strategy

We now relax the assumption that all households in the U.S. share homogenous preferences for hot and cold weather. Furthermore, 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 (3) and illustrated in figure 2. Given a nonlinear hedonic price function $\hat{\boldsymbol{Q}}(\boldsymbol{Z}_j, \xi_j)$, the MWTP of households located at j for a given characteristic k is simply given by $\partial\hat{\boldsymbol{Q}}(\boldsymbol{Z}_j, \xi_j) / \partial Z_k$. Thus, flexible estimation of $\hat{\boldsymbol{Q}}(\boldsymbol{Z}_j, \xi_j)$ 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 residents of 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. This function seems likely to be concave in temperature; households should have particularly large MWTPs to avoid severe heat and cold (at the far extremes, for example, the issue of survival becomes relevant). 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.[14]

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[14] Should the hedonic price function $\hat{\boldsymbol{Q}}(\boldsymbol{Z}_j, \xi_j)$ exhibit any concavities, the linear WTP assumption implies that at a concavity in $\hat{\boldsymbol{Q}}(\boldsymbol{Z}_j, \xi_j)$ a household satisfying the FOC will actually be locally minimizing utility rather than maximizing utility. The present version of the paper ignores this possibility. In future versions, we will address this

To flexibly estimate $\hat{\boldsymbol{Q}}(\boldsymbol{Z}_j, \xi_j)$, 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 $j*$, $\hat{\boldsymbol{Q}}(\boldsymbol{Z}_j, \xi_j)$ satisfies (7) below:

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

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

$$\boldsymbol{\beta}^{j*} = \arg\min_{\boldsymbol{\beta}} (\hat{\boldsymbol{Q}} - \boldsymbol{Z\beta})' \boldsymbol{W} (\hat{\boldsymbol{Q}} - \boldsymbol{Z\beta}) \tag{8}$$

$$\hat{\boldsymbol{Q}} = \left[\hat{Q}_j\right]; \quad \boldsymbol{Z} = \left[Z_j\right]; \quad \boldsymbol{W} = \operatorname{diag}\left[K_h(\boldsymbol{Z}_j - \boldsymbol{Z}_{j*})\right] \tag{9}$$

$\boldsymbol{W}$ is a matrix of kernel weights so that, in the estimation of prices local to $j*$, locations that are similar to $j*$ in characteristics space will receive the greatest weight. We use a normal kernel function with a bandwith h of 2, per (10) and (11) below. $\hat{\sigma}_k$ denotes the standard deviation of characteristic k across the sample.

$$K(\boldsymbol{Z}) = \prod_k N(Z_k / \hat{\sigma}_k) \tag{10}$$

$$K_h(\boldsymbol{Z}) = K(\boldsymbol{Z}/h)/h \tag{11}$$

In our specification of the climate variables in $\boldsymbol{Z}$, we retain the 4$^{\text{th}}$ degree cubic spline function of temperature used in section 4.2. This spline specification, in combination with the local linear regression approach, introduces considerable flexibility into how households in different locations can value heat and cold. The MWTP for extreme heat varies not just with the climate of a given location, but also with other characteristics. For example, residents in mountainous locations are permitted to have relatively strong preferences for cold weather and residents in urban areas are permitted to be relatively averse to heat.

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issue by determining the minimum amount of concavity in the utility function necessary such that the second order condition for utility maximization is satisfied at all points on the hedonic price function.

5.2 Estimation results

Figure 8 displays estimated MWTP curves as a function of temperature at four locations: Ann Arbor, MI; Boston, MA; Houston, TX; and San Francisco, CA. The specification in each case includes all natural and demographic controls but no state fixed effects. We conservatively force the MWTP curves to be flat outside the temperature support of each location.

The differences in the MWTP curves across locations broadly conform to intuition. Aversion to extreme temperatures is estimated to be greatest in San Francisco, which has both a very mild climate and high cost of living. In Houston, which has a relatively warm climate, the estimated MWTP curve has a maximum greater than 70°F, which is not the case in any of the other three cooler locations. In Ann Arbor, which is subject to both very cold and very hot days, aversion to extreme temperatures is estimated to be relatively weak. In all four locations, however, aversion to extreme heat is greater than aversion to extreme cold, consistent with findings from the homogenous models.

Figure 9 presents maps that illustrate the estimated variation in preferences across the U.S. Panel (A) maps preferences for cold weather: the distribution of MWTP for an additional day of 20-21°F, relative to 65-66°F. Aversion to cold is generally estimated to be strongest in the Southeast, along the coasts, and in urban areas (the positive MWTPs in the north-central part of the country are not statistically significant). Panel (B) maps preferences for hot weather: the distribution of MWTP for an additional day of 80-81°F, relative to 65-66°F. We estimate that this MWTP is negative at nearly all locations, and is largest in magnitude along the coasts and in urban areas. Aversion to heat is generally lower in far-north or far-south areas than in "central" states such as Kentucky.

The summary welfare results for climate change to 2090-2100 from the heterogeneous preferences model are presented in table 5 for four different specifications. When preference heterogeneity is allowed for, the welfare estimates are fairly stable across different controls and inclusion or exclusion of state fixed effects: the point estimates range from -2.2% to -3.0% of income. Including demographic controls results in a slight decline in estimated welfare losses, while inclusion of state fixed effects results in a modest increase. With the exception of specification II, in which the presence of state fixed effects and the lack of demographic controls generate large confidence intervals, the welfare estimates are statistically significant at the 5% level. We calculate standard errors via a clustered bootstrap on metropolitan statistical area (msa), thereby assuming that the disturbances within each msa are perfectly correlated. The reported standard errors may therefore be conservative.

The distribution of welfare impacts is presented in figure 10. The map in panel (A) includes all natural and demographic controls, and the map in panel (B) also includes state fixed effects. In both maps, welfare losses are generally greater in southern states, though not to the same extent as when preferences are assumed to be homogenous. This change in distribution reflects the estimated preference-based sorting of households: those with strong aversion to heat tend not to live in very hot areas such as Texas and Florida. California, with a population that is estimated to particularly dislike extreme weather, is estimated to suffer the most from climate change, while some northern areas are projected to benefit.

Overall, these estimation results indicate that the impact of climate change through 2090-2100 on QOL is most likely to be between -2.2% to -3.0% of income. The results and confidence intervals generally rule out positive overall welfare effects. In addition, the results indicate substantial heterogeneity in the distaste for hot and cold weather, which in turn impacts the distribution of climate change’s impacts.

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.[15] 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 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.

Assume that the housing supply is given by a function with a constant elasticity ε^s. Denote the climate-driven QOL change in county j by $\Delta\hat{Q}_j$ and the U.S. average QOL change by $\Delta\hat{Q}_{avg}$. In the absence of impacts over overcrowding on QOL or firm productivity,[16] the log change in population in county j, denoted ΔN_j, is given by:

$$\Delta N_j = \varepsilon^s (\Delta\hat{Q}_j - \Delta\hat{Q}_{avg}) \tag{12}$$

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 county-specific impacts of climate change on QOL from section 4, then yields estimates of county-level migration.

Estimated average QOL impacts, post-migration, are displayed in table 6 for four preference models: the HDD and CDD model with and without fixed effects, and the spline

[15] Forecasting migration in a model with heterogeneous preferences requires simulation that is beyond the scope of the present paper. We are considering such modeling in future work.

[16] 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 elasticity ε^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 ε^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.

model with and without fixed effects. All natural and demographic controls are included in all four cases. We find that, even with a large housing supply elasticity of 5, migration does not substantially attenuate the estimated climate change impacts: the largest reduction in the magnitude of the welfare loss across all models is 12.9%.

The importance of migration for the estimated welfare impacts is small despite the fact that some models predict substantial migration. In the spline specification with state fixed effects, for example, Dallas, Texas is estimated to lose one-third of its population. However, the value of this migration is constrained by the fact that our QOL estimates suggest that there are few locations that will improve as a result of climate change. That is, some households will move from locations that become substantially worse-off to locations that become somewhat worse-off, but few will move to locations that become better-off. In addition, even with an elasticity of 5, these movements ultimately become constrained by price increases associated with crowding into the relatively more desirable locations. 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 because we want our estimates to reflect the potential for climate adaptation. This approach does raise concerns regarding omitted location-specific factors: we address this issue by examining the robustness of our estimates to alternative specifications and controls, including models that include state fixed effects.

Our preferred econometric model allows for preference heterogeneity and sorting across households. This model yields aggregate estimates of welfare losses from climate change that are reasonably stable once natural county characteristics such as precipitation and mountainousness are controlled for. We estimate that the most likely welfare impact of climate change on quality of life will be between -2.2% and -3.0% of income on average. The confidence intervals around our estimates generally rule out positive welfare impacts. Welfare losses are estimated to be particularly severe in California, and are generally large in southern states and urban areas. In addition, we find that migration is likely to play only a minor role in mitigating these effects.

Our results also suggest that the amenity costs of climate change are likely to be convex. The A2 scenario predicts a temperature increase by 2100 that is approximately 2.5 times as great as the projected 2050 increase, yet the welfare loss we estimate for 2100 is four to six times greater than that estimated for 2050. This finding aligns with research into the agricultural sector (Schlenker *et al.* 2006, Schlenker and Roberts 2009) in indicating that the costs of climate change will be substantially driven by the increased incidence of extremely hot days. The importance of these extreme days suggests that carbon abatement programs that reduce temperature increases by a few degrees, potentially at low cost, may be highly valuable in mitigating climate change damages.

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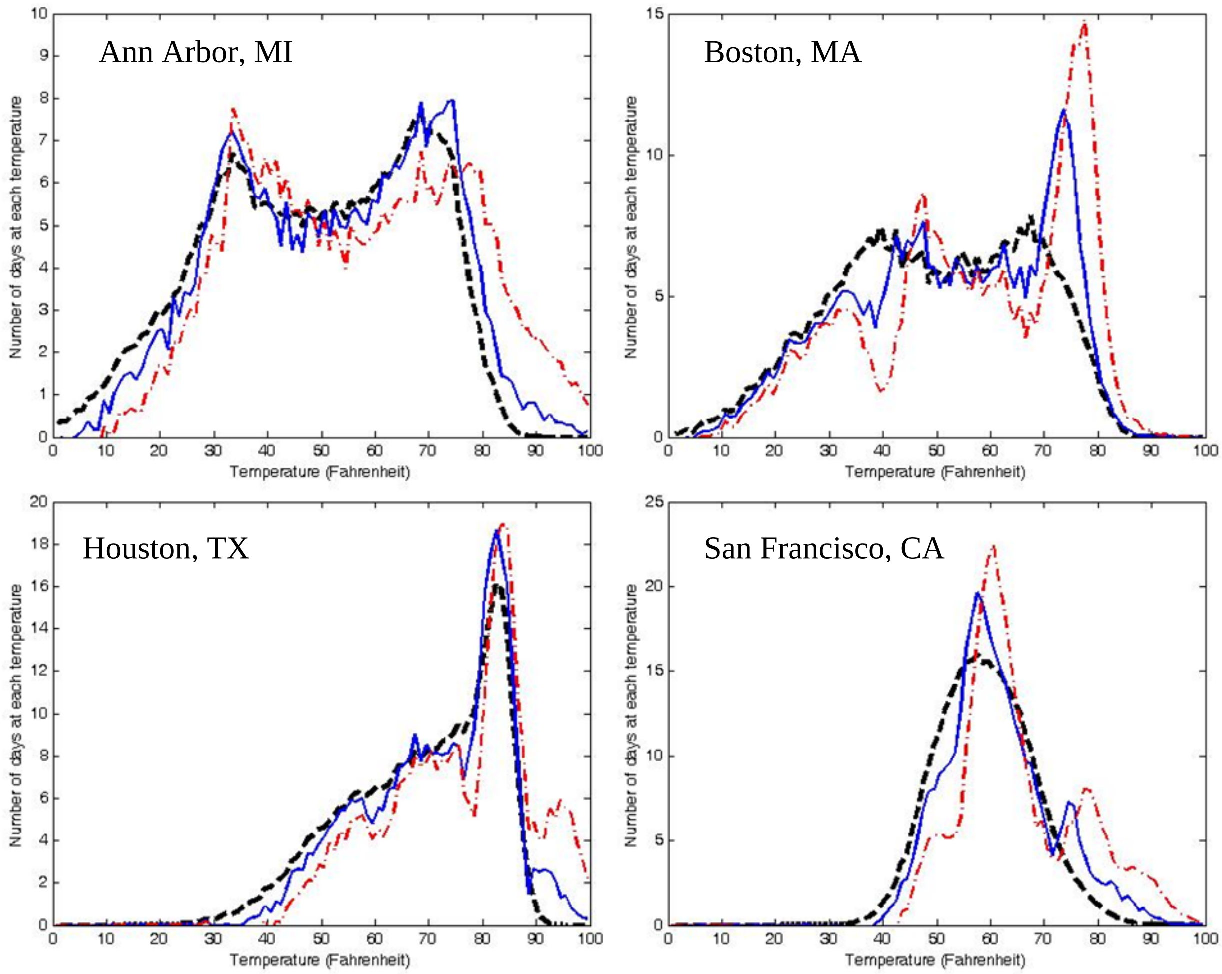
Figure 1: Present and projected future climates in select locations

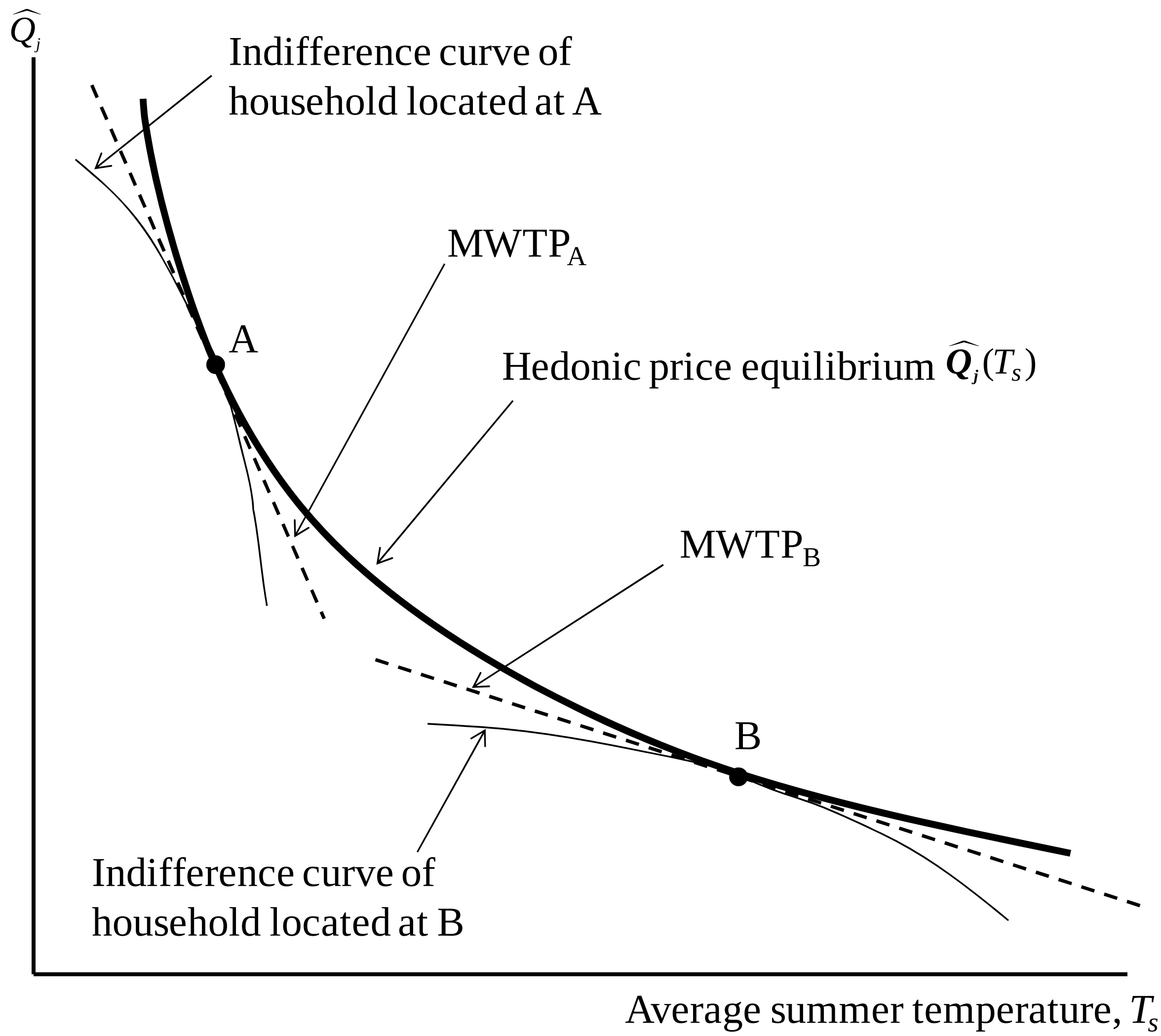
Projections use the IPCC A2 scenario



Lines indicate the average number of days in which the average temperature falls within each one-degree temperature bin

Thick black dashed line: present climate, 1960-1990
Thin blue solid line: projected climate, 2040-2050
Thin red dash-dot line: projected climate, 2090-2100

Figure 2: Illustrative hedonic price function with demand-side equilibrium FOC's satisfied



The quality of life hedonic price measure $\hat{Q}_j$ reflects both local housing cost and wage differentials and is derived in section 2.1

Figure 3: Quality of life (QOL) differentials in 2000

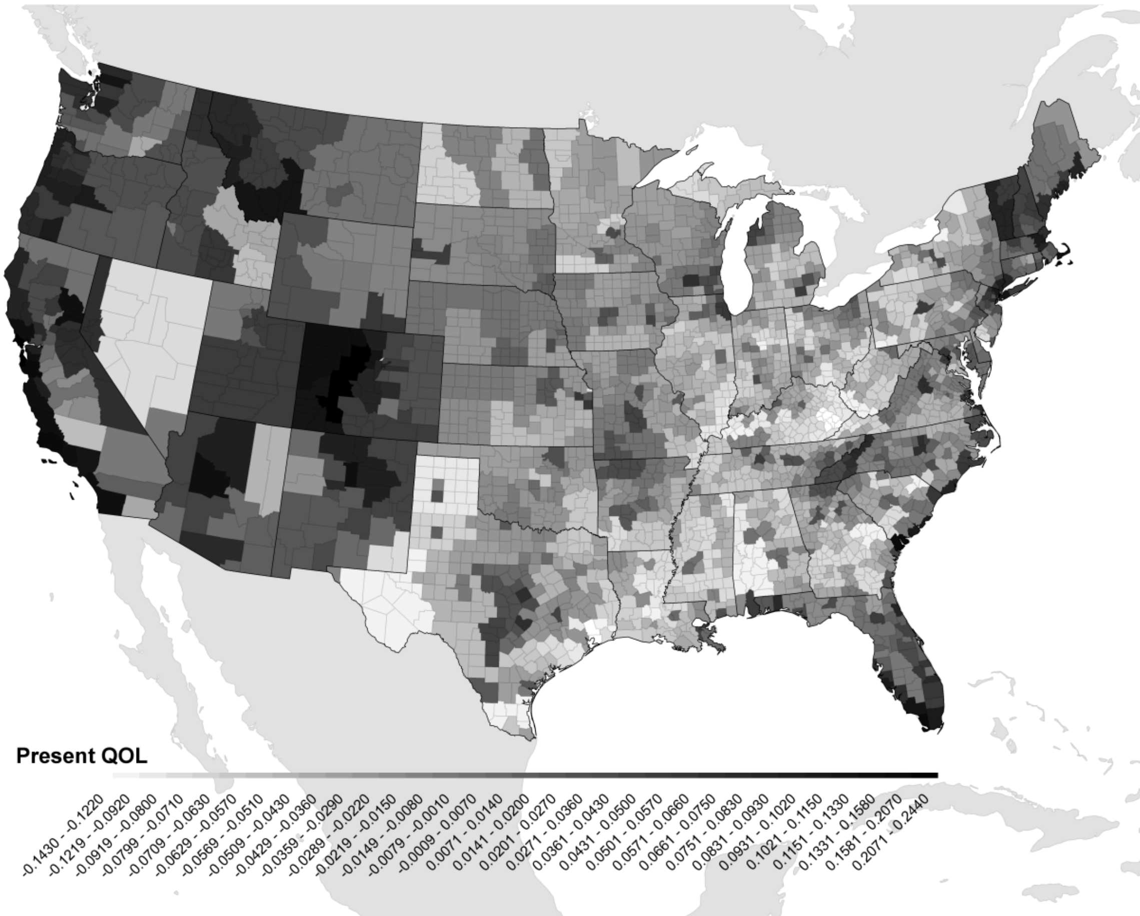


Figure 4: Maps of present (1960-1990) and projected (2090-2100) heating degree days

Projections based on the IPCC A2 scenario

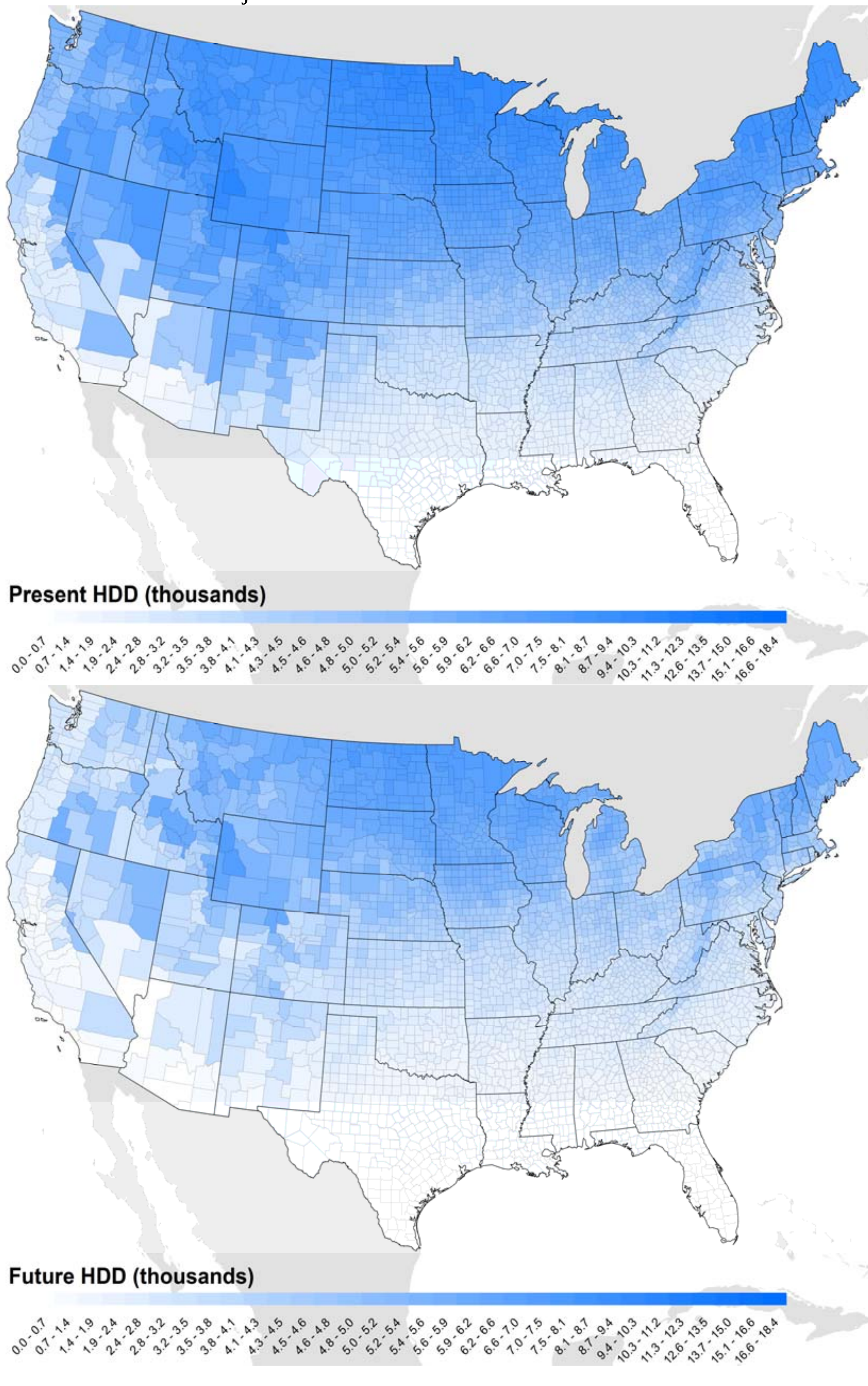


Figure 5: Maps of present (1960-1990) and projected (2090-2100) cooling degree days

Projections based on the IPCC A2 scenario

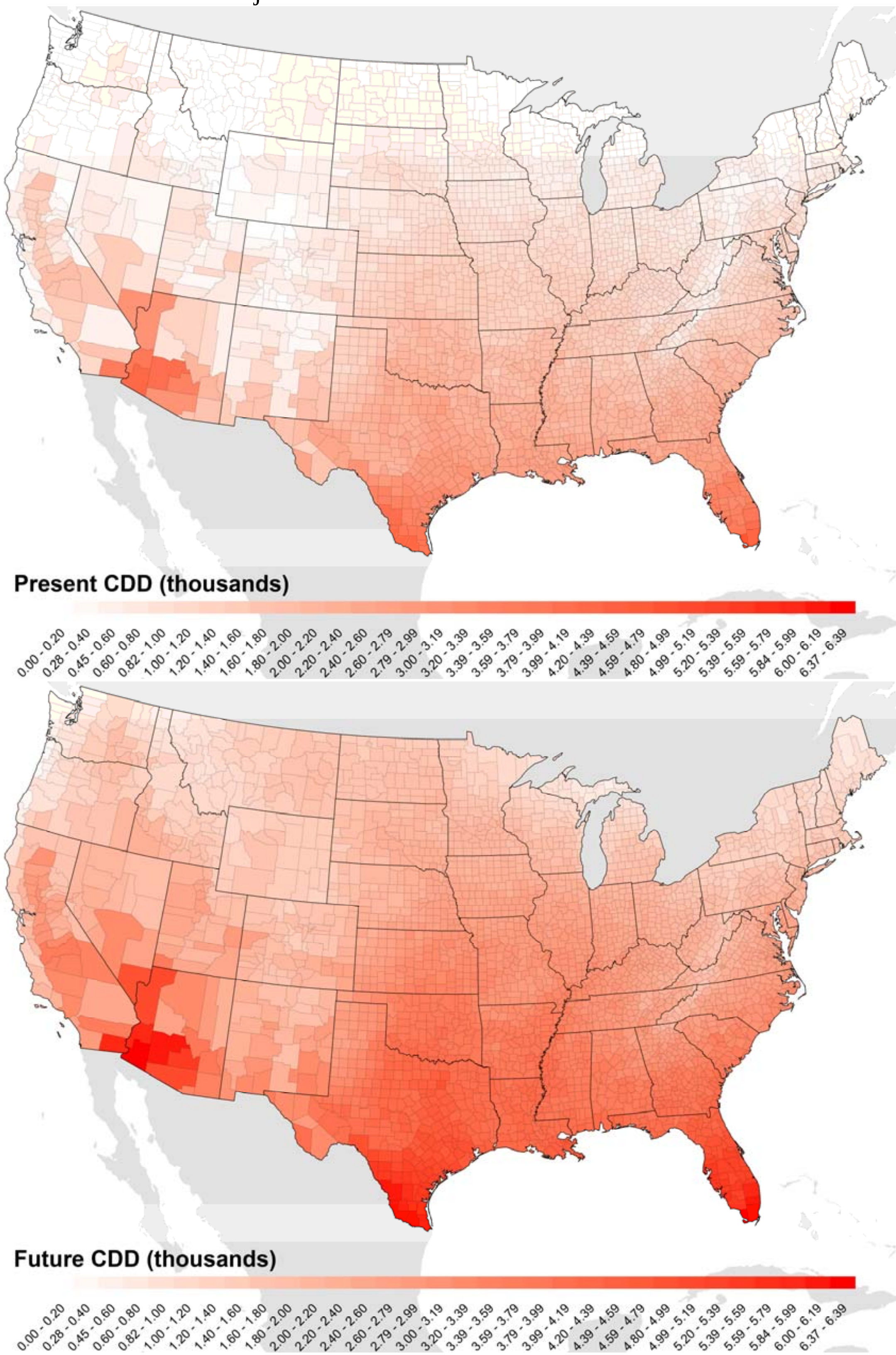


Figure 6: Predicted change in QOL as percent of income; linear homogenous preferences model with climate variables in HDD and CDD (tables 2 and 3, column IV)

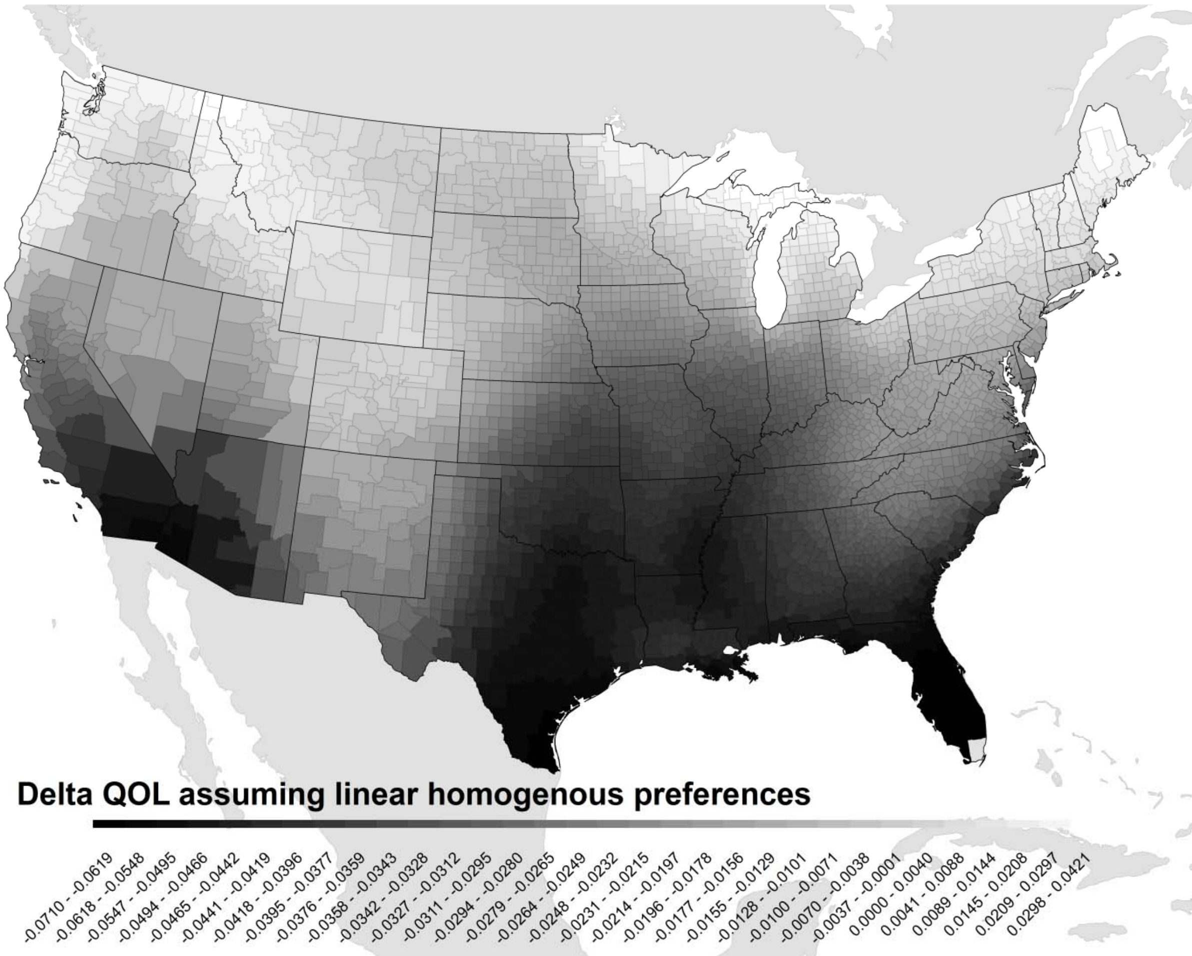
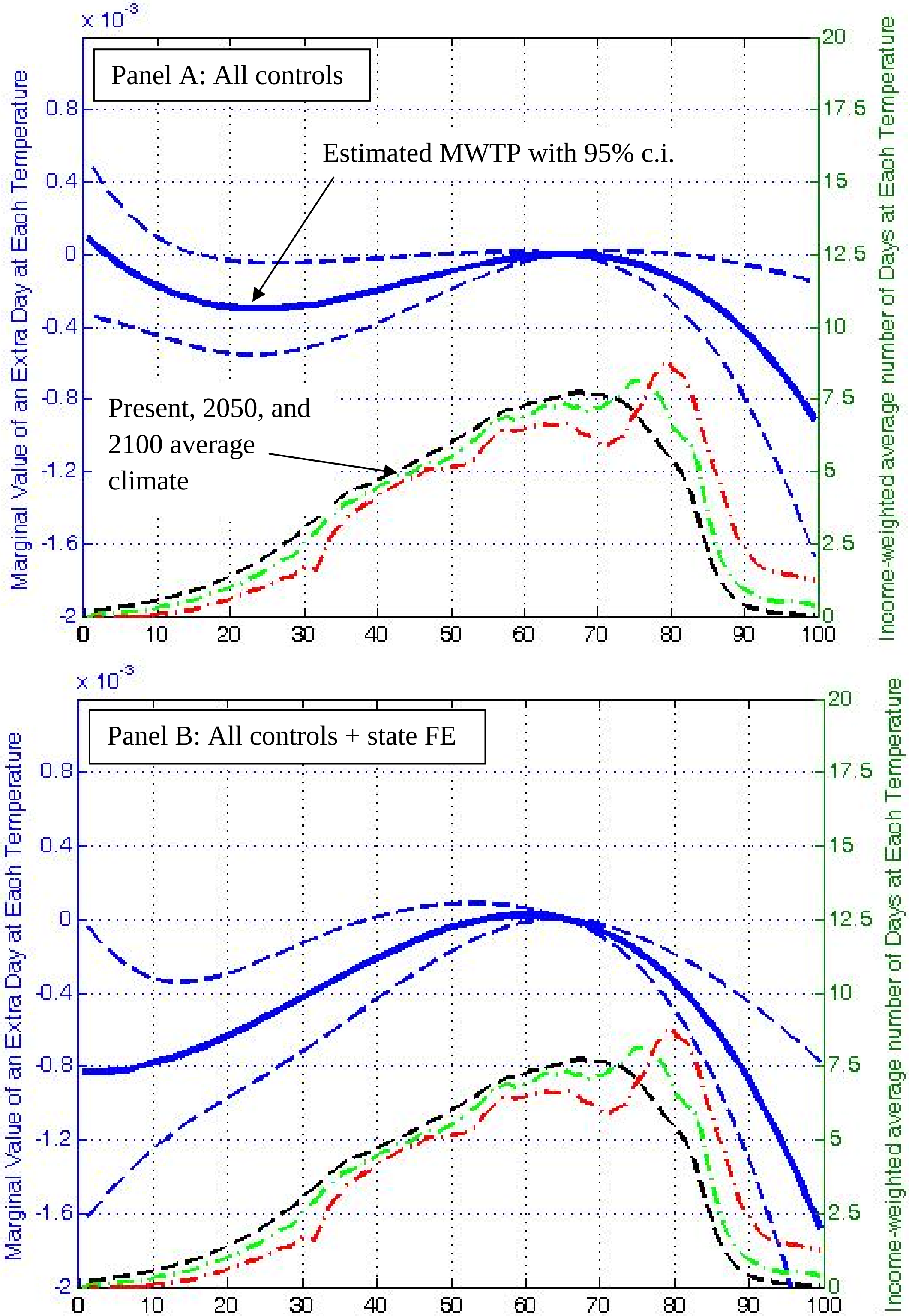


Figure 7: Estimated climate preferences from homogenous preferences model

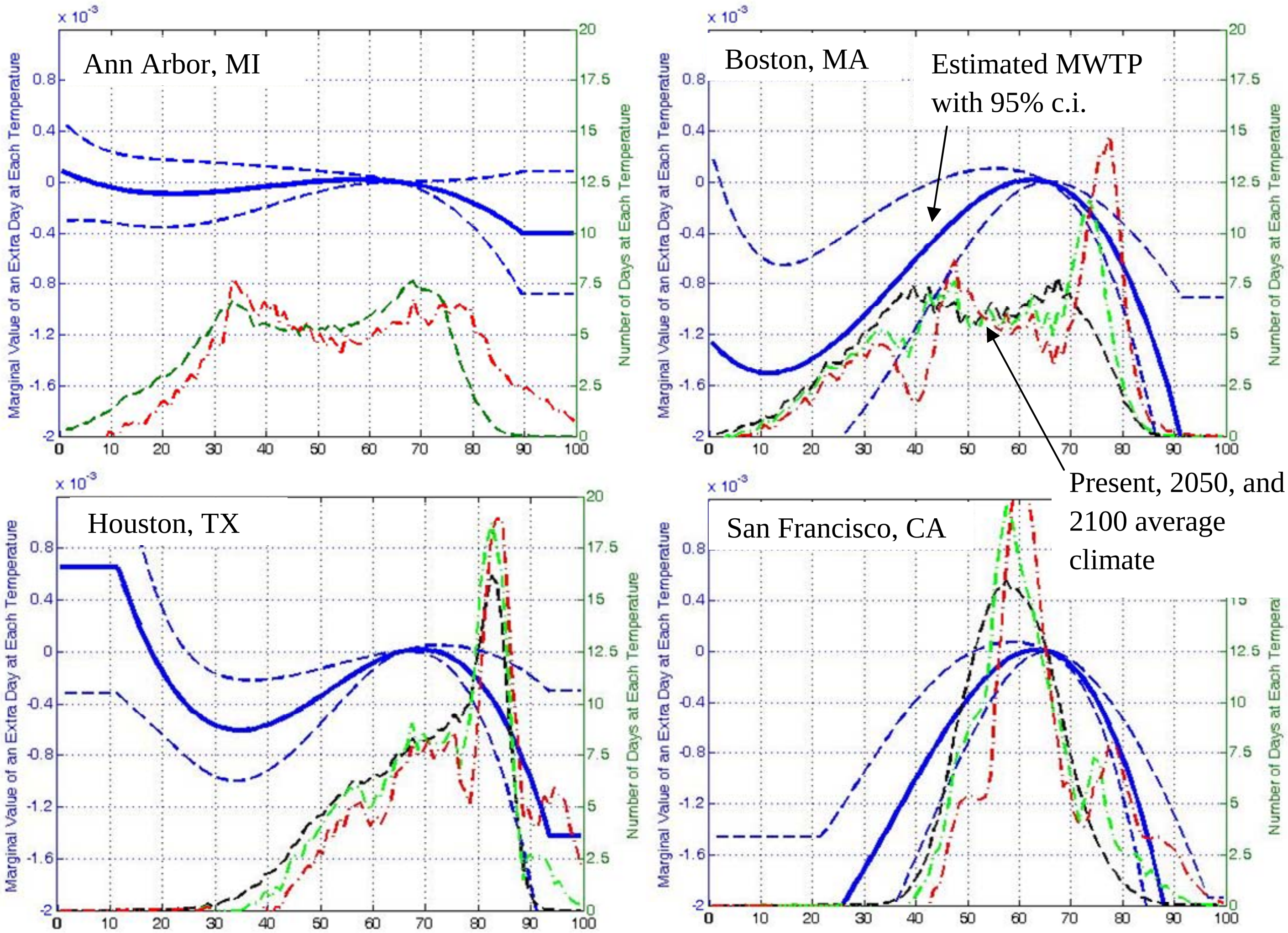
Functional form is a 4th-degree cubic spline over one-degree temperature bins



Climate averages are the income-weighted average number of days in each temperature bin
MWTPs are for an additional day in each temperature bin relative to a day at 65-66°F

Figure 8: Estimated climate preferences from heterogeneous preferences model

Functional form is a 4th-degree cubic spline over one-degree temperature bins



MWTPs are for an additional day in each temperature bin relative to a day at 65-66°F

MWTP is assumed to be constant outside the support of the current temperature distribution in each location

Specification includes all controls, no state fixed effects

Figure 9: Estimated climate preferences from heterogeneous preferences model

Functional form is a 4th-degree cubic spline over one-degree temperature bins

Model shown includes all controls, no state FE

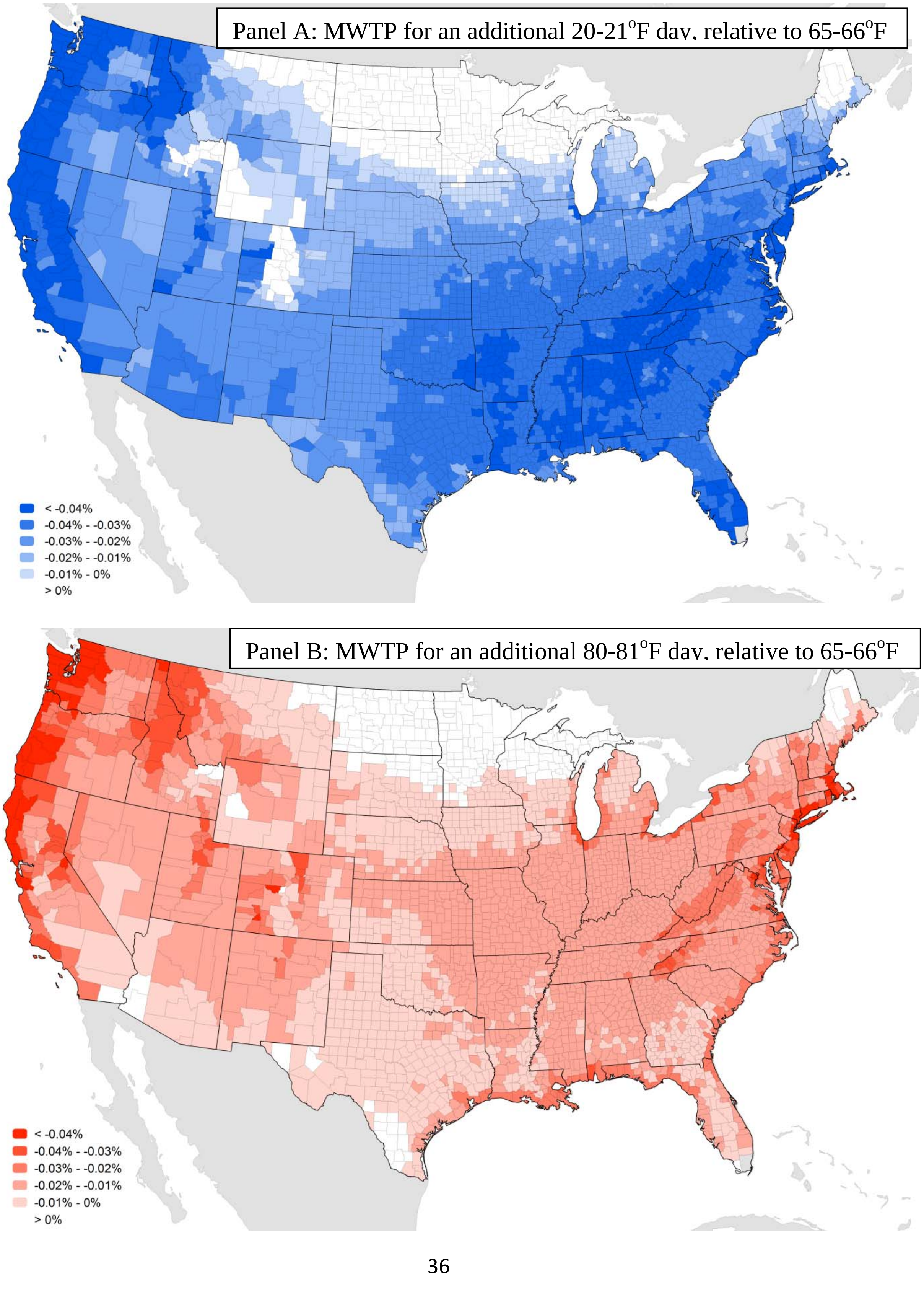
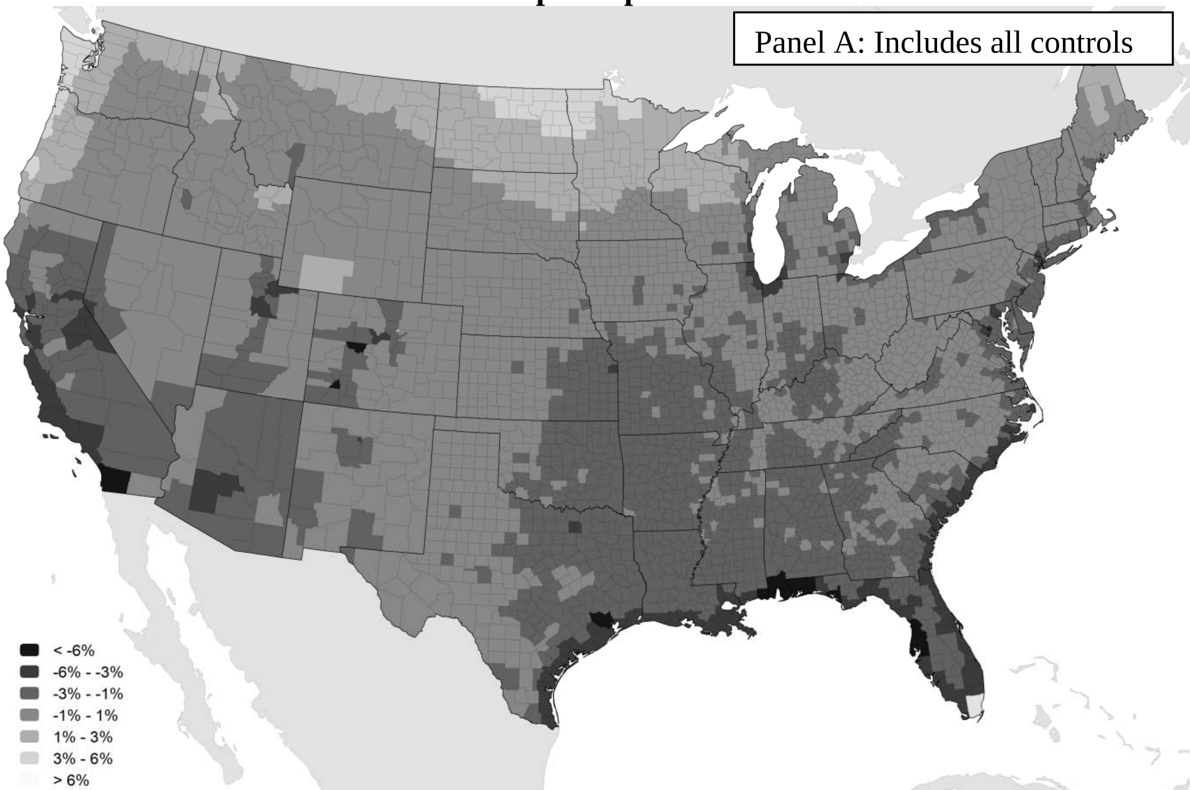


Figure 10: Predicted change in QOL as percent of income; heterogeneous preferences model with spline specification



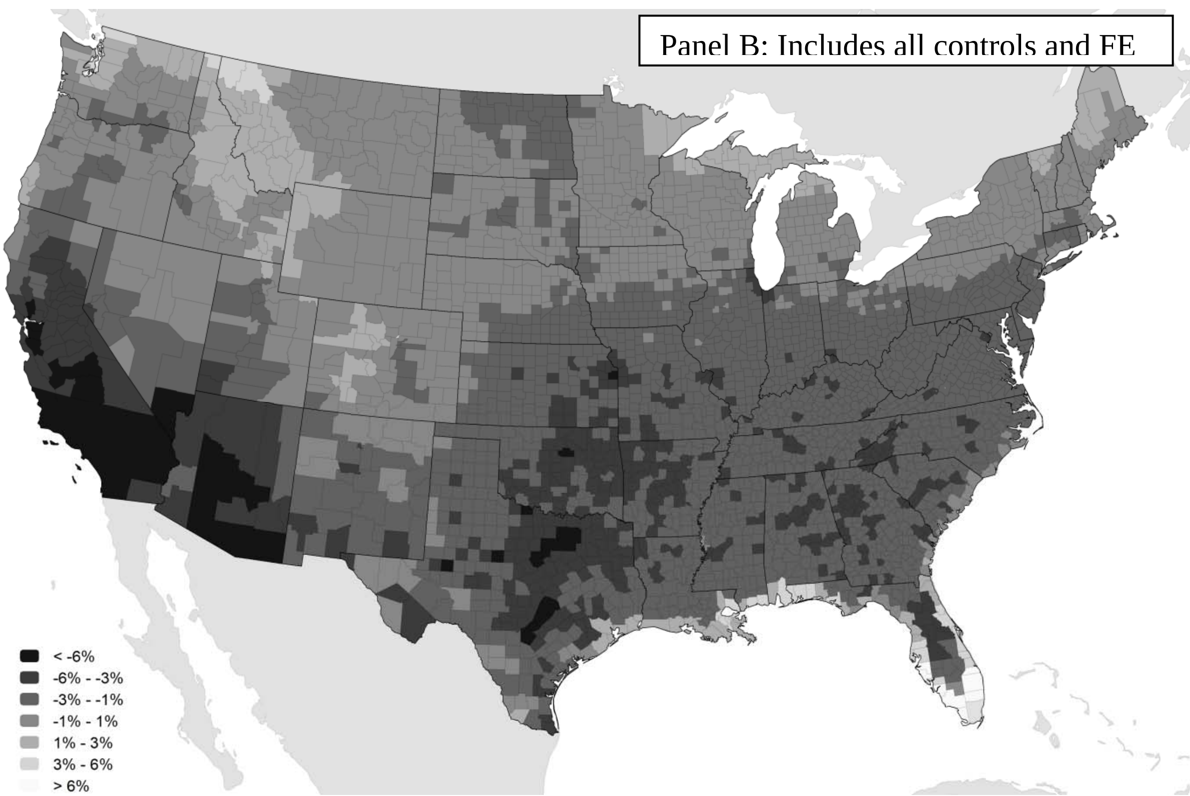


Table 1: Descriptive statistics for county-level dataset

	Mean	Std. Dev	Minimum	Maximum
Avg annual heating degree days (1000s), 1961-1990 data	4.960	2.133	0.088	10.568
Avg annual cooling degree days (1000s), 1961-1990 data	1.257	0.768	0.021	4.633
Projected annual 2090-2100 heating degree days (1000s), IPCC A2	3.337	1.657	0.000	8.055
Projected annual 2090-2100 cooling degree days (1000s), IPCC A2	2.711	1.021	0.283	6.388
Precipitation (meters)	1.448	0.532	0.063	2.550
Dummy for bordering ocean	0.082	0.275	0	1
Dummy for bordering a Great Lake	0.027	0.161	0	1
Average land slope (degrees)	1.104	1.451	0	11.174
Population density (log of people per sq. mile)	10.234	1.402	4.205	16.069
Percent high school graduates	0.773	0.087	0.347	0.970
Percent college graduates (bachelors)	0.165	0.078	0.049	0.638
Population (1000s)	89.3	291.1	0.1	9519.3
Quality of life differential (in logs)	-0.017	0.050	-0.143	0.244
Productivity differential (in logs)	-0.063	0.107	-0.267	0.450

Apart from climate and projected climate, all variables are based on the year 2000 census

Data include 3105 counties

Table 2: Estimated determinants of quality of life and productivity
Results from linear homogenous preference model; climate variables are HDD and CDD

	Dependent variable: QOL differential				Dependent variable: Productivity differential			
	I	II	III	IV	V	VI	VII	VIII
	No controls	"Natural" controls	All controls	All controls and state FE	No controls	"Natural" controls	All controls	All controls and state FE
Avg. annual heating degree days (1000s)	-0.025*** (0.004)	-0.008** (0.003)	-0.008*** (0.003)	-0.019*** (0.003)	-0.033*** (0.009)	-0.012 (0.010)	-0.010* (0.005)	0.003 (0.009)
Avg. annual cooling degree days (1000s)	-0.053*** (0.010)	-0.019** (0.008)	-0.014** (0.006)	-0.037*** (0.007)	-0.092*** (0.023)	-0.056** (0.022)	-0.037*** (0.013)	-0.001 (0.012)
Precipitation (meters)		-0.235*** (0.053)	-0.218*** (0.040)	-0.118 (0.108)		-0.38** (0.169)	-0.347*** (0.098)	0.389*** (0.135)
Dummy for bordering ocean		0.065*** (0.012)	0.041*** (0.008)	0.032*** (0.006)		0.149*** (0.028)	0.055*** (0.014)	0.019** (0.008)
Dummy for bordering a great lake		0.019 (0.019)	0.014 (0.014)	0.007 (0.010)		0.071** (0.036)	0.022 (0.015)	-0.003 (0.011)
Average land slope (degrees)		0.009*** (0.002)	0.010*** (0.002)	0.008*** (0.002)		-0.006 (0.005)	0.004 (0.003)	-0.006* (0.004)
Population density (log of people per sq. mile)			0.004 (0.003)	0.006*** (0.001)			0.034*** (0.003)	0.025*** (0.004)
Percent high school graduates			-0.001 (0.053)	-0.051 (0.037)			0.092 (0.070)	0.098 (0.073)
Percent college graduates			0.255*** (0.037)	0.258*** (0.028)			0.495*** (0.081)	0.522*** (0.056)
State fixed effects	N	N	N	Y	N	N	N	Y
Number of observations	3105	3105	3105	3105	3105	3105	3105	3105
R^2	0.289	0.498	0.681	0.785	0.150	0.355	0.736	0.845

Parenthetical values indicate standard errors clustered on metropolitan statistical area (non-msa counties are clustered at the state level)
*,**,*** indicate significance at the 10%, 5%, and 1% level.
Values of constant and state fixed effects not shown
Regressions weighted by population in each county

Table 3: Climate changes and projected welfare impacts using the IPCC A2 scenario for 2090-2100 and preference estimates from the linear homogenous preference HDD and CDD models

	I	II	III	IV
	No controls	"Natural" controls	All controls	All controls and state FE
Impact of change in heating degree days				
Mean change in heating degree days (1000s)	-1.623	-1.623	-1.623	-1.623
Mean QOL change as fraction of income	0.038	0.013	0.013	0.029
Aggregate QOL change in billions of 2008$	474.6	158.5	160.4	359.0
Impact of change in cooling degree days				
Mean change in cooling degree days (1000s)	1.454	1.454	1.454	1.454
Mean QOL change as fraction of income	-0.075	-0.027	-0.020	-0.052
Aggregate QOL change in billions of 2008$	-925.4	-330.6	-249.1	-639.1
Overall impact of climate change				
Mean QOL change as fraction of income	-0.036	-0.013	-0.007	-0.023
	(0.009)	(0.008)	(0.006)	(0.007)
Aggregate QOL change in billions of 2008$	-450.8	-158.5	-88.7	-280.1
	(115.5)	(95.1)	(69.6)	(80.8)
Percent of population losing	90.3%	92.8%	80.1%	87.5%

Parenthetical values indicate standard errors clustered on metropolitan statistical area (msa)
Regressions weighted by population in each county

Table 4: Projected welfare impacts using the IPCC A2 scenario and preference estimates from the homogenous preference spline models

	I	II	III	IV
	"Natural" controls	"Natural" controls and state FE	All controls	All controls and state FE
Impacts of climate change through 2090-2100				
Mean QOL change as fraction of income	-0.025	-0.044	-0.020	-0.038
	(0.016)	(0.025)	(0.010)	(0.016)
Aggregate QOL change in billions of 2008$	-308.8	-549.3	-250.0	-468.1
	(198.1)	(312.8)	(125.6)	(203.5)
Impacts of climate change through 2040-2050				
Mean QOL change as fraction of income	-0.006	-0.008	-0.005	-0.008
	(0.004)	(0.007)	(0.003)	(0.005)
Aggregate QOL change in billions of 2008$	-76.6	-96.0	-55.9	-96.8
	(49.0)	(89.3)	(32.6)	(57.2)

Parenthetical values indicate standard errors obtained via clustered bootstrap on msa
Regressions weighted by population in each county

Table 5: Projected welfare impacts using the IPCC A2 scenario and preference estimates from the heterogeneous preference spline models

	I	II	III	IV
	"Natural" controls	"Natural" controls and state FE	All controls	All controls and state FE
Impacts of climate change through 2090-2100				
Mean QOL change as fraction of income	-0.024 (0.012)	-0.030 (0.018)	-0.022 (0.009)	-0.026 (0.011)
Aggregate QOL change in billions of 2008$	-301.1 (143.1)	-366.9 (228.8)	-269.7 (113.5)	-323.7 (135.7)
Impacts of climate change through 2040-2050				
Mean QOL change as fraction of income	-0.007 (0.003)	-0.005 (0.006)	-0.005 (0.003)	-0.004 (0.004)
Aggregate QOL change in billions of 2008$	-80.5 (41.1)	-64.8 (72.3)	-65.1 (33.5)	-53.9 (45.0)

Parenthetical values indicate standard errors obtained via clustered bootstrap on msa
Regressions weighted by population in each county

Table 6: Projected welfare impacts using the IPCC A2 scenario for 2090-2100 and preference estimates from the homogenous preference models, allowing for migration

	I	II	III	IV
	HDD/CDD model, all controls	HDD/CDD model, all controls + state FE	Spline model, all controls	Spline model, all controls + state FE
Mean QOL change as fraction of income	-0.007	-0.020	-0.019	-0.033
Aggregate QOL change in billions of 2008$	-84.0	-253.0	-233.2	-407.6
Reduction in magnitude of QOL change relative to no-migration cases	5.3%	9.7%	6.7%	12.9%

Mobility modeled as described in section 6, with a local housing supply elasticity of 5 and no migration outside U.S. borders