Geographic Heterogeneity in Climate Change Adaptation: Behavioral Evidence from Participation in Outdoor Activities

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November 19, 2020

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Abstract

This research examines the role of non-market behavioral adaptation to climate change in the United States for the case of outdoor leisure with a novel estimation procedure that accounts for both short-run weather and long-run climate adjustments. First, I comprehensively review the temperature sensitivity of all activities in the American Time Use Survey using a flexible non-linear estimation procedure. Predictably most activities are found to be unresponsive to temperature with the exception of those that take place outdoors. Time spent outdoors is studied further using the Climate Adaptation Response Estimation approach, which allows for temperature responses to vary geographically. I find the sensitivity to temperature varies across the country, and this variation is especially pronounced for cold-weather cities in which inhabitants modify their outdoor and physical activities in response to temperatures more than warm-weather cities. Simulating the expected change in outdoor activity time using climate models compiled by the Intergovernmental Panel on Climate Change implies a large increase in outdoor time driven by warmer winters.

Keywords: Climate Change Adaptation, Time Use, Temperature Response Estimation
JEL Codes: Q50, Q54, D13

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[†]Thanks to Dan Hicks, Kevin Kuruc, Myongjin Kim, Pallab Ghosh, John McFadden, Jadwiga Ziolkowska, and the participants of the University of Oklahoma's Applied Microeconomics Seminar Series for their helpful recommendations.

1 Introduction

Globally, the past five years mark the five hottest since record keeping began in 1880, with 2020 on track to be the hottest ever.[1] As concerns about warming have increased, the economics literature has made major progress in evaluating the costs of climate change. Early work on the topic studied the effect on agriculture (e.g. Mendelsohn et al. (1994)), but the literature has expanded to include the effect on health and mortality (Deschênes and Greenstone (2011), Heutel et al. (2017), Barreca et al. (2016)), energy consumption (Davis and Gertler (2015), Mansur et al. (2008), Auffhammer (2018)), and worker productivity (Adhvaryu et al. (2019), Colmer (2019)), among others.[2]

Within the climate economics literature, few causal estimates exist of the role geographic heterogeneity plays in determining outcomes. In the United States, regions are expected to be exposed to different extreme weather events that will increase in frequency and intensity as climate change progresses. Wildfires in the West, hurricanes in the South and East, and droughts in the Midwest are all examples of headline weather events that fit this criteria and are well-understood by the public. Despite the prominence of these events, the broader and more gradual effects of climate change will also vary across regions. By expanding our understanding of the geographic heterogeneity of climate responses, we get a more complete picture of the welfare effects of climate change. This research studies the role geography and climate play in Americans' participation in outdoor nonmarket activities with data from the American Time Use Survey (ATUS).

To this end, I estimate the sensitivity of outdoor activities to both short-run weather and long-run climate in cities across the United States and project the results forward to predict future welfare changes. My findings formalize intuition about outdoor activities: doing things outdoors is more pleasant than indoors, and because outdoor activities are sensitive to hot and

[1] https://www.washingtonpost.com/weather/2020/04/21/earth-warmest-year-likely-2020/

[2] Many articles reviewing outcomes exist. For agriculture see Auffhammer and Schlenker (2014), for energy see Auffhammer and Mansur (2014), for conflict see Burke et al. (2015), and for a general overview of climate econometrics, see Hsiang (2016). Finally, Massetti and Mendelsohn (2018) reviews the adaptation literature.

cold temperatures, American cities with low average temperatures will gain days with pleasant outdoor weather due to warmer winters. This stands in contrast to cities with warm average temperatures, which don't gain from warmer winter days but may lose outdoor time due to extreme hot summer days. To complete the analysis, three questions must be asked. First, which household activities are sensitive to temperature? The activity set is narrowed to those that exhibit some response to temperature, leading to the second question: do these temperature sensitivities vary by local climate? I estimate the temperature response function for outdoor nonmarket activities separately for each city in the United States. Finally, having recovered the city-level response to temperature, the final question is: how will activity time allocation in the United States change when the climate distribution shifts? This is done using climate prediction models from the Intergovernmental Panel on Climate Change (IPCC). My research estimates which activities are sensitive to temperature, how these sensitivities vary by local climate, and how we should expect the amount of time dedicated to these activities to change with the climate.

The non-linear model suggests that most activities Americans spend time on are not influenced by the weather. Although respondents do not adjust their time spent doing particular activities, they do adjust where they do them. Consistent with results in Zivin and Neidell (2014), I find that outdoor activities are very sensitive to temperature. This intuitive result underscores the importance of considering a wider range of outcomes when thinking about climate change. Rather than merely being an extension of past work, these responses likely have large implications for human welfare. Figure 1 plots the share of time certain activity groups are unpleasant, based on the U-Index developed by Kahneman and Krueger (2006). Non-market activities are less unpleasant when they take place outdoors; averaged across all activities, the U-Index is two-thirds lower outdoors than in. The public health and psychology literature find similar positive benefits associated with spending time outdoors.[3] If climate change alters the indoor-

[3]For a meta-analysis of public health research, see Bowler et al. (2010). For a review of the psychology literature, see Pearson and Craig (2014). And for a meta-analysis of the role greenspace plays in health outcomes, see Twohig-Bennett and Jones (2018).

outdoor margin through changes in the weather, there could be large welfare implications – either warmer summers induce more time inside or warmer winters induce more time outside.

Those living in warm-weather cities may response differently in ways relevant for understanding climate adaptation. To capture the climate effect, I use a novel estimation procedure developed by Auffhammer (2018) which allows for agents' temperature sensitivity to vary across geography. The method, referred to as Climate Adaptation Response Estimation (CARE), models the relationship between climate and economic outcomes in two stages. In the first stage, CARE estimates a non-linear temperature response function. This non-linear approach has become common in the climate literature because it relaxes parametric assumptions regarding the temperature response function. The key innovation of the first stage is that the function is estimated separately for each geographic unit in the sample. Due to the large number of cities in the ATUS sample and the non-linear functional form, the first stage produces a large number of estimated temperature coefficients. In the second stage, these estimated coefficients are regressed on the long-run temperature averages, which reflect the local climate. As a result, the first stage can be thought of as the response to weather and the second stage how sensitive the weather response is based on the local long-run climate. The estimated temperature response function from the first stage is then projected forward using climate models aggregated by NASA, which allows for simulation of the potential welfare effects of future climate change under two different emissions scenarios.

The results of the climate model illustrate significant geographic heterogeneity in the United States. There are three primary results from the CARE method and its projection: first, the temperature response function from stage one reflects a distinct inverse-U shape. That is, people spend less time outdoors at both hot and cold temperatures relative to a baseline "nice" day in the 60-70 degree Fahrenheit range. This suggests that individuals avoid extreme temperatures at both the high and low end of the temperature distribution. Then the estimated coefficients from the first stage are regressed on the long-run climate of their respective metropolitan area. My results demonstrate that metropolitan areas with large shares of cool days are generally more temperature sensitive than those with a greater share of warm days. While both cold and warm climate cities decrease the amount of time spent outside when it is very cold and very hot (i.e. the first stage), cold climate cities have more extreme responses.

This result is the first contribution of my research, suggesting that agents in cold climate cities are more sensitive to temperature than their warm climate counterparts. The stage one estimates measured a temperature response function – i.e. how activity time allocation changed as a result of short term weather events. The weather is a particular day's temperature, precipitation, or humidity. These weather results are informative, but do not reflect how climate may mediate these outcomes. For example, the climate of Minnesota is quite different from the climate of Florida. If Floridians are less sensitive to hot days, these results can teach us about how the response of Minnesota may change when Minnesota warms. Similar research estimating the relationship between outdoor activities and the weather take a non-linear approach but do not provide estimates of the climate effect.

The most similar research to this exercise is Chan and Wichman (2020), which uses a non-linear fixed effects model to estimate how recreational cycling responds to weather fluctuations. The authors find cyclists are more sensitive to cold temperatures than warm, similar to the results presented here. These results should not be a surprise, as human physiology bounds the range of temperatures that we find desirable (Arens and Bosselmann (1989); Höppe (2002); Stathopoulos et al. (2004)). Importantly, the results of this research demonstrate heterogeneous preferences for temperature across the United States.[4] In a time use setting, the reallocation of time from outdoors to indoors and from active to passive will have a profound effect on welfare as different regions warm at different rates.

The second contribution is to provide evidence for the relationship between weather and the universe of non-market activities in the American Time Use Survey. The American Time Use Survey provides a nationally representative sample of agents' time use patterns and is not restricted to a particular subset of activities. Empirical exercises of time use surveys date back

[4]This conclusion is intuitive. As Senator Bernie Sanders, a Vermont native, put it in an August 2020 interview: "When I'm in Washington, I don't go outside, and when I'm in Vermont, I don't go inside. So there you go."

to the 1970s (Gronau (1976a), Gronau (1976b)), and the theory of time use and allocation to the 1960s (Becker (1965), Johnson (1966)), but my research is the first to provide comprehensive estimates of temperature response functions for all the activities included in the time use survey. I exploit within-city variation in weather to identify the non-linear relationship between temperature and the universe of activities in the American Time Use Survey.

The paper proceeds as follows. Section 2 clarifies the distinction between weather and climate as it pertains to the econometric model, details the data being used, and motivates the research with a descriptive empirical exposition. Section 3 outlines the two-step estimation procedure used in the CARE model. Section 4 estimates both the short-run temperature response function and the long-run climate adaptation model. Section 5 projects the results of the model forward using General Circulation Models (GCMs) from NASA, and Section 6 concludes.

2 The Weather, Climate, and Americans' Daily Activities

This section discusses of the difference between the weather and climate, which is key to understanding the CARE methodology. Then, to establish a relationship between the weather and activity time allocation, a series of non-linear temperature response functions are estimated using data from the American Time Use Survey. Outdoor activities stand out for their relationship with the weather, leading to the climate analysis in the following section.

2.1 The Difference Between Weather and Climate

The climate literature in economics has taken two broad approaches to estimating the effect of climate and economic outcomes. The first, established in Mendelsohn et al. (1994), uses long-run values of a region's weather outcomes as a proxy for the local climate. The economic outcome of interest is regressed on these long-run values (typically the seasonal or monthly averages of the preceding two-to-three decades) cross-sectionally. The alternative approach, which has increased in popularity in the last decade, uses fluctuations in weather to identify the relationship between the outcome and climate. Identification requires panel data in which the researcher observes regions repeatedly over time. The distinction between these two approaches is that the former explicitly models the climate effect, whereas the latter estimates the weather effect with an assumption that this is informative for climate responses. Understanding the difference is important in interpreting the results of the two stage CARE approach used in this paper.

Early research measuring climate adaptation estimated the effect of weather on different outcomes using cross-sectional data. Mendelsohn et al. (1994), for example, regressed county farm prices in the United States on monthly average temperatures. This approach has the advantage of estimating the true climate effect since farmers are aware of prior climate information at their location, allowing them to optimize production and investment, and therefore are able to maximize returns for their property on the market. The major disadvantage of the cross-sectional approach — and the reason it has fallen out of favor in the climate literature — is that it is susceptible to omitted variable bias. By estimating the temperature response function with panel data and fixed effects, and then recovering the long-run climate effect using cross-sectional data and the estimated coefficients from the first stage, CARE recovers the climate effect while avoiding the pitfalls typically associated with cross-sectional data.

The key idea in the panel data-weather fluctuations approach is that weather observations are draws from the climate distribution. To demonstrate this idea, Figure 2 plots a simulation of the climate distribution under the current climate and a future climate where the mean temperature increases by 3° Celsius (5.4° Fahrenheit). This is a hypothetical scenario, as the true temperature distribution for the United States is not as neatly normal as the distributions depicted due to regional differences. Any individual day's temperature (or precipitation, humidity, etc.) is the realized value of the climate distribution. Figure 2 assumes that the two distributions are different due to the nature of time and expected changes in the climate, but the two could distributions could also reflect the difference in climate between regions. For example, the current climate could instead represent the cold climate of Boston and the future climate could represent the warm climate of Los Angeles.

A common approach in the climate literature estimates an outcome variable on temperature with location and time fixed effects to adjust for unobservable characteristics unique to a place and time. The downside of such models is that fixed effects impose that the estimated temperature response function is the same for each location in the sample (Auffhammer and Schlenker (2014)). As a result, the coefficients reflect only the response to deviation in weather, not climate. The practical implication is that Minnesotans and Floridians are assumed to have the same reaction to a 95° day.[5] Much of the recent climate literature has taken this approach despite its limitations.

The CARE method marries the two approaches by estimating both the short-run weather effect and the long-run climate effect, although it is not the first to consider geographic heterogeneity when estimating climate adaptation. Barreca et al. (2016) estimate the relationship between temperature and monthly mortality rates separately for each of the nine Census regions, reporting results for each individually. Similarly, Butler and Huybers (2013) regress maize yields on growing and killing degree days in approximately 1000 counties in the United States. Heutel et al. (2017) take a slightly different approach, interacting a non-linear temperature response function with indicators for whether a U.S. ZIP code falls in the top/middle/bottom climate tercile. The advantage of CARE over these other approaches is that it estimates the temperature response function for each geographic unit using panel data in the first stage and then allows the estimated coefficients to vary cross-sectionally in a second stage.

[5] Time fixed effects impose the same assumption but over time. This is less of a concern, because this style of models typically uses data that spans years, not decades, so the potential for short-term adaptation is limited.

2.2 Data

A number of data sources are used in the analysis, including time use survey data from the U.S. Bureau of Labor Statistics, the Current Population Survey from the United States Census Bureau, and meteorological data from the University of Idaho.

2.2.1 Time Use Data

The primary source of data comes from the Census Bureau and the Bureau of Labor Statistics' American Time Use Survey (ATUS). The ATUS randomly selects one member of a household that has completed eight consecutive months of the Current Population Survey (CPS) to fill out a time use diary. This diary asks that the respondent log the amount of time they spent completing all activities over a 24-hour period. Importantly for this research, the respondents are asked where each of their activities takes place, which helps distinguish between weather sensitive and weather insensitive activities.

Activities are first separated by the categories defined by the BLS. The categories include household activities, education, work and work-related activities, socializing, and others. These groups are quite broad. For example, household activities include meal preparation and gardening. Following Zivin and Neidell (2014), any activity that takes place "outdoors, away from home" or makes references to the exterior of the home, such as "gardening" or "exterior maintenance" is encoded as an outdoor activity. As Zivin and Neidell note, some activities are said to take place "at the home or yard," but since this categorization is ambiguous, it is encoded as not taking place outdoors.

Table 1 presents the summary statistics for each activity group in the ATUS data and for all activities which are coded as occurring outside. Six categories of activities are considered: household labor, market labor, market consumption activities, leisure activities, outdoor activities, and miscellaneous activities. The sub-categories correspond to the 18 major categories defined by the BLS, plus five outdoor activities created for the purpose of this research. Both the unconditional number of minutes spent doing an activity and the number of minutes conditional on participation (i.e. the number of minutes > 0) are included. The three largest activities by time allocation are sleeping, engaging in market labor, and leisure time. Only about a third of respondents participate in outdoor activities but, conditional on participation, respondents average more than ninety minutes outdoors per day. To get a better idea of which activities take place outdoors, Figure 4 plots the share of time each of the major activity categories takes place outdoors. Household activities, including activities such as yard maintenance and pet care, and sports and exercise take place outdoors approximately twenty-five percent of the time, by far the largest out of the major activity groups.

Because the ATUS is administered to individuals who have completed eight rounds of the CPS, the ATUS data can be matched to the CPS data at the individual level. A large number of variables from the CPS are used, including the respondent's age, sex, race, educational attainment, household income, marital status, the number of children, and homeownership status.

2.2.2 Meteorological Data

Meteorological data are obtained from the University of Idaho's gridMET dataset (Abatzoglou, 2013). gridMET provides daily ground-level meteorological data at a 4-km spatial resolution. The sample used in this research starts at the beginning of 1979 (the earliest year available in gridMET) and ends in 2018. From 1979 to 2004, the only variables derived from gridMET are maximum and minimum daily temperature. As is common in the climate literature, these two variables are averaged to produce daily mean temperature. Starting in 2005 other meteorological measures, including maximum and minimum relative humidity, mean wind speed, and the precipitation amount, are also imported from gridMET.

The most disaggregated geographic level in the ATUS data is the Census' metropolitan statistical area (CBSA). A CBSA TIGER shapefile from the Census is used to merge the gridMET and ATUS data. Since the gridMET is measured continuously in space, the values in each CBSA must be aggregated. For each meteorological variable, the median value in a CBSA is extracted from the continuous gridMET data (Dorman et al., 2020). The value extraction derives meteorological data for each CBSA-day in the ATUS data.

2.2.3 Miscellaneous Data

In addition to the time use and meteorological data, there are a handful of other data sources used. Elevation data is from the R package "elevatr" (Hollister and Shah, 2020), which provides access to Amazon Web Services' Terrain Tiles via an API. End-of-century climate projections come from the NASA Earth Exchange Global Daily Downscaled Projections (NEX-GDDP). Twenty-one General Circulation Models (GCMs) conducted under the Coupled Model Intercomparison Project Phase 5 (CMIP5) provide daily maximum temperature, minimum temperature, and precipitation. I calculate daily mean temperature for each metropolitan-date between 2080-2099. Creating these daily means allows me to match the expected mean temperature in 2080-2099 to the day that a respondent in the ATUS filled out their diary. NEX-GDDP includes projections for two Representative Concentration Pathways (RCPs): RCP4.5 and RCP8.5. RCP4.5 trajectories model emissions as peaking in 2040 and declining after that. In RCP8.5 models, emissions continue to rise throughout the 21st Century. RCP8.5 models are typically referred to as "business as usual" models. Figure 3 shows the number of days per year in temperature bins of 5° under three climate scenarios. The light green color reflects the current climate in the United States, the middle green shade the RCP4.5 scenario, and the darkest green shade the RCP8.5 scenario. There is a clear rightward shift in the average temperature distribution. A large number of cold-weather days in the current climate are lost in both RCP scenarios, while there is a marked increase in the number of days in the top two temperature bins.

2.3 Empirical Justification

Before estimating the full model, we first need to determine what (if any) household activities are weather sensitive. This first exercise demonstrates that – unsurprisingly – outdoor and physical activities are most sensitive to the weather.

It is assumed that temperature affects some activities more intensely than others. For example, due to the prevalence of air conditioning in the United States, we should not expect that passive indoor activities such as watching television are influenced by weather conditions outside. The ATUS enumerates a large number of activities over which respondents participate. This allows for an analysis of the temperature sensitivity of different activities. This temperature response function can be represented by:

$$y_{it} = \sum_{b \in B \setminus \{60-70\}} \beta_b D_{ibt} + \gamma X_{ijt} + \alpha_{jm} + \phi_{my} + \epsilon_{it} \tag{1}$$

where y_{it} represents the number of minutes respondent i spent doing activity y at time t and D_{ibt} is an indicator for whether the temperature experienced by respondent i at time t falls into temperature bin b. The model allows for non-linearities in the temperature-outcome relationship by including these indicators. X_{ijt} is a vector of confounding variables which are adjusted for, including other weather variables (precipitation, humidity, and wind speed), demographic characteristics of respondent i from the Current Population Survey (age, race, marital status, number of children, education, household income, home ownership status), ATUS diary information (day of the week the diary was completed for, an indicator for whether the diary day was a holiday) and region j geographic and economic characteristics (elevation, slope, air conditioning prevalence). α_{jm} are region-month fixed effects and ϕ_{my} are month-year fixed effects. The set of fixed effects absorb unobserved region-month and month-year determinants of time allocation.

Table 2 displays the results of the model. The coefficients should be interpreted as the change in the number of minutes for a particular activity as the result of the daily temperature falling into one of eight temperature bins, relative to a baseline day of 60-70°. Broadly there are five categories considered: household labor, market labor, consumer activities, leisure, and outdoor activities. The first four categories are exclusive of one another, but outdoor activities is inclusive of the others. For example, the sub-category “exercising outside” is a subset of the “exercising” category in the leisure group.[6] Looking at the results in Table 2, it is clear that ac-

[6]The categorization is inherently subjective, something that many time use research projects have contended with.

tivities which either occur outside or are physically active are those that are most sensitive to temperature. All of the outdoor activities have significant negative coefficients, especially in the bottom half of the temperature distribution. The effects are less pronounced at the top of the distribution however. Physical activities, including exercising and participating in sports similarly show significant negative effects when the weather is the coldest but little when it is hottest. Interestingly, general leisure time increases by a large amount in the lower bins.

Having established that the number of minutes spent outdoors is particularly susceptible to temperature, Figure 5 estimates the outdoor time response function for metropolitan areas in the bottom and top quantile of the temperature distribution separately. This approach is common in the climate literature.[7] The quantiles here were chosen to demonstrate potential divergences in the temperature response function as a function of local climate. Figure 5 shows that the coldest metropolitan areas are consistently more temperature sensitive than the hottest metropolitan areas. It should be noted that although the estimated coefficients in the hottest areas are significant and negative for the second (20-30°) and third (30-40°) bins, they do not experience any days in the first bin (<20°). The coldest areas, on the other hand, do experience days in the ninth bin (>90°). In general the hottest cities have a flatter response curve than the coldest cities, supporting the notion that there are heterogeneous temperature preferences in different climate regions.

To further support the notion that different regions of the country have heterogeneous preferences for outdoor activities, Figure 6 plots the daily number of minutes spent outdoors each month by state. The graph displays the unconditional survey-weighted average amount of non-work time spent outside. Although the share of time outside is generally quite low, states in Mountain West, North West, and North East increase their shares substantially in the Spring

Aguiar and Hurst (2007) and Ramey and Francis (2009) attempt to create a framework for time use allocation in the context of shifts in Americans' labor-leisure intensive margin adjustments, but come to different conclusions due to the subjectivity of the categorization process. Krueger and Mueller (2012) creates two methods based on the respondents' emotional state while carrying out the activities. Since this research does not study time-use trends, the categorization here is strictly for presentation purposes and does not have bearing on the conclusions reached.

[7] Barreca et al. (2016) and Heutel et al. (2017) similarly estimate the temperature-mortality relationship for different time periods and different percentiles of the temperature distribution respectively.

and Summer months relative to the Winter. Surprisingly, the share levels in the South East and South West are quite low and do not vary much throughout the year. The pattern suggests that there is large geographic and temporal heterogeneity in preferences for outdoor time use in the United States. These seasonal and geographic patterns emphasize the need to estimate temperature response functions separately across states, rather than assuming average effects are uniform throughout the country.

3 Empirical Strategy

The previous section demonstrated that weather influences the decision to spend time outside. In order to establish the relationship between weather, climate, and leisure time, I use data from the American Time Use Survey and remote sensing organizations. Following Auffhammer (2018), I detail the Climate Adaptation Response Estimation (CARE) method. Doing so allows me to estimate both the short-run behavioral response to temperature and the long-run response to local climate, allowing for geographic heterogeneity across the United States.

3.1 Estimation Strategy

The CARE method estimates both a short-run temperature response function and a long-run climate adaptation effect. The two step procedure is estimated separately for each metropolitan area in the United States, which allows for the current geographic heterogeneity in climate preferences.

In the first stage I measure the temperature response function for each CBSA in the ATUS sample. The model is represented by:

$$y_{it} = \sum_{b \in B \setminus \{60-70\}} \beta_{jb} D_{ibt} + \gamma X_{it} + \alpha_m + \phi_y + \epsilon_{it} \tag{2}$$

where y_{it} is the number of minutes spent by individual i doing some activity on day t. The explanatory variables of interest are represented by D_{ibt}, which are dummy variables indicating whether the average temperature experienced by individual i on day t falls in temperature bin b. In addition X_{it} is a vector of observed confounders, including individual characteristics from the CPS and other non-temperature meteorological variables such as the relative humidity and precipitation. α_m and ϕ_y are month and year fixed effects, respectively.

Potential non-linearities in the relationship between temperature and the time spent per day in various activities are captured by the temperature bins b (Schlenker and Roberts (2009); Deschênes and Greenstone (2011)). As in Auffhammer (2018), the bins are split by decile with exceptions at the top and bottom of the temperature distribution, where they are further divided to create bins for the first, fifth, ninety-fifth, and ninety-ninth percentiles. In total, there are fourteen bins created. Each of the estimated β_{jb} coefficients should be interpreted as the temperature response function relative to the baseline category of the eighth temperature bin. That is, the eighth temperature bin (from 60°to 70°F) serves as a baseline and the deviation measured by the β_{jb} coefficients is not the effect of a day in bin b on y_{it}, but the effect of replacing a day in temperature bin eight with a day in temperature bin b.

One of the primary strengths of this research approach is that the binned temperature coefficients are estimated separately for each CBSA j. The exclusion of location fixed effects — a typical feature in the climate literature — reflects the estimation strategy. By recovering a non-linear temperature response function for each CBSA, CBSA fixed effects are implicitly included. It is also common to interact location fixed effects with time fixed effects to adjust for seasonal characteristics unique to a particular location. Again the nature of the CARE estimation procedure makes the location-time interaction implicit with month and year fixed effects. Still, the exclusion of individual-level fixed effects could create biased estimates if there are unobservable characteristics that influence time-use patterns and are correlated within a geographic location. To account for this, a large number of individual covariates from the CPS are included.

Another key difference between the CARE method and other estimation methods in the climate literature is the inclusion of a second stage. The estimated $\widehat{\beta_{jb}}$ coefficients from the first stage are used as the dependent variable to estimate the sensitivity of CBSA j's temperature response function to the long-run climate. The second stage model can be represented by:

$$\widehat{\beta_{jb}} = \omega_0 + \omega_1 C_{jb} + \omega_2 Z_j + \eta_{jb} \tag{3}$$

where $\widehat{\beta_{jb}}$ are the estimated coefficients from the first stage. C_{jb} is the share of days in CBSA j that occur in temperature bin b from 1979 to 2004. This variable reflects the long-run climate in CBSA j. Z_j is a vector of confounders in a metropolitan area which could influence the long-run response to climate, including income and population density. Adjusting for these variables is important as they could reflect adaptation mechanisms taken through geographic sorting. For example, if cold weather adaptation is more expensive than warm weather adaption due to heating costs and the costs of heavier winter clothing, then failing to account for income should bias estimated coefficients downward.

The coefficients of interest are the C_{jb} terms. To clarify interpretation, consider the unconditional number of minutes spent participating in outdoor activities in Table 1. The mean number of minutes outdoors is 32.5 across the sample. In the first stage, if the time response to a day in the 80-90 degree bin relative to a day in the 60-70 degree bin is a decrease of ten minutes, then this would reflect a thirty-three percent decrease in the amount of time spent outdoors on average. Extending the interpretation to the second stage, if the share of days a city experiences above 80 degrees each year increases by ten percent, an estimated coefficient of positive one would be interpreted as an increase in the slope of the first stage coefficient by one minute. More concisely: the hotter a climate is (or becomes), the less sensitive it becomes to hot temperatures. This interpretation can be thought of as the difference under future climates within a city and as the difference between cities with different climates currently.

The purpose of the second stage is to capture geographic differences in the temperature response function that are due to climate. This can be thought of as a cross-sectional approach, in the tradition of Mendelsohn et al. (1994). The preferences of metropolitan areas for various temperature-sensitive activities reflects not just the temperature on that day, but also the long-run climate as a result of geographic sorting. Deschênes and Greenstone (2011) and Aroonruengsawat and Auffhammer (2011) use a similar approach, but observations of the estimated first stage parameters were at the Census division level, so the results from the second stage were imprecise with only nine observations per temperature bin. The first stage in this research is estimated at the metropolitan level, which provides for many more observations per temperature bin.

4 Results: How Weather and Climate Explain Leisure Behavior

Section 4 implements the Climate Adaptation Response Estimation procedure. The first stage recovers the temperature response function for each metropolitan area in the sample. The resulting parameters are then used to estimate how much of a city's long-term climate influences its sensitivity to temperature in the second stage. Results suggest that cold-weather areas are more temperature sensitive and therefore would be expected to respond (or adapt) most aggressively to climate change.

4.1 First Stage

The first stage estimates the temperature sensitivity of household activities separately for each metropolitan area in the American Time Use Survey dataset. The results support heterogeneous temperature preferences across the country.

Figure 7 plots the estimated coefficients following Model 2, with the number of minutes spent outside per day as the dependent variable. In total there are 31 metropolitan areas in the sample. The orange line represents the median response among the metropolitan areas, with each successive ribbon of blue representing a 20% change in percentile. Since the reference bin is from 60-70°, the coefficients can be interpreted as the change in the number of minutes spent outside from the daily average temperature falling in bin b, relative to a day with average temperature between 60-70°. The curve has a vague inverse-U shape, but there is significant heterogeneity between the cities in the sample. Estimates in the bottom half of the temperature distribution are more consistently negative than those in the top of the temperature distribution. Response heterogeneity is reflective of the different temperature response functions in Figure 5, where the hottest twenty percent of metropolitan areas have much flatter estimated coefficients than those in the coldest twenty percent. Figure 8 plots the temperature response curve for each city separately. The cities are arranged to closely resemble their relative geographic position, so New York City is in the top (north) right (east) and San Diego is in the bottom (south) left (west).

To make the comparison more clear, Figure 9 represents a placebo exercise which estimates the same equation separately for each metropolitan area, but now the dependent variable is the number of minutes spent shopping per day. Shopping was arbitrarily chosen as it was one of the activities in Table 1 which demonstrated no relationship to temperature. Relative to the results in Figure 7, the estimates of β_{jb} are flat and close to zero across the temperature distribution. The effects, when compared to those in Figure 7, are much smaller in magnitude and do not exhibit the same inverse-U shape. These results support the idea that there are certain activities which are uniquely vulnerable to the weather and to climate change, which imply long-run welfare effects since the margin for adaptation is limited.

4.2 Second Stage

In this section, estimated coefficients from the first stage are used as the dependent variable to recover the effect of local climate on temperature sensitivity. The cross-sectional approach demonstrates the role of the long-run climate distribution on preferences.

Table 3 presents the results. The coefficients of interest are the "Bottom Bin Shares" and the "Top Bin Shares," which are the pooled shares of days in the bottom five and top three bins over the twenty-five years prior to the start of the ATUS data (1979-2004). The model is estimated at the metropolitan level. A pooled model is estimated because not every metropolitan area experiences days in the most extreme bins, so results are more stable than estimating the climate response on the share of each bin separately. That being said, columns (1) and (2) regress the estimated coefficients for the bottom five bins in stage one on the share of days in those bins, and columns (3) and (4) do the same for the subset of coefficients for the top five bins. Since the slope of the estimated coefficients from stage one can differ dramatically at the extreme bins, columns (2) and (4) include interaction terms for a bin estimate being in the bottom and top three bins.

The coefficients can be interpreted as the change in the slope of the first stage coefficients from increasing the share of days in the bottom/top bins by ten percent. In plain terms this means that the coefficients represent the change in the temperature sensitivity of outdoor time due to the relative coldness/hotness of the local climate. A positive (negative) slope in the first two columns would indicate that a higher share of cold days would induce more (less) time outside when the weather is cold.

The results in columns (1) and (2) suggest that a ten percent increase in the share of cold days makes the slope of the temperature response function *more* negative. For reference, a two minute decrease in the slope of the first stage temperature response curve accounts for approximately ten percent of the total temperature response. That is, as the share of cold days increases in a city, the less time people spend outdoors on cold relative to pleasant days. Although these results appear counter-intuitive at first glance, they reflect the disparity in adaptation measures already taken with respect to cold weather across the United States. For example, Minneapolis, Minnesota has an eight-mile system of enclosed pedestrian footbridges which connect buildings in the city's downtown, making navigation of the harsh winter more manageable. Avoidance behavior is itself adaptation, and so it should not be a surprise that those most experienced with cold weather are those most able to avoid it. The same experience cannot be said of hot cities with respect to hot weather, however; results for the top bins in columns (3) and (4) are statistically insignificant with large standard errors.

To demonstrate the effect more clearly, Figure 10 plots the predicted second stage values for two representative cities: one cold city with the share of cold days equal to that of the tenth percentile in cold day shares, and one hot city with the share of hot days equal to that of the ninetieth percentile in hot day shares. The cold city is predicted to spend much less time outdoors as the share of cold days increases but not change when the share of warm days increases, all else equal. On the other hand, the hot city spends slightly less time outdoors with a higher share of cold days but more time outdoors with a higher share of hot days. The hot city-hot days relationship is less than half that of the cold city-cold days relationship, suggesting that there is more room for adaptation in cold weather than there is in hot weather.

4.3 Robustness Checks

If the first stage results are biased I would expect to see a knock-on effect in the second stage, so in this section I run a number of robustness checks to establish that the first stage results are not biased. First, in order to ensure that the shape of the non-linear temperature response function is not being driven by intertemporal substitution, Figure 13 presents the same model as in Equation 2 with lags for the mean daily temperature in city j over the three days prior to the respondents' diary days. If respondents were engaging in intertemporal substitution of outdoor activities, we would expect the temperature response function to be flatter across the eight estimated temperature bin than it is in Figure 7 where no temperature lags are included. However, what it observed in Figure 13 is consistent with previous estimates, exhibiting large negative effects for temperatures below the reference bin and no or little effect in the top temperature bins.

In the main specification of the CARE model, month and month-year fixed effects are used to adjust for seasonal and contemporaneous unobserved confounders. The model is also estimated separately for each metropolitan area in the sample, so location fixed effects are implicit. Although the location "fixed effects" cannot be omitted due to the model specification, the month and month-year fixed effects can be. If the results without time fixed effects maintain their shape (i.e. large negative responses below the 60-70°reference bin and small flat responses above the reference bin), a conclusion can be drawn: the sample period of 2005-2018 does not contain enough temporal variation to alter the results. This suggests that — apart from the seasonality implied by the temperature bins — the time horizon is not long enough to capture any change in the climate. The first stage estimates the short-run temperature response function, not the climate effect, so omitting time fixed effects should have no impact on results. Figure 14 plots the first stage model with no time fixed effects. As expected, the temperature response curve maintains its shape.

5 Outdoor Leisure in a Changing Climate

The practical implications of the previous estimates depends on the climate changing over the course of the coming decades. Shifting the climate distribution to the right will mean more warm days and fewer cold days. Using a suite of General Circulation Models (GCMs) from the Intergovernmental Panel on Climate Change, this section explores how a warming world could change non-market behavior in the United States and its welfare implications.

5.1 Forecasting the Effect of Climate Change on Outdoor Time

Estimates from Section 4 are used to project the effect of end-of-century warming on the amount of time spent outdoors. There are two competing effects happening. First, there will be more extremely hot days which – absent of adaptation – should decrease outdoor time. On the other hand, an increase in average temperatures could induce more time outside in the winter as the cost and prevalence of cold weather decreases. The change in the time outside can be represented by:

$$\Delta y_j = \frac{y_{jt+\text{inf}}}{y_{jt}} = \frac{\sum_j \widehat{\beta_{jb}} \times \Delta \text{Mean Temp}_j}{\sum_j \text{Mean Time Outdoors}_j} \tag{4}$$

where Δy_j is the percentage change in the amount of time spent outside in city j between the current period and the RCP4.5 and RCP8.5 GCMs. β_{jb} are the estimated coefficients from Stage 1 of the CARE method from Equation 2 which are multiplied by the change in the number of days in bin b for each city j under the two GCM scenarios. This estimate of the change in the amount of time spent outdoors is divided by the average number of minutes spent outdoors in city j during the ATUS sample period (2005-2018). The resulting quotient is the percentage change in the number of minutes spent outside each year for city j.

Daily downscaled projections of the future climate come from NASA's Earth Exchange Global Daily Downscaled Projections (NEX-GDDP) dataset. The data are at a 25km × 25km grid. NASA publishes 21 climate models from international research groups, each of which provide estimates for the RCP4.5 and RCP 8.5 scenarios. The models are weighted following the methods used in the Fourth National Climate Assessment (Sanderson and Wehner (2017)). The RCP4.5 scenario assumes that greenhouse gas emissions (CO_2, CH_4, N_2O, etc.) plateau in the early 2040s and decline in the subsequent years. This is in contrast to the RCP8.5 scenario, which assumes a "business as usual" approach to greenhouse gasses. Emissions continue to rise throughout the century under the RCP8.5 scenario. As a result, the RCP8.5 scenario projects upwards of four degrees Celsius of warming, whereas RCP4.5 results in between two and three degrees of warming.

I will focus on the RCP4.5 scenario for two reasons. First, the 2014 IPCC Fifth Assessment Report (AR5) which established the RCP system, presented the RCP8.5 scenario as an unlikely worst-case scenario with "with low income, high population and high energy demand due to only modest improvements in energy intensity" (Riahi et al. (2011)). The "business as usual" moniker then is somewhat misleading, since greenhouse gas-abatement technologies such as solar energy become increasingly cost effective. It is unlikely that the current energy status quo persists to the end of the century. Second, uncertainty of natural processes which create deviations in climate models are especially pronounced in RCP8.5 models, where warming feedback loops compound uncertainty. Cloud dynamics, for example, have proven especially difficult to project (Meehl et al. (2020)). For the purpose of this research then, the primary results will be those of the RCP4.5 scenario.

Figure 11 presents the results of the simulation. The cities featured are those included in the first stage of the CARE method in Section 3.1. Each city has two bars: one for the RCP4.5 scenario and one for the RCP8.5. The change in the amount of time outside is displayed in green if it is increasing and in orange if it is decreasing. Broadly, cities in the top (northern) half of the graph experience increases in their outdoor time, whereas cities in the bottom (southern) half see decreases. The results are reflective of the conclusions from Stage 2 of the CARE method which suggested that cold weather cities spent more time indoors when the weather was cold. In general, it appears that there are margins for increasing outdoor time in northern cities due to warmer winters, but that margin doesn't exist in southern cities where winters are already warm enough to enable outdoor activities. Instead, these southern cities will likely lose outdoor time as their hot summers become more extreme.

5.2 Back of the Envelope Welfare Calculations

Finally, to provide a rough approximation of the welfare consequences of climate change as a result of shifting time use patterns in the United States, I return to the U-Index measure developed by Kahneman and Krueger (2006). Figure 12 plots the change in the U-Index due to the change in the present climate to the predicted end of century climate in cities with at least 1000 ATUS diary day observations. The change is calculated by multiplying the outdoor-indoor U-Index ratio by the expected change in time outdoors for each city, as presented in Figure 11. An increase in the U-Index ratio implies that the share of time spent doing activities outdoors — and therefore time spent doing activities that are more pleasant — increases. A five percent increase in the U-Index ratio means a five percent increase in the amount of time spent doing outdoor activities, which in general are more pleasant than indoor activities. The results of this simple exercise reflect the results of the CARE model: many of the cities that stand to benefit the most are cold-weather cities which will see a decrease in the number of cold days, allowing for more time outdoors. In contrast, the cities most negatively affected are largely warm-weather cities with mild winters already but hot summers, leading to less outdoor time in the aggregate.

6 Conclusion

This paper illustrates the importance of accounting for non-market adaptations to climate change. There are two implications of the work. First, the role of behavioral change is considered as a margin for adaptation. Frequently the climate change literature in economics focuses on market activities and investment as the means of adapting, but time use surveys provide a non-market vector of change. Additionally, the surveys are both familiar to economists and will continue to update as the climate changes. Second, there are behavioral preferences for climate that vary within the United States. The breakdown of time spent indoor versus outdoors depends to a great extent on where in the country a person lives. There are clear non-linearities in the temperature response function which are most pronounced in the coldest regions of the country. These areas are expected to warm the most in the coming century, leading to large welfare changes as winters become more mild and summers more extreme. These heterogeneous climate preferences reflect both long-term adaptation and geographic sorting.

One of the benefits of extending the climate literature to non-market activities using time use surveys is that similar surveys are carried out in a number of countries, including in Europe and East Asia. Further research estimating non-market adaptation in other national contexts could provide new and potentially more generalizable results, especially in the developing world. This research includes strong assumptions about the ability to adapt to temperatures at the top of the climate distribution which have not yet been realized in the United States, so there may be countries or regions with weather observations that are outside the sample used here that might preview what is to come.

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Table 1: Summary Statistics for Time Use Activities

Number of Minutes per Day

	Unconditional			Conditional on Minutes > 0		
Activity	Mean	Median	Share Zeros	Mean	Median	N. Obs.
Household Labor						
Personal Care	47.1	35	19.8%	58.7	45	141,331
Doing Housework	115.5	65	21.5%	147.2	105	138,209
Caring for HH Member	33.9	0	71.1%	117.1	80	50,986
Caring for non-HH Member	8.2	0	88.2%	69.3	20	20,721
Traveling/Commuting	75.3	60	15.1%	88.6	70	149,569
Market Labor						
Working	157.6	0	62.1%	415.6	460	66,778
Working Outside	0.7	0	99.7%	230.0	120	530
Market Consumption Activities						
Shopping	25.9	0	57.3%	60.6	40	75,159
Using Services	5.0	0	92.3%	65.6	45	13,519
Using HH Services	0.9	0	97.9%	43.3	20	3,709
Sports	19.3	0	80.9%	101.5	60	33,568
Leisure Activities						
Eating/Drinking	68.4	60	4.2%	71.4	60	168,723
Leisure	295.0	255	4.7%	309.7	270	167,802
Using the Telephone	7.7	0	84.0%	47.9	30	28,205
Exercising	17.5	0	81.7%	95.9	60	32,164
Outdoor Activities						
Outdoors	32.5	0	62.5%	86.6	50	66,109
Outdoor Dining	0.3	0	99.3%	39.7	30	1,202
Outdoor Exercise	5.0	0	94.5%	90.4	60	9,686
Outdoor Non-work	31.8	0	62.6%	84.9	50	65,938
Miscellaneous Activities						
Sleeping	529.1	520	0.1%	529.6	520	175,956
Education-Related Activities	16.3	0	94.0%	272.5	240	10,516
Religious Activities	12.9	0	88.0%	107.2	85	21,152
Volunteering Activities	8.9	0	93.5%	136.1	100	11,500

Table 2: Change in the Number of Minutes Spent by Acitivity

Relative to a Day with Max Temperature from 60-70°

Activity	Temperature Bins								R^2
	<20°	20-30°	30-40°	40-50°	50-60°	70-80°	80-90°	>90°	
Household Labor									
Caring for HH Member	-4.3 (2.6)	-1.2 (2)	-1.8 (1.6)	-0.4 (1.1)	1.1 (1)	-0.4 (1.1)	-0.5 (1.8)	0.3 (4.6)	0.235
Doing Housework	-2.3 (4.1)	-4.3 (3.6)	-3.8 (2.6)	-3.8 (2.2)	-1.3 (1.9)	0.2 (1.8)	-0.8 (2.9)	15.1 (8.4)	0.162
Caring for Non-HH Member	-1.4 (1.2)	0.2 (1)	0.2 (0.9)	0.1 (0.6)	0 (0.6)	0.1 (0.7)	1.3 (1)	-1.2 (2.5)	0.072
Personal Care	0.1 (1.7)	0.5 (1.2)	0 (1)	-0.4 (0.9)	-0.8 (0.7)	-0.8 (0.8)	0.2 (1.2)	-3.2 (4.4)	0.091
Traveling/Commuting	-1.2 (2.8)	-3.5 (2.7)	-3.2 (1.8)	-3.5 (1.3)	-0.9 (1.1)	0.8 (1.1)	0 (2)	-9.9 (4.6)	0.071
Market Labor									
Working	-13.4 (9.1)	-2.9 (5.4)	-2.6 (5.2)	-0.1 (4.1)	2.1 (3.5)	0.8 (4)	-3.1 (7.8)	-9.4 (16.7)	0.380
Working Outside	0 (0.6)	0 (0.5)	0.4 (0.4)	0.3 (0.3)	0.5 (0.2)	0 (0.3)	0.2 (0.5)	2.6 (1.9)	0.054
Market Consumption Activities									
Using Government Services	-0.2 (0.2)	0 (0.2)	0.2 (0.2)	0 (0.1)	0 (0.1)	0.1 (0.2)	0 (0.2)	-0.1 (0.3)	0.048
Using HH Services	0 (0.2)	0 (0.2)	0.1 (0.2)	0.1 (0.2)	0 (0.1)	0 (0.2)	0.4 (0.3)	-0.2 (0.6)	0.040
Using Services	-0.5 (0.7)	0 (0.6)	-0.1 (0.5)	0.2 (0.3)	0.5 (0.3)	-0.1 (0.4)	-0.3 (0.6)	-0.1 (2)	0.059
Shopping	0.1 (1.7)	-0.2 (1.2)	0.1 (1)	0.5 (0.9)	0.4 (0.8)	0.1 (0.9)	-0.4 (1.2)	5.6 (5.2)	0.107
Sports	-4.4 (1.7)	-4.2 (1.2)	-4.1 (1)	-2.8 (1)	-1.1 (0.8)	1.3 (1)	3.7 (1.7)	-1.2 (4.9)	0.080
Leisure Activities									
Exercising	-4.3 (1.7)	-3.5 (1.2)	-3.5 (1)	-3 (0.9)	-1.6 (0.8)	1.4 (1)	3.8 (1.5)	-1.3 (4.5)	0.079
Eating/Drinking	-0.3 (1.8)	-1.3 (1.3)	0.4 (1.2)	-0.7 (0.8)	0.1 (0.8)	0 (0.8)	2 (1.1)	5 (4)	0.085
Leisure	21.8 (5.7)	15.1 (4.5)	9.8 (3.8)	6.9 (3.1)	0.6 (2.3)	2 (3.2)	4.3 (4.7)	11.6 (13)	0.195
Using the Telephone	0.7 (0.7)	0.3 (0.6)	0.4 (0.4)	-0.2 (0.3)	-0.4 (0.3)	0 (0.3)	0 (0.5)	2.4 (1.4)	0.071

Outdoor Activities									
Outdoor Dining	0 (0.1)	0 (0.1)	-0.1 (0.1)	0 (0.1)	0 (0.1)	0 (0.1)	0 (0.1)	-0.2 (0.2)	0.041
Outdoor Exercise	-1.7 (0.9)	-1.3 (0.8)	-2 (0.6)	-1.2 (0.6)	-0.8 (0.5)	0 (0.4)	0.3 (0.7)	-1.1 (1.2)	0.069
Outdoor Leisure	-0.5 (0.5)	-0.7 (0.5)	-0.5 (0.4)	-0.6 (0.4)	-0.3 (0.4)	0.5 (0.4)	0.4 (0.6)	0.4 (1)	0.058
Outdoors	-10.2 (2)	-11.1 (2)	-11 (1.7)	-7.5 (1.5)	-2.6 (1.3)	-0.1 (1.3)	-0.2 (2)	-2.2 (4)	0.111
Outdoor Non-work	-10.1 (2.1)	-11.2 (2.1)	-11.5 (1.7)	-7.8 (1.5)	-3.2 (1.2)	-0.1 (1.3)	-0.5 (1.8)	-4.9 (2.9)	0.115
Miscellaneous Activities									
Education	0.4 (2.4)	-1.1 (1.8)	-1.2 (1.8)	-0.4 (1.3)	-1.2 (0.9)	-1.4 (0.8)	-2.5 (1.1)	1.9 (5.9)	0.136
Religious Activities	0.7 (1.3)	-0.2 (1)	0.3 (0.8)	0.4 (0.7)	0.5 (0.7)	0 (0.6)	0 (1)	-1.9 (2.5)	0.134
Sleeping	5.1 (5)	2.9 (3.9)	5.7 (2.7)	4.8 (2.3)	0 (2)	-2.7 (1.7)	-2.9 (2.9)	-9.8 (9.7)	0.167
Volunteering	-1.2 (1.3)	0.1 (1.1)	-0.8 (0.9)	0 (0.7)	-0.2 (0.6)	-0.3 (0.7)	-0.8 (1.1)	-1.9 (2.6)	0.064

Note: Each activity is estimated separately as a dependent variable with city-month and month-year fixed effects. Standard errors in parentheses are clustered at the state level.

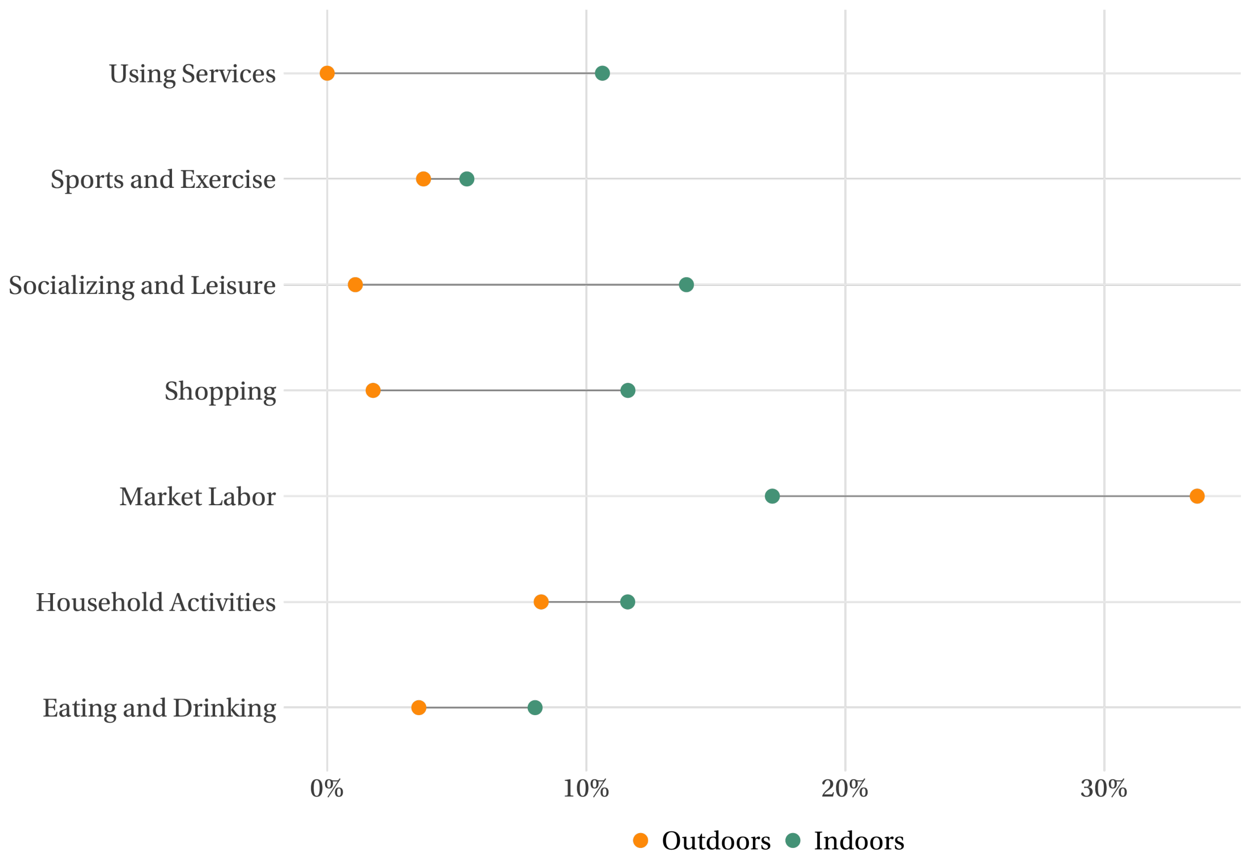
Table 3: CARE Stage 2

	Bottom Bins		**Top Bins**	
	No Interactions	Interactions	No Interactions	Interactions
Bottom Bin Shares	-2.47***	-1.94**		
	(.913)	(.816)		
Top Bin Shares			2.63*	3.89**
			(1.35)	(1.77)
Num.Obs.	160	160	79	79
R2	0.101	0.104	0.092	0.104
Bin FE	Yes	Yes	Yes	Yes
SE	White	White	White	White

* p < 0.1, ** p < 0.05, *** p < 0.01

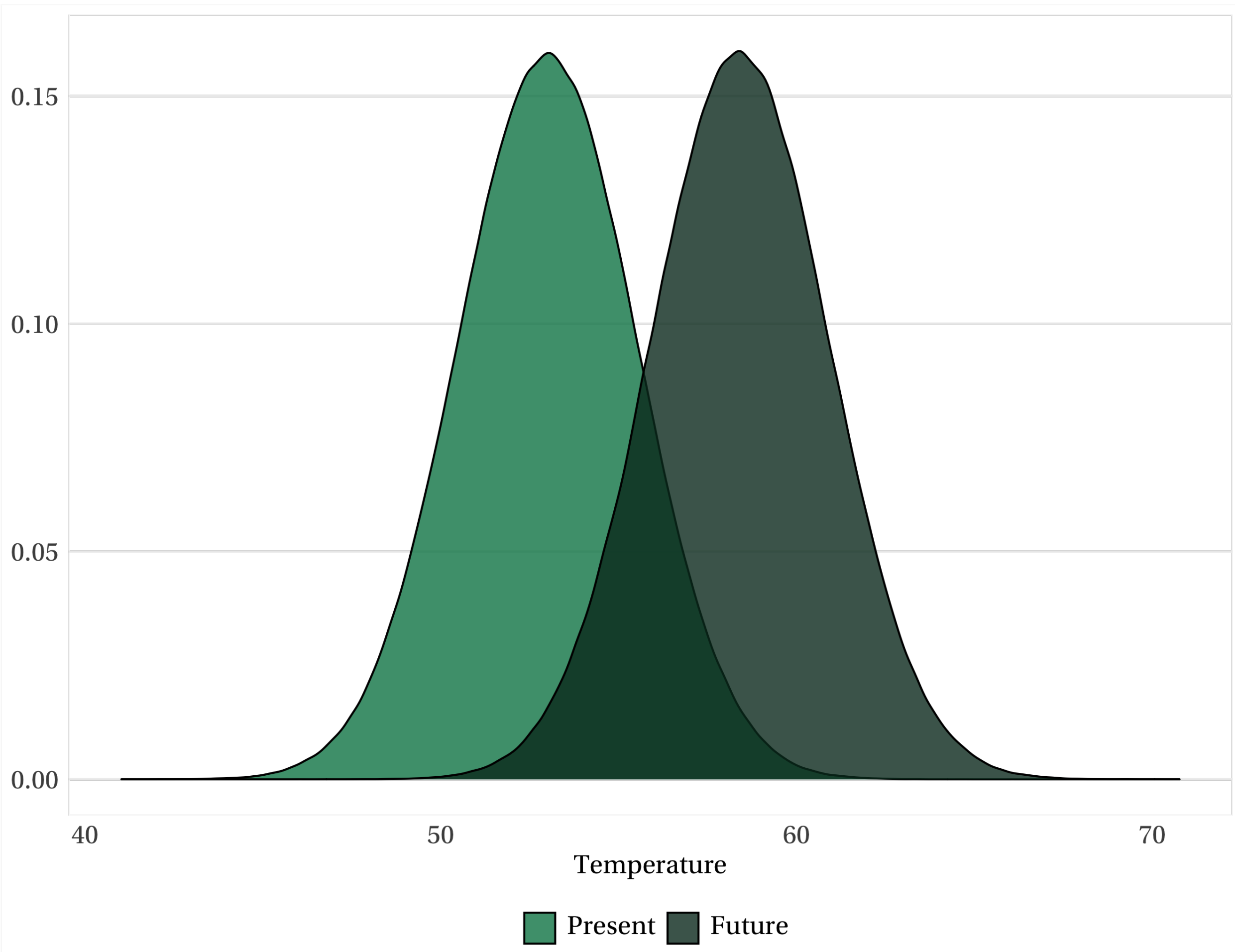
Figures

Figure 1: Outdoor Activities More Pleasant



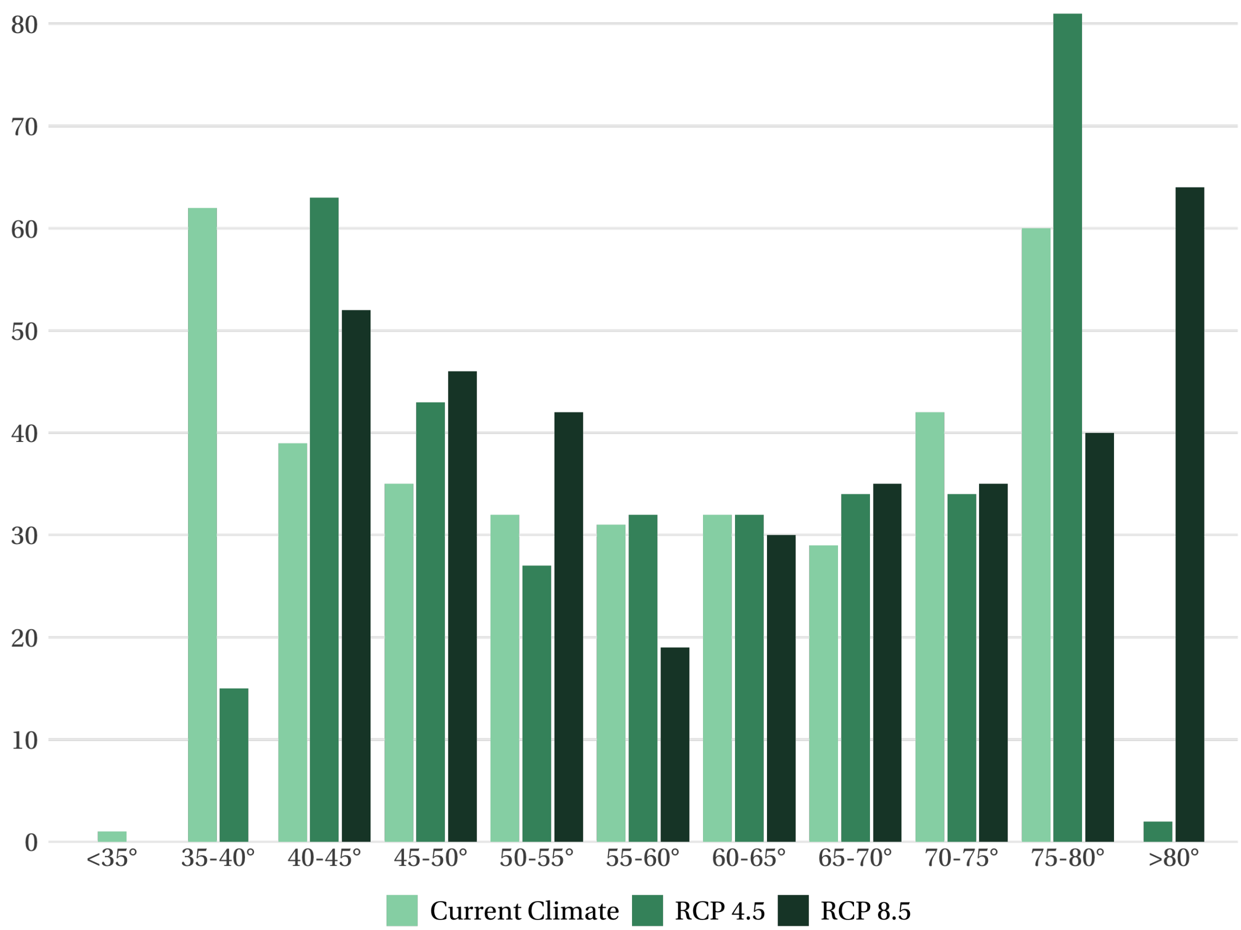
Note: The U-Index (Kahneman and Krueger (2006)) calculates the share of time an activity is reported as being unpleasant by survey respondents. If the primary emotion during the activity is negative (e.g. if the respondent reports being more unhappy than happy), then the activity is coded as unpleasant for that respondent. The index is the weighted average of all such responses from the American Time Use Survey's Wellbeing module. The graph demonstrates that activities which take place inside are more unpleasant than the same activities when they take place outside.

Figure 2: Simulation of the Temperature Distribution Shifting 3° Celsius



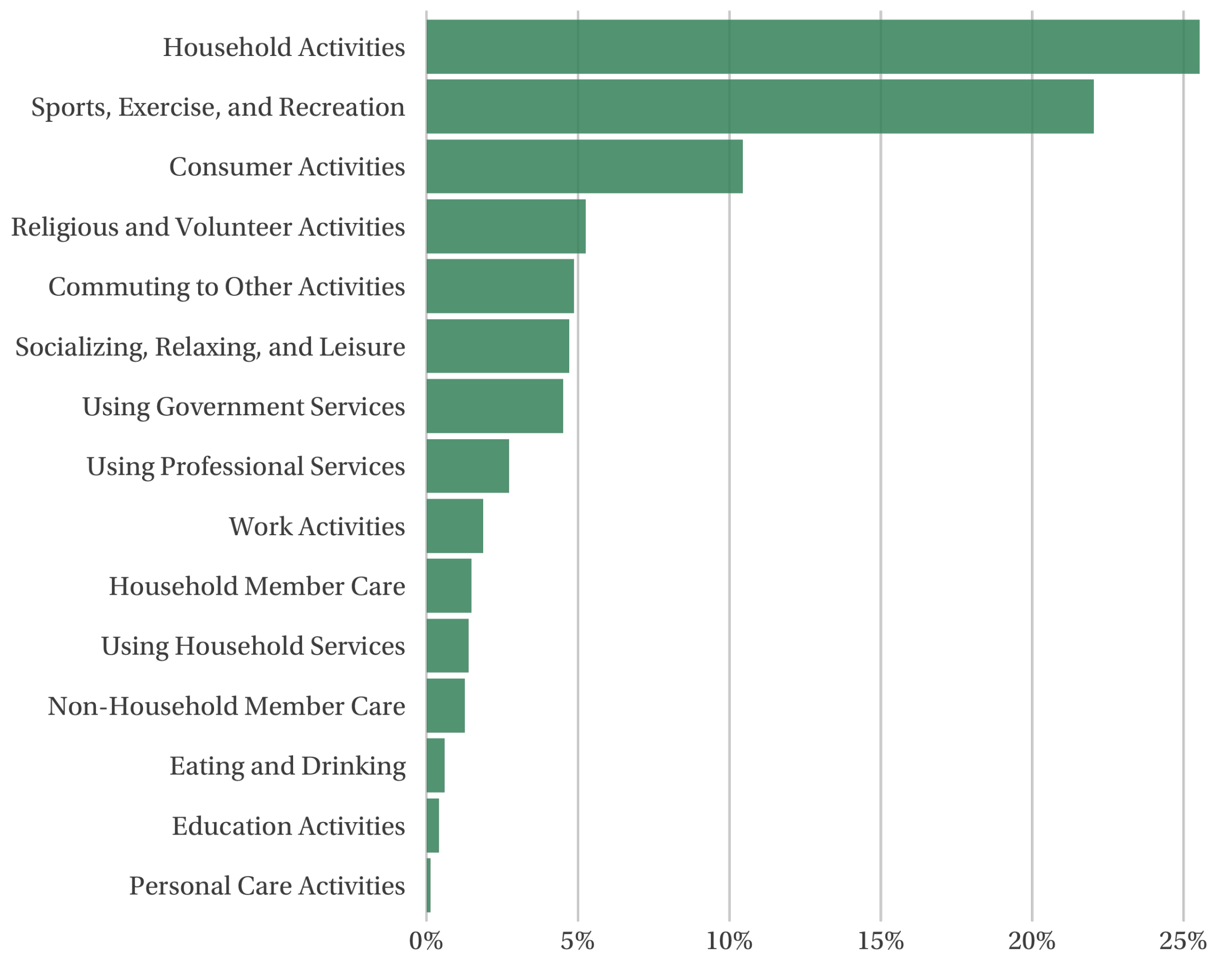
Note: This simulation reflects the change in the temperature distribution of the United States given a three degree Celsius increase in daily average temperatures. The numbers are simplified for demonstration purposes; different areas of the United States are expected to warm at different rates. Plotting the average national temperature distribution ignores the heterogeneous response to climate change across the country.

Figure 3: Annual Number of Days with Average Temperature in 5° F Bins Under Three Climate Scenarios



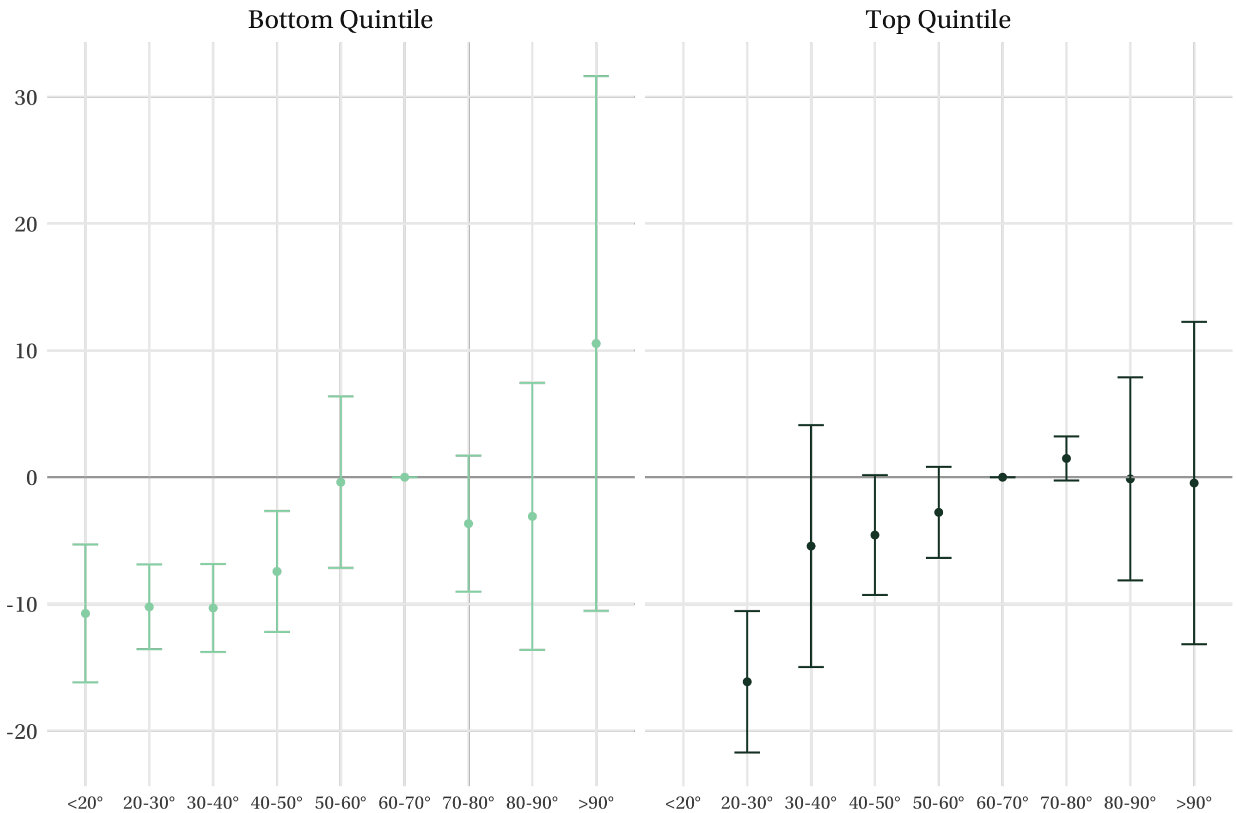
Note: The figure presents the average temperature under three climate scenarios in the sample locations. First in light green is the current climate, defined as the period from 2005 through 2018. The second is the Intergovernmental Panel on Climate Change's (IPCC)Representative Concentration Pathway (RCP) 4.5 in which greenhouse gas emissions peak between 2040 and 2045 and then begin to decline. This intermediate scenario implies global temperatures rise by 2-3° Celsius. Finally, the darkest shade represents RCP 8.5, under which emissions continue to rise unabated and global temperatures increase by more than 4° Celsius.

Figure 4: The Share of Time Spent Outside by Activity Group



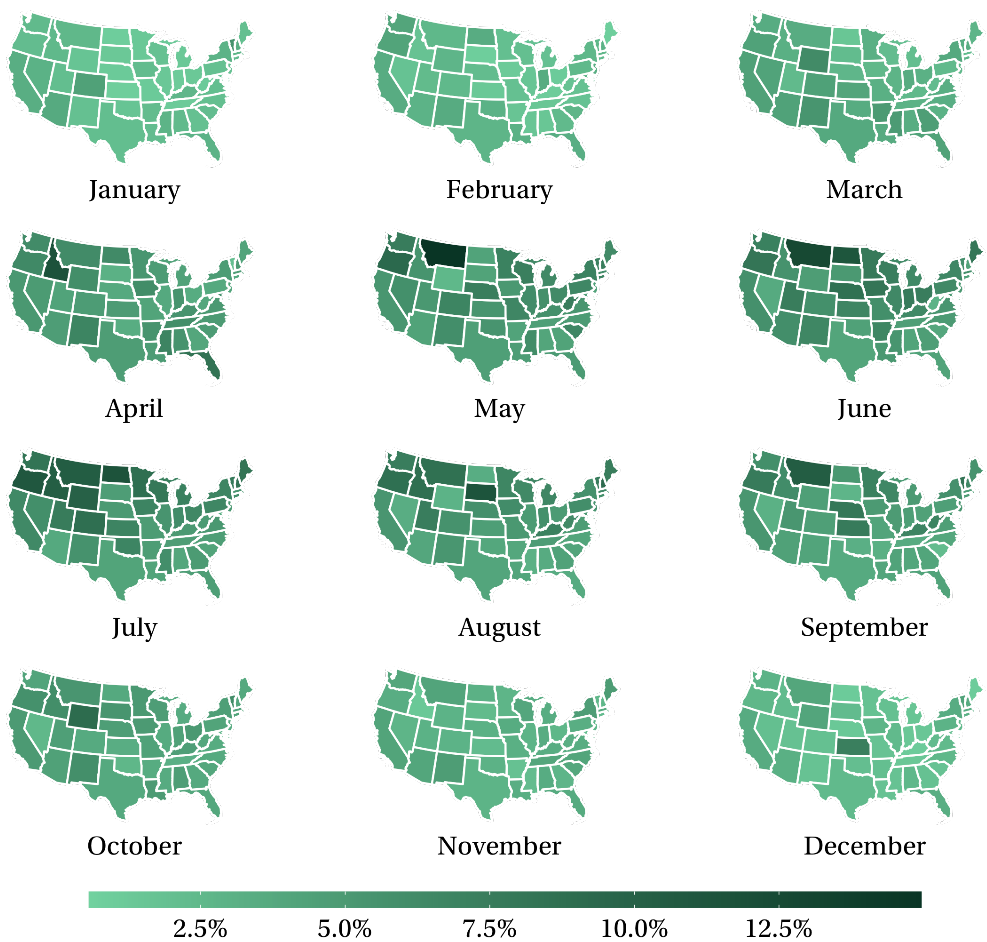
Note: Household activities — including gardening, yard maintanence, and pet care — and participation in sports and recreation take place outside approximately one quarter of the time. Other activity groups have much smaller shares of time spent outside.

Figure 5: Estimated Change in the Number of Non-Work Minutes Spent Outside in Cities in the Bottom and Top Quintiles of the Temperature Distribution



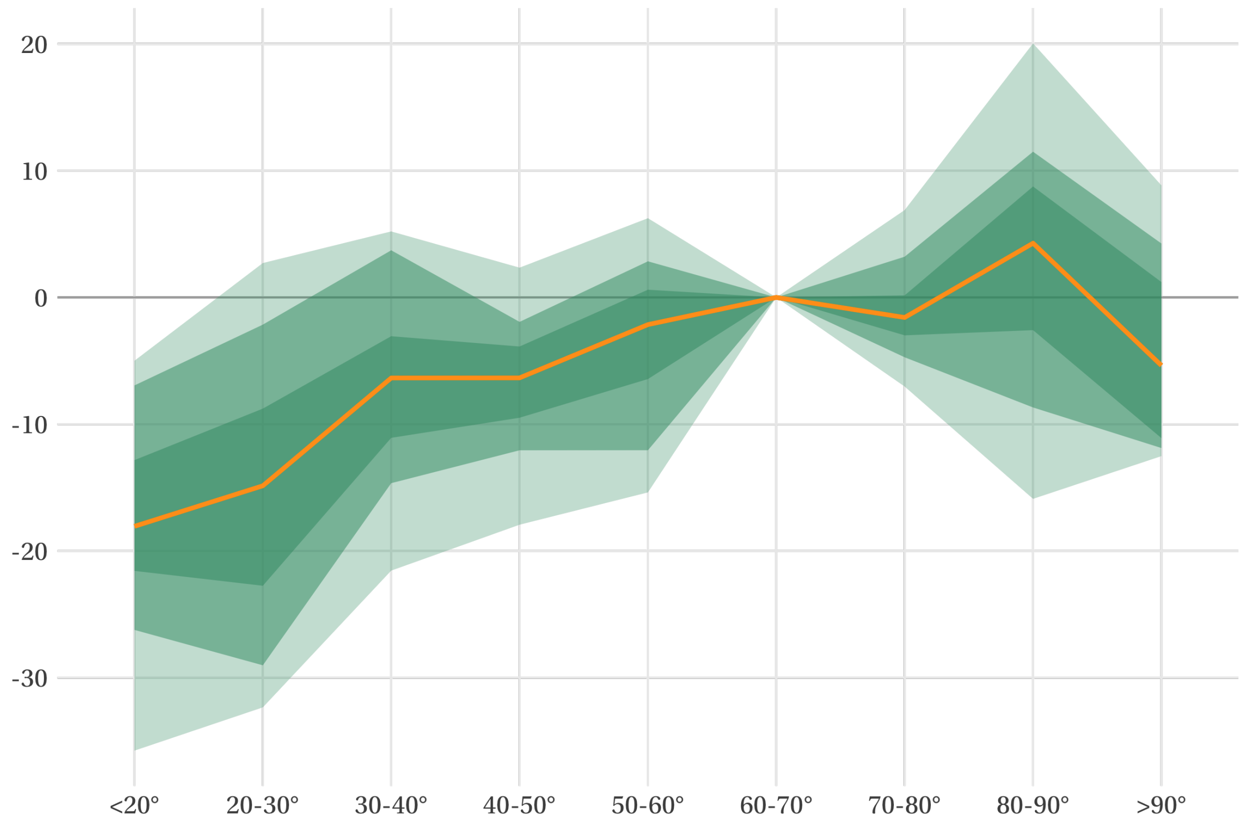
Note: The temperature response function is estimated for the bottom and top quintiles of the average temperature distribution. The coldest metropolitan areas appear to be more consistently sensitive to temperature for the coldest bins and are clearly more sensitive than the top quintile at extremely hot temperatures.

Figure 6: Daily Share of Non-Work Time Spent Outside



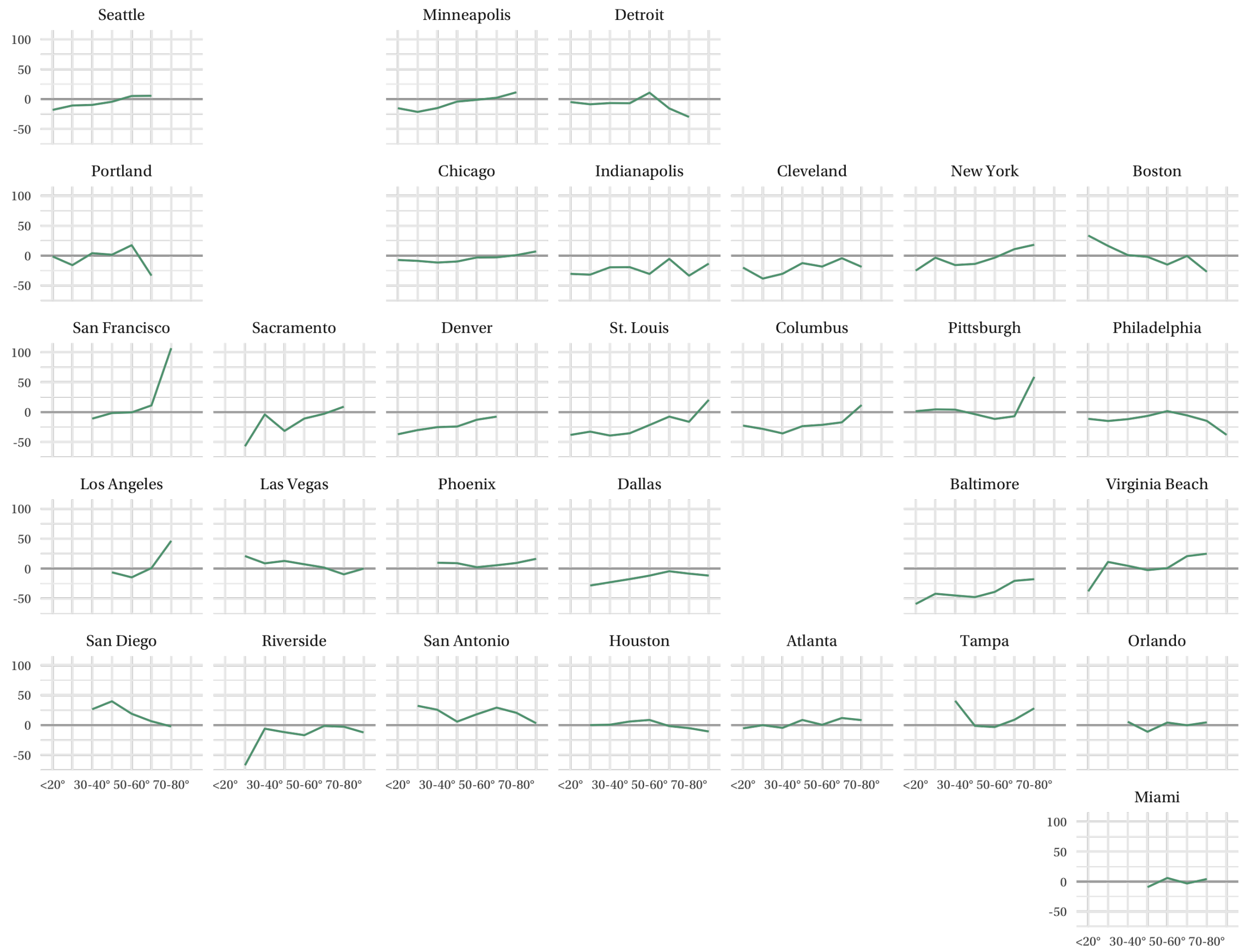
Note: The graph above calculates the daily share of non-work time spent outside by dividing the total number of minutes reported outside by the number of non-work and non-sleeping minutes. Large heterogeneous seasonal patters across states emphasize the importance of not assuming constant temperature reaction functions.

Figure 7: Distribution of Stage 1 Temperature Response Coefficients for Outdoor Time



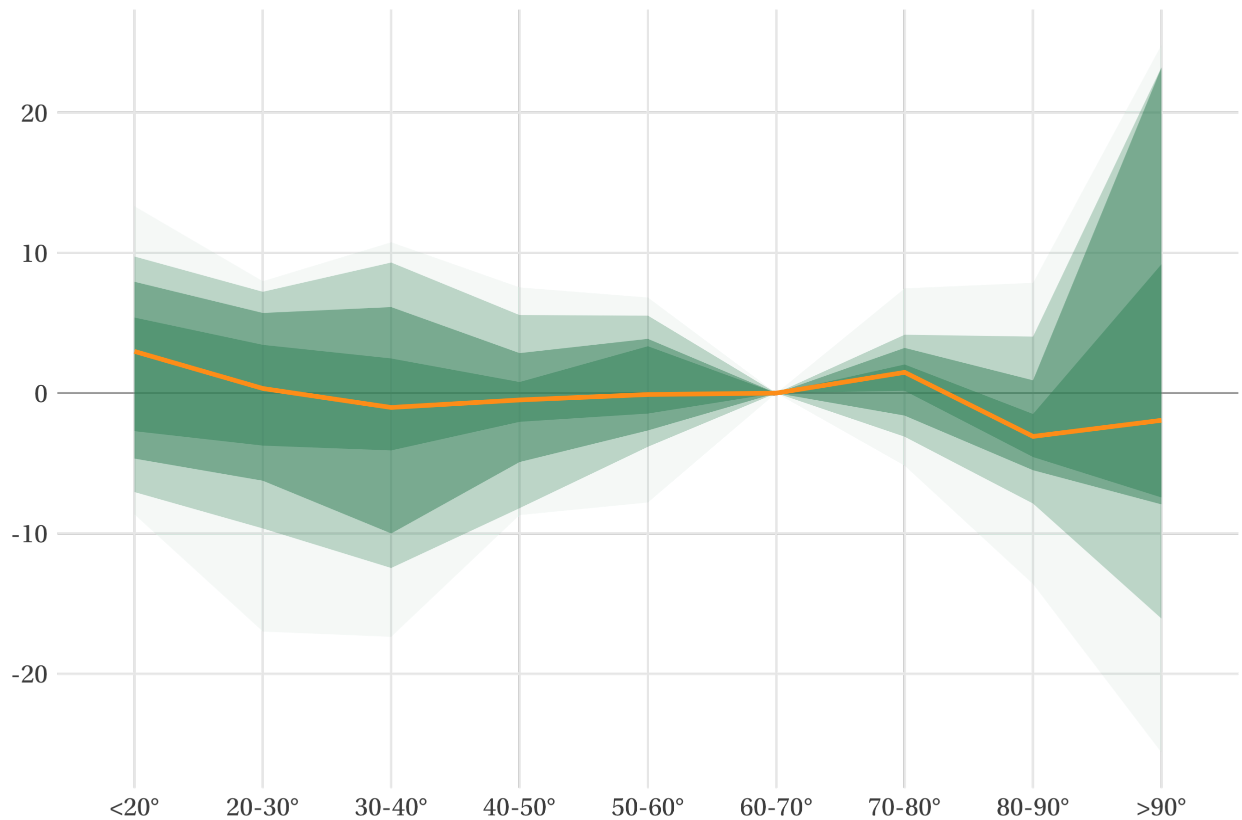
Note: The solid orange line represents the median response, and each shaded green area represents the surrounding high and low decile. For example, the darkest shaded area is the estimated coefficients that are in the 40th to 60th percentile of the coefficient distribution. The coefficients are interpreted as the change in time outside as a result of being in a particular temperature bin relative to a day in the 60-70°bin.

Figure 8: Stage 1 Temperature Response Function Across Cities



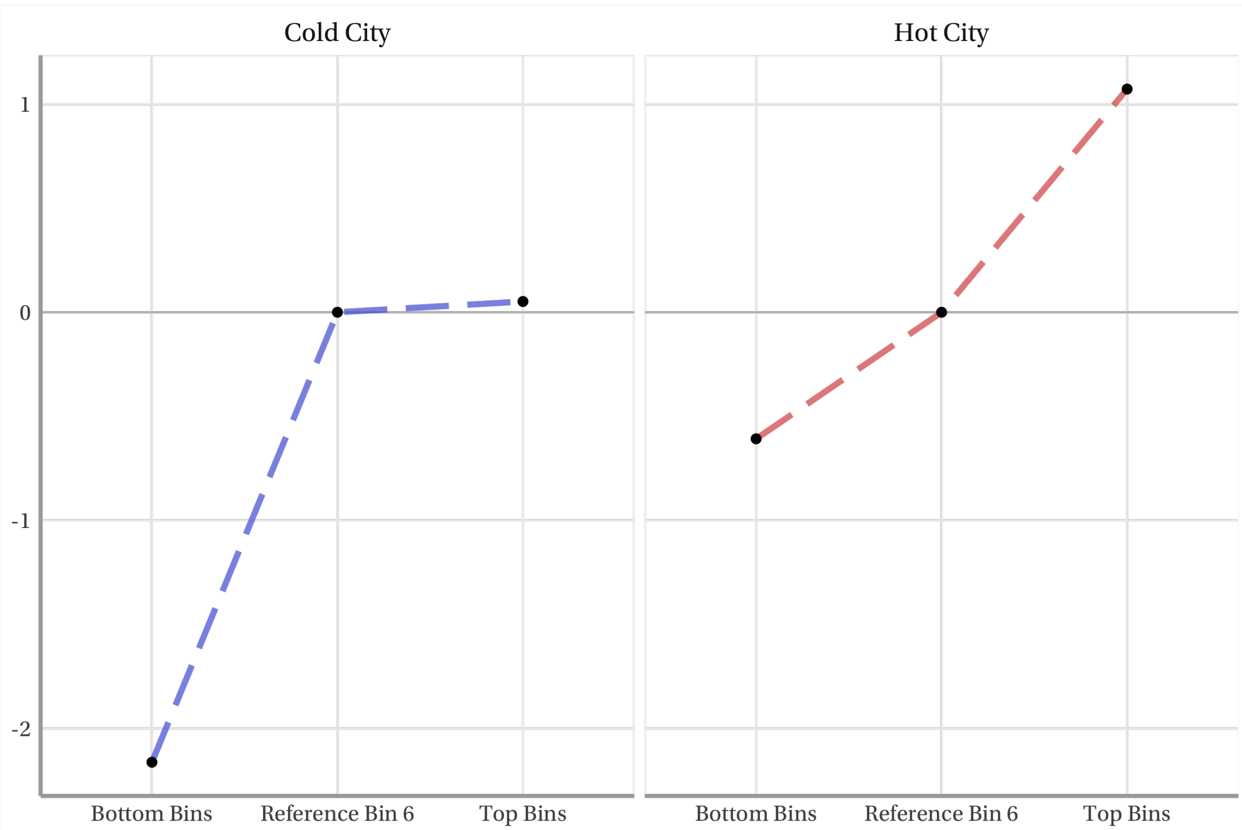
Note: This figure displays the results for each city with at least 1000 ATUS respondents as estimated in Stage 1 of the CARE method. The results in Figure 7 are an aggregation of the city-level results presented here. The cities are arranged approximately geographically.

Figure 9: Placebo Exercise: No Pattern for Shopping



Note: The specification for this figure is the same as in Figure 7, but with shopping as the dependent variable. The median response to temperature on shopping is much flatter than the response on time spent outdoors, supporting the conclusions from Section 3 that there are some settings that are more temperature sensitive than others.

Figure 10: Predicted Second Stage Response in a Synthetic Cold and Hot City

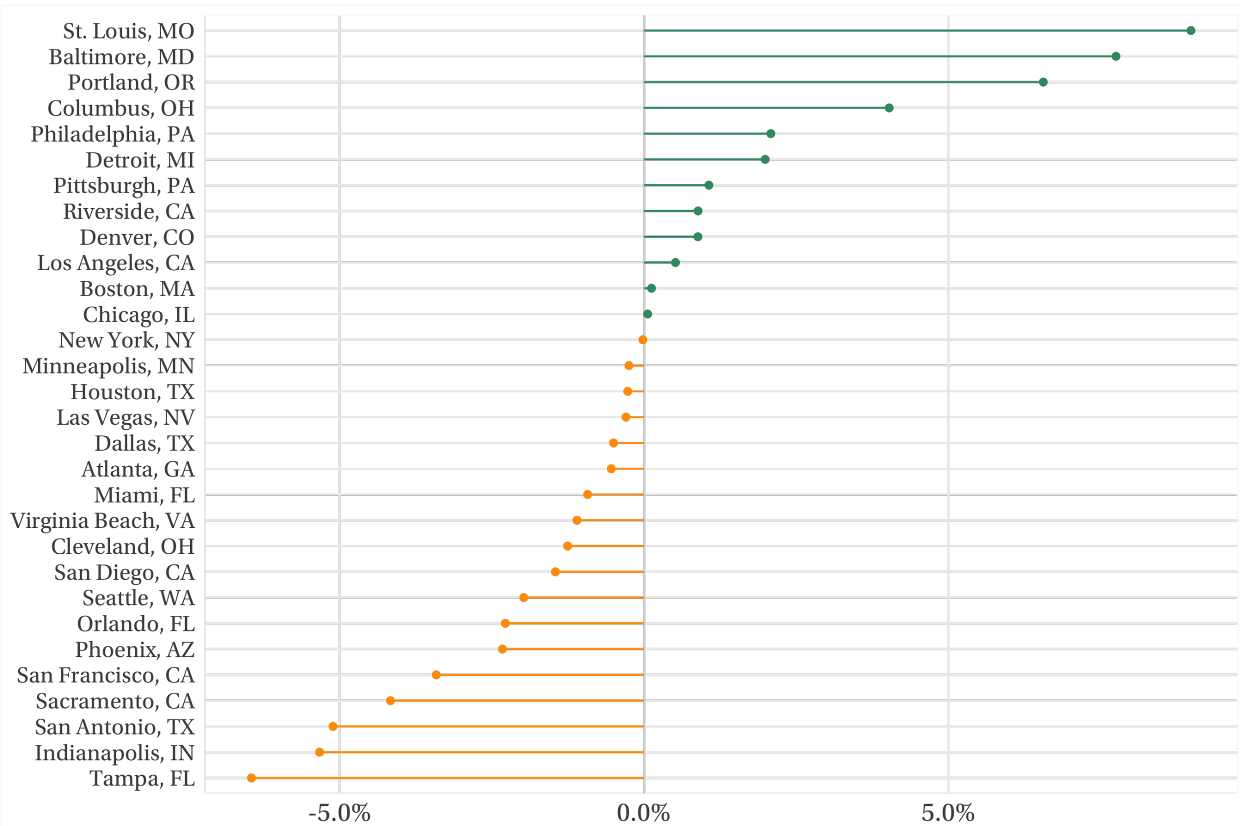


Note: This figure presents the percentage change in the number of minutes spent outside for the in-sample cities under the RCP4.5 and RCP8.5 climate scenarios published by the IPCC. Similar to Figure 8, the cities are arranged approximately geographically for visualization purposes. Green indicates an increase in time outside and orange indicates a decrease.

Figure 11: Percentage Change in the Amount of Time Spent Outside

Note: This figure presents the percentage change in the number of minutes spent outside for the in-sample cities under the RCP4.5 and RCP8.5 climate scenarios published by the IPCC. Similar to Figure 8, the cities are arranged approximately geographically for visualization purposes. Green indicates an increase in time outside and orange indicates a decrease.

Figure 12: Change in the U-Index Under the RCP4.5 Scenario

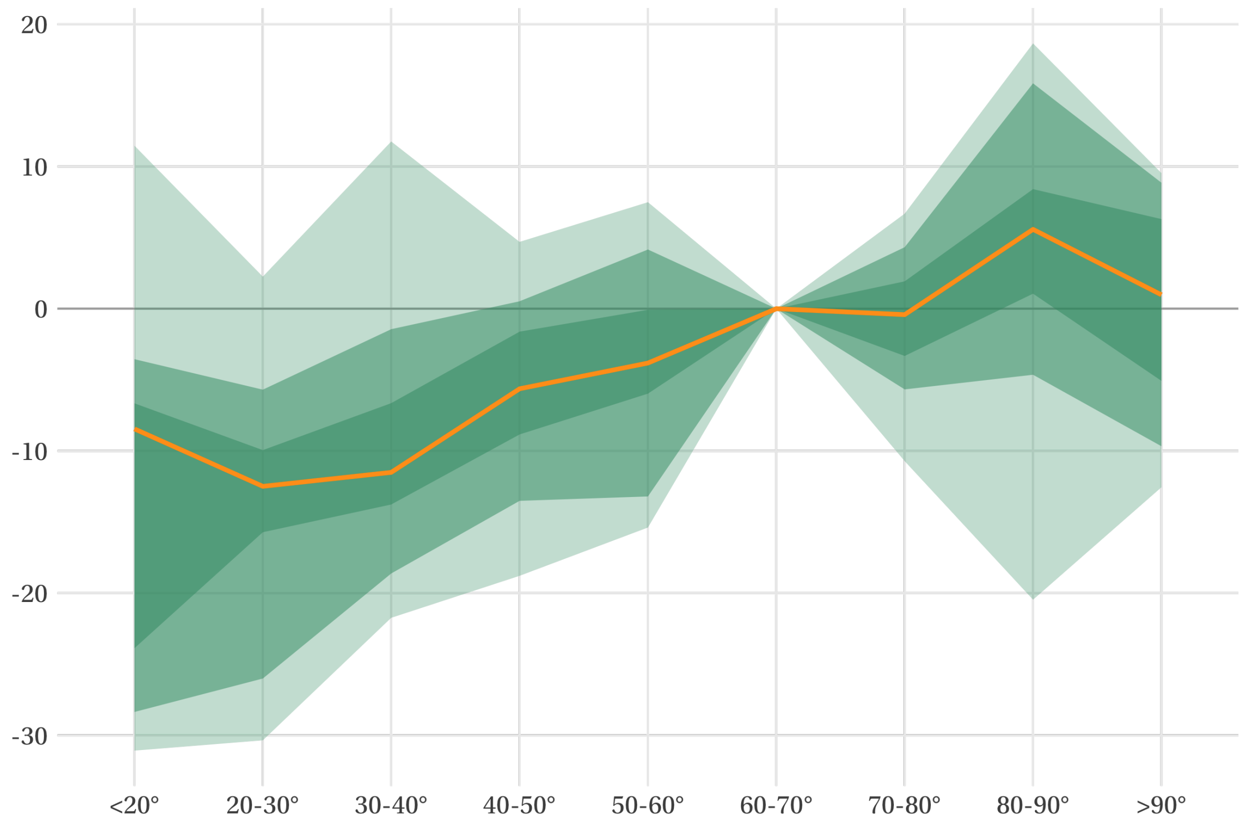


Note: This figure presents the percentage change in the number of minutes spent outside for the in-sample cities under the RCP4.5 and RCP8.5 climate scenarios published by the IPCC. Green indicates an increase in time outside and orange indicates a decrease.

Appendices

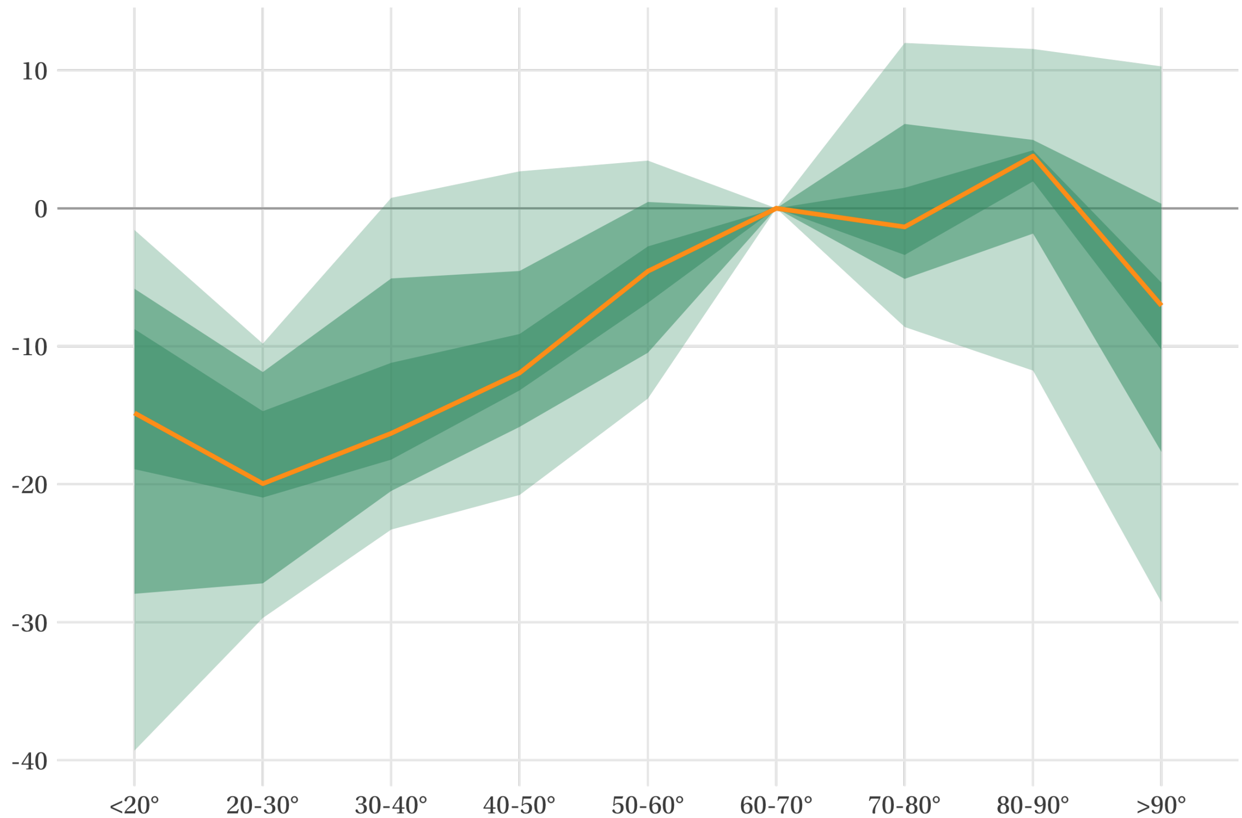
A Robustness Checks

Figure 13: Distribution of Stage 1 Temperature Response Coefficients for Outdoor Time with 3-Day Temperature Lags



Note: The solid orange line represents the median response, and each shaded green area represents the surrounding high and low decile. For example, the darkest shaded area is the estimated coefficients that are in the 40th to 60th percentile of the coefficient distribution. The coefficients are interpreted as the change in time outside as a result of being in a particular temperature bin relative to a day in the 60-70°bin.

Figure 14: Distribution of Stage 1 Temperature Response Coefficients for Outdoor Time with No Fixed Effects



Note: The solid orange line represents the median response, and each shaded green area represents the surrounding high and low decile. For example, the darkest shaded area is the estimated coefficients that are in the 40th to 60th percentile of the coefficient distribution. The coefficients are interpreted as the change in time outside as a result of being in a particular temperature bin relative to a day in the 60-70°bin.