**Preliminary and incomplete. Please do not cite.**

# Climate Change and the Allocation of Time

Joshua Graff Zivin
UC San Diego and NBER

and

Matthew Neidell
Columbia University and NBER

March 2009

Abstract: In this paper we estimate the impacts of climate change on the allocation of time using econometric models that exploit plausibly exogenous variation in daily temperature over time within counties. Our results reveal a starkly asymmetric inverted U-shaped relationship between temperature and outdoor activities, with a nearly one-to-one rate of substitution between these activities and sedentary indoor activities. Similar relationships arise using cross-sectional models, suggesting limited scope for long-run adaptation given the current technology environment. Our estimates imply on average the allocation of time will change very little under various climate change scenarios, but tremendous heterogeneity throughout the country point towards potentially interesting implications for population health and internal US migration in the future.

Climate change is expected to warm the earth considerably in the coming decades. Even a dramatic reduction in greenhouse gas emissions would not avert substantial increases in temperature. These temperature changes, in turn, are likely to exert profound impacts on the way in which humans interact with the planet.[1]

One fundamental aspect of life that may be altered under this new climatic paradigm is individuals' allocation of time. People may respond to temperature changes by altering the amount of leisure time allocated to outdoor activities because of a general preference for being outside in more pleasant weather.[2] Time allocated to physical activities may also change because ambient temperatures have significant impacts on endurance and fatigue.[3] These changes in marginal utility derived from leisure alter the relative attractiveness of other activities, yielding potentially important changes in time allocated to non-leisure activities as well.

In this paper, we estimate the impacts of climate change on individuals' time allocation, which is important for at least three reasons. First, time is a limited but extremely valuable resource. We use our time to earn income, invest in human capital, develop social and familial relationships, and engage in leisure. If individuals have optimally allocated their time under current climate conditions, then alterations in time allocation resulting from climate change will induce significant costs to society.

Second, time is an essential input into the production of health. Time engaged in physical activities has been widely demonstrated to provide numerous benefits for health, including body weight, cardiovascular disease, cancer, diabetes mellitus, osteoarthritis,

---

[1] Numerous studies have examined the potential impacts of climate change on a wide range of activities, such as agriculture and mortality (e.g., see Schlenker et al., 2005 and Deschenes and Greenstone, 2007a,b).
[2] See Ma et al., 2006; Pivarnik et al., 2003; U.S. Department of Health and Human Services, 1996; Eisenberg and Okeke, 2008.
[3] See Gonzalez-Alonso et al., 1999; Galloway and Maughan, 1997; Nielsen et al. 1993.

osteoporosis, and mental health.[4] Time can also be used as a form of avoidance behavior to reduce exposure to risk by, for example, spending more time indoors on poor air quality days (Neidell, 2009; Mansfield et al., 2006). These changes in behavior may have subtle but important impacts on health typically overlooked in climate change research.

Third, time allocation provides a source of short-run adaptation to climate change. Time spent outdoors is a direct route through which climate change will affect human health, so people may self-protect by limiting time outside in response to a change in temperature.[5] Furthermore, individuals may compensate for changes in temperatures through intra- and inter-temporal substitutions, such as spending more time outside in the morning and evening hours during extremely hot periods. Such adaptations, while costly to individuals, may offset some of the welfare effects from climate change. Since some warming appears unavoidable in the near future, understanding the extent of individual level adaptation is essential for developing appropriate policy responses to climate change.

Importantly, the net impact of climate change on time allocation is not a priori obvious. While summer in many locations may become too hot for many outdoor activities, the other seasons may become more pleasant. Similarly, hot regions may become less hospitable while cooler ones become more attractive. From an empirical perspective, the challenge to assessing these changes lies at the high end of the temperature distribution where observations are limited. Only 1 percent of all days in an average year in the United States exceed 100 degrees Fahrenheit, but forecasts suggest

---

[4] There are also some negative effects of exercise, such as joint diseases, but the benefits from physical activities are typically considered to outweigh the costs.

[5] In a similar vein, Deschenes and Greenstone (2007b) explore short run adaptation by examining the impact of temperature on electricity consumption using within state variation.

that this number will climb to a staggering 16 percent within the coming century.[6] Given the paucity of data, most research to date on the economic consequences of climate change has been forced, at least implicitly, to rely on out-of-sample predictions from lower temperature levels (Loomis and Crespi, 1999, Mendelsohn and Markowski, 1999, Deschenes and Greenstone, 2007b). Since humans, and many other life forms, begin to reach biological limits when ambient temperature exceeds that of the body, the reliability of these extrapolations is unclear, making it crucial to carefully model the upper end of the temperature distribution.

We estimate the impacts of climate change on time allocation using individual level data from the 2003-2006 American Time Use Surveys (ATUS), a nationally representative survey that provides estimates of how and where individuals spend their time. Based on county of residence and date of survey, these data are linked to daily weather data from the National Climatic Data Center and other potential confounders, such as daily pollution levels and hours of daylight. Our econometric models estimate the impact of temperature on activity duration by including year-month and county fixed effects, which enables us to identify the effects of temperature using the plausibly exogenous variation in temperature over time within counties and within seasons. We flexibly model temperature by including a series of indicator variables for each five degree temperature bins, with the highest bin for days over 111 degrees. One of the tremendous advantages of using the ATUS is that we can exploit data from the 2006 heat wave that produced high temperatures across much of the United States to produce more reliable estimates of behavioral responses at the high end of the temperature distribution.

[6] This number is based on Hadley 3 climate predictions with unabated greenhouse gas emissions. This climate forecast model is described in more detail in the data section.

Our results confirm the importance of explicit modeling the upper end of the temperature distribution. We find a starkly asymmetric inverted U-shaped relationship between temperature and outdoor physical activities – outdoor time is gradually increasing in temperature up to 70˚F, is relatively stable until roughly 100˚F, and drops-off rapidly at temperatures above 100˚F. Indeed, by 110˚F the amount of time spent outdoors is not distinguishable from zero. Likewise, the relationship between temperature and indoor sedentary activities, such as television watching, follows a U-shaped pattern that mirrors the relationship between temperature and physical activities. This glaring asymmetry in the response function suggests that, like agricultural crops (Schlenker and Roberts, 2008), humans begin to reach their biological limits at high levels of heat stress. We find little changes in other activities, such as labor supply and sleep, suggesting the substitution between outdoor physical activities and sedentary indoor activities is the predominant adjustment in time allocation in response to temperature changes. We also find some evidence that individuals compensate for higher temperatures by shifting activities within and across days to periods of more favorable weather conditions, but these changes are small in magnitude. Thus, the broad set of behavioral substitutions induced at the high end of the temperature distribution have important implications for population health that must be balanced against the more modest benefits of increased non-sedentary activity over a wider range of temperatures at the lower end of the distribution.

The regressions that generated the results discussed thus far assume that time spent outdoors is the primary means of responding to deviations from ideal temperature. While it is impossible to know what new inventions will be created to insulate humans from inclement weather, we can examine longer-run adaptation based on the current feasible set of technologies by estimating the cross-sectional relationship between temperature and time allocation. If individuals that live in hotter climates have had incentives to invest in technologies that make it easier to cope with high temperatures, then individuals that live in cooler places would invest in similar technologies as they become warmer. The cross-sectional estimates, which allow for individuals to adjust to local climates, are, however, quite comparable to fixed effect estimates, suggesting little scope for longer-run adaptation given the current technology environment.

Given our climate response function and the limited opportunities for adaptation, we conclude our analysis by projecting changes in outdoor and indoor time under various IPCC climate change scenarios. In contrast with the work that has found large projected increases across several outdoor recreation activities (Loomis and Crespi, 1999, Mendelsohn and Markowski, 1999)[7], we find aggregate time spent outdoors will change very little. The sharp decreases in outdoor time over the narrow range of higher temperatures almost completely offset the warming that yields modest increases in outdoor time over a wide range of lower temperatures. Average weekly outdoor time will increase by approximately seven minutes by 2020-2049 and by eleven minutes by 2070-2099, which represent a modest 2-4% increase. Aggregate sedentary indoor activities are also predicted to change minimally.

Our projections also suggest important heterogeneity throughout the country. Texas, the biggest loser, will experience an approximately 32 minute decline in weekly outdoor time – the equivalent of nearly one day's worth of outdoor time per week – and

[7] This is also a growing body of research that focuses on particular activities in specific places (e.g., see Whitehead et al. 2008; Englin and Moeltner, 2004; Richardson and Loomis, 2004), with results varying depending on the region and activity examined.

80 minute increase in indoor sedentary activities. At the other end of the spectrum, Northeastern states will see roughly 40 minute increases in weekly outdoor time and 20 minute decreases in sedentary indoor activities. These changes in energy expenditure are likely to have substantial impacts on population health. While beyond the scope of this paper, these heterogeneous impacts also point towards potentially interesting impacts on internal US migration in the future.

## 2. Data

### 2.A. ATUS

The American Time Use Survey (ATUS) is a nationally representative survey available from 2003-06 describing how and where Americans spend their time. Respondents are individuals over age 15 randomly selected from households that have completed their final month in the Current Population Survey (CPS). Each respondent completes a 24-hour time diary for a pre-assigned date, providing details of the activity undertaken, the length engaged in the activity, and where the activity took place. In order to capture a complete picture of leisure activities, half of all surveys target Saturday or Sunday. Each respondent is interviewed the day after the diary date, and are contacted for 8 consecutive weeks to obtain an interview.

Since indoor and outdoor activities may respond differently to temperature, it is essential we separately identify each. Despite information on where the activity took place, there is no single comprehensive indicator of indoor versus outdoor activities. For example, a potential response to where an activity took place is “at the home or yard”, so we can not isolate whether individuals were inside or outside. As a result, we use several methods to construct a measure of time spent outdoors, and (for the time being) all remaining activities are coded as indoor activities.  First, we code outdoor time if the respondent reported the activity was "Outdoors, away from home."  Second, we include activities where the respondent was traveling by foot or bicycle.  Third, we included activities that did not fall into the previous two categories but, based on the activity code, were unarguably completed outdoors. For example, if a respondent was "at the home or yard" and performed "exterior maintenance" or "lawn maintenance", we coded this as an outdoor activity.  It is not possible for us to code certain activities as indoors or outdoors, such as "socializing, relaxing and leisure" that occurred at home, so our measurement of total time spent outdoors will understate actual outdoor time.

Although the ATUS was not specifically designed to measure energy expenditure in each activity, we use the metabolic equivalent of task (MET) coding of ATUS activities developed by Tudor-Locke et al. (in press) as supported by the National Cancer Institute within the National Institutes of Health.  In that study, the primary activities of the ATUS were linked with the Compendium of Physical Activities (Ainsworth et al., 1993; Ainsworth et al., 2000), which contains estimates of energy expenditure for physical activities where a MET of 1 is assigned to the task of sitting quietly and all METs are assigned relative to this task.  This publicly available crosswalk (http://riskfactor.cancer.gov/tools/atus-met/met.php) was specifically designed to enable the rich activity data from the ATUS to be used for public health research.

To obtain information on the residential location of the individual in order to assign local environmental conditions, we link individuals to the CPS to get their county or MSA of residence.  County and MSA are only released for individuals from more populated places to maintain confidentiality, so geographic identifiers are only available for 3/4 of the sample, though we assess external validity below. Since our weather data is at the county level, we assign individuals with only an MSA reported to the county with the highest population in the MSA. Although spatial variation in weather is unlikely to be substantial within MSAs, we also assess the sensitivity of this assumption by limiting analyses to individuals with exact county identified.

2.B. Weather

We obtain historical weather data from National Climatic Data Center (NCDC) TD 3200/3210 "Surface Summary of the Day" file. This file contains daily weather observations from roughly 8,000 weather stations throughout the US. The primary data elements we include are daily maximum and minimum temperature, precipitation, snowfall, and humidity. Humidity is typically only available from select stations, so we impute humidity from neighboring stations when missing, though excluding humidity entirely from our regression models had little impact on results. The county of each weather station is provided, and we take the mean of weather elements within the county if more than one station is present in the county.

Climate change predictions are based on the Hadley 3 Model using four carbon dioxide emissions scenarios. We focus on the business-as-usual scenario that assumes no change in fossil fuel use (A1) and the scenario that assumes the greatest decrease in fossil fuel use (B1) to provide a range of climate change impacts. Since we primarily focus on maximum temperature, we follow the approach taken by Schlenker and Roberts (2008) to obtain predicted maximum temperature. The Hadley 3 Model gives the predicted change in the monthly mean of the maximum temperature for 216 grid points within the US from 1960-89 to 2020-2049 (medium-term) or 2070-2099 (long-term). We compute the change for each county as a weighted average of the four closest grid points from the population weighted centroid of the county, where weights are the inverse of the distance squared. Lastly, we add the county level monthly changes to the 1960-89 county level daily levels. This amounts to shifting the historical distribution for each emission scenario to preserve the spatial and temporal variation in the data.

### 2.C. Other sources

Air quality is highly correlated with temperature and is an important predictor of time spent outside (Neidell, 2009), and is likely to exert an even greater influence on time spent engaged in vigorous activities. Therefore, it is essential that we control for air quality as a potential confounder. Detailed data on atmospheric pollution can be accessed from the technology transfer network air quality system database maintained by the U.S. Environmental Protection Agency (EPA) (http://www.epa.gov/ttn/airs/airsaqs/detaildata/downloadaqsdata.htm). These data contain hourly measurements for relevant criteria pollutants (ozone, particulate matter, carbon monoxide, nitrogen dioxide, and sulfur dioxide) for all air pollution monitors in the US, along with the exact location of the monitor. We compute daily measures of each pollutant that corresponds with National Ambient Air Quality Standards, such as the eight-hour maximum ozone level at each monitor. Because only county is available in the ATUS, we also compute a county-wide pollution average (for each pollutant) if there are multiple air quality monitors within a county.

Daylight is positively correlated with temperature, and also is likely to influence the amount of physically active time spent outdoors, making it a potential confounder. To compute the hours of daylight for every day in each county, we compute daily sunrise and sunset times based on equations from Astronomical Algorithms (Meuus, 1991) using the latitude and longitude of the county centroid (obtained from the MABLE/Geocorr2K maintained by the Missouri Census Data Center), adjusting for daylight savings time. The sunrise and sunset results have been verified to be accurate to within a minute for locations between +/- 72° latitude. Since this is an algorithm, we are able to compute this data for every single county.

2.D. Merged data

We merge the ATUS and weather data by the county and date, leaving us with a final sample of just over 40,000 individuals with valid weather data. Many demographic variables from the CPS are brought forward to the ATUS, providing a large pool of potential covariates for our analysis. Table 1 presents summary statistics for our final sample.

Figure 1 shows the distribution of maximum temperatures from 2003-06 for those county-dates from which we have observations in our sample, along with the forecasted distribution for the medium and long-term future years under emissions scenarios A1 and B1 for the same counties in our final sample. Under either scenario, the distribution is expected to shift almost uniformly to the right, suggesting that while summers may become unpleasantly hot, winters may become more pleasantly temperate. At the high end of the distribution, it is worth noting that the number of days that exceeded 100 degrees is expected to rise from roughly 1% of days in the historic period to more than 15% of days in the period 2070-99 under the A1 scenario. Given that these days are likely to be concentrated in the summer months, it is expected that greater than 50% of summer days will experience temperatures that exceed 100 degrees. This dramatic shift underscores the importance of exploring the tails of the distribution.

2.E. Sample representativeness

A potential concern with the ATUS is non-response – not all individuals selected for the ATUS agree to participate, and this may bias our analysis. While others have assessed the degree of non-response bias with respect to socio-demographic factors (Abrams et al. 2006), our concern is that temperature may affect whether an individual participates in the survey. Because the weather data applies to the universe of observations, we can assess whether temperature is related to survey participation by plotting the distribution of temperature for counties in our final sample for both the days time diaries are available and the days time diaries are unavailable. Shown in Figure 2, the distribution of temperature across the two groups is nearly identical, suggesting non-response bias is likely to be minimal in our analysis.

An additional concern is that the external validity of our sample is compromised by only obtaining geographic residence for 3/4 of our sample. To examine this issue, we also plot the temperature distribution for counties that are not included in the ATUS for the same dates as ATUS respondents' diaries. Also shown in Figure 2, we find little difference between the two distributions, suggesting external validity is unlikely to be compromised.

## 3. Econometric Model

3.A. Short-run estimates

To examine the relationship between temperature and engagement in specific activities, we estimate the following econometric model with county fixed effects:

(1) $Y^k_{ict} = \sum_j \beta_j \, temp_{ct} + \delta_1 Z_{ct} + \delta_2 X_{ic} + DOW_t + f(t) + \alpha_c + \varepsilon_{ict}$

where $Y$ is the number of minutes spent in activity $k$ for individual $i$ in county $c$ on date $t$. We specify $Y$ in levels rather than logs because 1) our ultimate focus is on the net change in time allocation and 2) individuals can report zero minutes in a particular activity (though we can divide our coefficients by the mean of the dependent variable to yield percentage impacts). *Temp* are dummy variables that flexibly model the relationship between daily maximum temperature and time allocation, described below. $Z_{ct}$ are other environmental attributes potentially correlated with temperature (daylight and air quality) and $X_{ic}$ are individual level covariates that capture preferences for particular activities, both listed in Table 1. $DOW_t$ are day of week dummy variables to account for changes in available leisure time. $f(t)$ are year-month dummy variables to control for seasonal and annual time trends. $\alpha_c$ are county fixed effects that capture all time invariant observable and unobservable attributes that affect $Y$, such as the average underlying propensity of county residents to participate in sports. Therefore, our parameters of interest that relate temperature to time ($\beta_j$) are identified from daily variations in weather within a county. We demonstrate below that our results are robust to numerous sensitivity analyses, supporting the validity of our model.[8]

It is essential that we flexibly model the relationship between temperature and time spent in certain activities given the expected non-linear relationship: increases in temperature may lead to increases in outdoor physical activities at colder temperatures, but beyond a certain point increases in temperature may lead to decreases in outdoor activities (Galloway and Maughan, 1997). Our model includes separate indicator

[8] Since multiple individuals can be observed on the same day within a county, we cluster standard errors on the county-date.

variables for every 5-degree temperature increments (as displayed in Figure 1), which allows differential shifts in activities within each temperature bin.[9] In this flexible specification, we omit the 76-80 degree indicator variable, so we interpret our estimates as the change in minutes spent outside at a certain temperature range relative to 76-80 degrees.[10] By modeling temperature flexibly, we are able to capture potentially important nonlinear impacts of temperature on time allocation.

In modeling temperature flexibly, we also examine implications from different assumptions about the impacts from the upper end of the temperature distribution.[11] Since the human body is considered particularly susceptible to the impacts of temperature above 105 degrees and climate change is expected to results in more days above this level, it is vital to explore the upper end of this distribution. Indeed, one of the great advantages of the ATUS data is that it includes observations from the heat wave that occurred in 2006, which allows us to populate a temperature bin that begins as high as 111 degrees. As we demonstrate below, results are dramatically impacted by the choice of the highest bin.

### 3.B. Long-run estimates

The econometric model described above, by including county fixed effects, allows little adaptation to changes in climate, and hence identifies short run behavioral responses to temperature. Since the biggest impacts of climate change are far into the future, long run adaptation will likely become more important. Adaptations may be

---

[9] We also estimated models with 2.5 degree size bins for temperature, and this has little impact on our estimates.

[10] We do not focus on the impacts of precipitation on outdoor time because there is considerable variation in precipitation within a day that we do not observe. Furthermore, climate forecasts do not provide a method for determining hourly precipitation forecasts.

[11] We also explored the impact from different assumptions regarding the lower end of the distribution, but this distinction had little impact because the amount of time spent outside at 20 degrees is already close to zero.

driven by both behavioral and technological changes. While biological adaptation is limited in scope[12], a learned tolerance for warmer or colder weather will allow individuals to respond differentially to changes in temperature.[13] Technological adaptation fixed to a particular location is driven by quality of air conditioning (e.g., window unit vs. central air)[14] and more subtle methods, such as installing window films or painting the exterior of a house a lighter color to reflect heat. While not currently available, portable technology may advance to make extreme heat more tolerable just as personal heaters and more advanced clothing have made extreme cold temperature more tolerable,.

While it is not possible to predict the types of technology that will develop in the future, we explore the impacts of long run adaptation based on current technology by estimating cross-sectional models. A cross-sectional analysis allows individuals to adjust to local conditions and hence provides estimates of long-run behavioral responses. For example, by comparing how an individual in New York, NY reacts to a hot day vs. an individual in Atlanta, GA, we are able to account for the fact that the individual in Atlanta has had a greater incentive to adapt to hotter weather on average. Therefore, if New York temperatures eventually become like Atlanta temperatures, the future responses in New York will likely follow the current responses in Atlanta. The only discrepancy will be the permanent differences between the two areas, such as proximity to oceans or mountains. To that end, we estimate (1) by replacing county fixed effects with permanent characteristics of the county that may affect activity choice: total land

[12] The body's ability to thermo-regulate is based on absolute temperature levels, as temperatures above 105 degrees are considered high risk to all.
[13] Although this is commonly referred to as blood "thickening" or "thinning", changes in weather tolerance are driven by a complex relationship between glands and the brain.
[14] There is little spatial variation in air conditioning ownership throughout the US.

area, permanent inland water area[15], minimum and maximum elevation, and an indicator for whether the county borders a major body of water.

A concern with cross-sectional estimates is individuals may sort into locations based on the local attributes of that area, such as climate (Cragg and Kahn, 1997; Deschenes and Moretti, forthcoming), so that individuals with a greater preference for a certain type of climate spend more time in certain activities on average. Although we control for many individual level covariates to capture sorting, we assess the sensitivity of our estimates to excluding these variables as a crude test for whether sorting on unobservables remains, and find little evidence sorting biases our estimates.

The types of adaptations available suggest an ambiguous relationship between short- and long-run estimates that may vary by season. Behavioral adaptation and portable technology suggest time will be less responsive to changes in temperature (i.e., long-run estimates smaller than short-run estimates). For example, outdoor time for a person living in Florida may be less affected by a 90 degree day than a person in Maine. On the other hand, fixed technological adaptation that improves the condition of the alternative environment may make people more responsive to changes in temperature. For example, if temperatures reach 90 degrees people may be more likely to shift from outdoor to indoor activities if they have a climate controlled indoor environment.

We hypothesize that, since nearly all individuals throughout the US have fixed technologies readily available during colder times of the year, portable technology and weather tolerance will dominate such that long-run estimates are smaller than short-run estimates in the winter. Since portable technologies for warmer weather are currently in

[15] While we recognize water area could conceivably change because of climate change, our results are insensitive to omitting this variable.

limited supply and there is more variation in fixed technologies (i.e., not everyone has central air conditioning), we can not ascertain *a priori* the relationship between short- and long-run estimates during the summer.

**4. Results**

4.A. Outdoor time

We first focus our analysis on total outdoor time to assess the adequacy of our econometric specification, and then proceed to other activities using our preferred specification. Our main results for the relationship between temperature and outdoor time are depicted in Figures 3. Defining 91+ degrees as the highest temperature bin reveals a nearly monotonically upward sloping relationship between temperature and outside time. Relative to 76-80 degrees, time outside decreases by 100 percent at temperatures below 20 degrees, with responses slowly increasing beyond that. In fact, only the coefficient in the 91+ temperature bin deviates from the upward trend, but it is not statistically significantly. These results imply that warmer temperatures will unarguably lead to increased outdoor time.

When we extend the highest temperature bin to 111+ degrees, our most flexible specification, we find dramatically different results at the upper end of the temperature distribution. Outdoor time steadily climbs from no time outside at less than 20 degrees until roughly 75 degrees, remains fairly stable until 100 degrees, and then begins precipitously falling after that. Relative to 76-80 degrees, outdoor time decreases by 23% at 101-105 degrees, 42% at 106-110 degrees, and 79% over 110 degrees, with the latter two estimates statistically significant. This asymmetric inverted U-shape differs dramatically from the upward sloping shape from a highest bin of 91+ degrees.

Importantly, these results now raise an ambiguity about whether the impact of forecasted temperatures on outdoor time will be positive or negative on net.

To further demonstrate the importance of modeling temperature flexibly, in Figure 3 we also include estimates using various higher order polynomials in temperature. A quadratic in temperature reveals no inflection point, suggesting warmer temperatures will unarguably lead to increased outdoor time. Both a cubic and quartic in temperature reveal inflection points in the upper 80s, but the quartic suggests a sharper drop off in outdoor time at higher temperatures. The quartic yields quite comparable results as the more flexible indicator variables, suggesting a potentially valid functional form to use, but this conclusion is only reached after knowing the non-parametric relationship.

In Figure 4, we display results from models that assess the sensitivity of our results to numerous specification checks. In our first check, we limit our sample to individuals where the exact county is known, but our results are largely unaffected by this adjustment. In the next three checks we assess potential confounding by modeling precipitation flexibly, including measures of air quality (which may be correlated with weather and outdoor time), and excluding humidity (which was imputed), but again find our results are largely unaffected. Last, we include county-season fixed effects, but find this, too, has minimal impact on our estimates. The results from these two figures suggest a robust relationship between temperature and outdoor time.

### 4.B. Type of activity

Given the robustness of our preferred specification, we now focus on estimating the effect of temperature and activities based on their level of physical intensity, shown in

Figure 5. Much of the response in outdoor time is driven by moderate and high intensity activity (>3 METs). Given that outdoor activities decrease at warmer and colder temperatures, indoor activities must increase, so we explore the type of indoor activities that increase. We find very little response in moderate and high intensity indoor activities, but a highly asymmetric U-shaped pattern for low intensity indoor activities.

Since we have similar issues coding activities as strictly indoors (as we did with coding strictly outdoor activities), we further probe indoor responses by focusing on an unambiguous indoor activity that consumes nearly 2.5 hours per day of individual's time: television viewing. Shown in Figure 6, we find that nearly all of the change in sedentary indoor activities is driven by changes in television watching. At colder temperatures, television viewing increases by 25-30 minutes (relative to 76-80 degrees), which explains nearly all of the 35-40 minute decrease in outdoor time. At the high end, however, television viewing increases tremendously, and in some instances by even more than the decrease in outdoor time. At 111+ degrees, television viewing increases by over 60 minutes, while outdoor time only decreases by 37 minutes, though confidence intervals suggest the differences are not statistically significant. The results thus far suggest a nearly one-to-one tradeoff between outdoor physical activities and television watching.

Since leisure and labor are commonly modeled as tradeoffs and the marginal utility from leisure time is affected by temperature, we next explore whether labor supply responds to changes in temperature. Also shown in Figure 6 is the relationship between temperature and time allocated to work. We find little evidence of an association between contemporaneous temperature and time allocated to work, which is consistent with a large body of literature that finds labor supply is highly inelastic in the short run (see, e.g., Card (1994)).

The last remaining activity where people spend time is sleeping, so we explore the effects of temperature on sleep. Shown also in Figure 6, we find little evidence of a relationship between temperature and sleep.

4.C. Compensatory behavior

Individuals may compensate for changes in temperatures by shifting the time of day they spend outdoors, such as increases in the morning and evening hours during extremely hot periods. In Figure 7, we display the results from models that separately examine responses before 10 a.m., between 10 a.m. and 4 p.m., and after 4 p.m.[16] We find generally comparable responses by time of day, though we find inflection points at higher temperature for the off-peak hours, suggesting some evidence of intratemporal substitution to compensate for warmer temperatures.

We next explore the interremporal relationship between temperature and outdoor time. Individuals may compensate for bad weather by shifting their outdoor activities across days. In Figure 8, we present evidence from a regression that includes indicator variables for lagged temperature (in addition to current temperature). Since people may not be able to substitute across immediately adjacent days, we specify lagged temperature as the maximum temperatures across the previous six days. We find some evidence that people compensate for warmer temperatures: responses are fairly flat until 105 degrees, at which point we see a small increase in outdoor time. However, these estimates are not statistically significant at conventional levels, suggesting limited evidence of intertemporal substitution.

[16] Results were also comparable when we choose 8 a.m. and 6 p.m. as cutoffs (not shown).

4.D. Cross-sectional estimates and long-run adaptation

Thus far we have assumed that all individual respond to temperatures in the same way, but there may be technological and behavioral differences throughout the country that enable heterogeneous responses to temperature extremes. To assess this, we estimate cross-sectional models of the responses to temperature, focusing only on outdoor time (sedentary indoor time results are again a mirror image). The results, shown in Figure 9, indicate comparable response functions for the panel and cross-sectional models. As hypothesized, at colder temperatures the long-run (cross-sectional) estimates are smaller than the short-run (fixed effect) estimates because of the near universal availability of heat. At warmer temperatures, however, short-run estimates are generally larger, though the differences are small: the turning point is at a slightly lower temperature and the decrease in outdoor time at the highest temperatures is slightly larger.[17]

As previously mentioned, a concern with cross-sectional models is sorting. We also show in Figure 9 estimates that exclude individual level covariates that may capture preferences for climate. While the fixed effect estimates are less sensitive to excluding individual level controls, suggesting the fixed effects absorb much of what drives sorting, the cross-sectional estimates are also quite insensitive to these controls, suggesting sorting does not appear to be a major concern. These results suggest that, given the current state of technology, there is limited scope for adaptation to temperature changes.

4.E. Climate change impacts

As previously mentioned, the U-shaped response function suggests net impacts on outdoor and indoor time from forecasted changes in climate could be positive or negative

[17] We also estimate both models by stratifying on historical climate, and also find little difference in responses.

depending on the empirical shift in temperature distribution. We assess which effect dominates this by combining our estimated relationship between temperature and outdoor and sedentary indoor time with climate change forecasts from the Hadley 3 model. To do so, we multiply our estimated coefficients ($\beta_j$) from equation (1) by the change in the distribution of temperature from 2003-06 to 2020-2049 (medium term) and from 2003-06 to 2070-2099 (long term). We explore both the highest (A1) and lowest (B1) emissions scenario to provide a range of estimated impacts. Shown in Table 2, we find positive but small net impacts on outdoor activities, with estimates ranging from 1 to 2 minute increases in daily time spent outdoors, and negligible impacts on indoor activities. These impacts differ quite markedly from previous research on climate change and outdoor recreation, which generally finds much larger positive impacts (Loomis and Crespi, 1999, Mendelsohn and Markowski, 1999). These differences are likely driven by our focus on a broader definition of outdoor time, rather than specific outdoor activities, and our more flexible modeling of the upper end of the temperature distribution, where outdoor time significantly decreases.

Although we find little net impacts of climate change on outdoor time overall, the effects could vary tremendously throughout the country because of different historical and forecasted temperature distributions. For example, shown in Figure 10 is the historical and forecasted temperature distribution for 2070-2099 under the A1 scenario for Maricopa (Phoenix) County, AZ, and Suffolk (Boston) County, MA. In Phoenix, roughly 27 percent of days exceeded 100 degrees from 2003-06, but this is expected to rise by 19 percentage points to 46 percent in 100 years. For Boston, the corresponding values are 0 and 7 percent, implying a 7 percentage point increase. For colder weather, roughly 10 percent of days in Phoenix from 2003-06 were below 65 degrees, and this is expected to drop 9 percentage points. For Boston, this is expected to change by 21 percentage points from 61 percent of days to 40 percent of days. We would expect these different changes in distributions to lead to rather distinct changes in outdoor time by location.

We assess this by multiplying our estimated coefficients ($\beta_j$) from equation (1) by the change in the distribution of temperature for each state from 2003-06 to 2070-2099, focusing on scenario A1 only. Estimating separate regressions for each state is not feasible given the need to flexibly model temperature, but our finding of common responses to temperatures based on historical climate suggests these estimates may not differ tremendously. The results, shown in Table 3, indicate that the already mild winters coupled with increases in extremely hot weather in the South will lead to net declines in outdoor time and increase in sedentary indoor time, with Texas witnessing a nearly 5 minute per day drop in time spent outdoors and 12 minutes rise in sedentary indoor activities. The lack of extremely hot weather combined with warming winters, on the other hand, is predicted to increase outdoor time in the Northeast, where Rhode Island, Massachusetts, New York, Connecticut, Vermont, New Hampshire, and Maine all expect over 5 minute per day increases in outdoor time and 3 minute decrease in sedentary indoor time. It is important to note that these estimates assume no migration in response to climate, an assessment of which is beyond the scope of this paper. If individuals move away from the warmer states to colder states, then the aggregate impacts on outdoor and indoor time in Table 2 may in fact be larger.

## 5. Discussion and conclusion

Warmer temperatures that have spread across the planet are likely to continue increasing in the future. Although abatement of greenhouse gas emissions is an essential part of policy responses to combat climate change, substantial increases in temperature are likely to occur even with an immediate halt in emissions growth. These changes are likely to have significant impacts on our daily lives, so understanding how individuals respond to these changes is essential for the design of well formulated policy.

In this paper, we examine the impact of temperature on time allocation across indoor and outdoor activities. Using time diaries from the American Time Use Survey, we estimate econometric models that identify the impacts of weather using plausibly exogenous changes within a county. We find a robust, starkly asymmetric inverted U-relationship between temperature and outdoor activities. Individuals largely replace these outdoor physical activities with television watching. In examining the role of adaptation we find little evidence of different responses using cross-sectional models, though longer-run technological adaptation could impact these findings. Using climate change predictions from the Hadley model, we find the overall net impacts are likely to be small, though they are likely to be heterogeneous throughout the country.

Our results have several implications. First, we find that flexibly modeling the upper end of the temperature distribution is essential for understanding the impacts of higher temperatures. When we lump together observations beyond 91 degrees, our inverted U-shape pattern completely disappears and instead becomes a monotonically increasing one. Since the forecasted shifts in the temperature distribution suggest many more days will exceed 100 degrees, and the goal of much climate change research, regardless of the outcome studied, is to make out of sample extrapolations based on climate change predictions, it is vital to account for the upper tail of the distribution.

This sharp drop off in outdoor time at the highest temperatures also has implications for understanding the relationship between temperature and heat-related illness. If people respond to these temperatures by reducing their exposure via time spent outside, then estimates of the impact of temperature will understate the full costs from warmer temperatures. Consistent with this, Greenstone and Deschenes (2007b) find that increased air conditioning use when temperatures increase offset much of the mortality impacts. Furthermore, heat warnings and alerts will likely play a larger role in reducing exposure, which can also impact the relationship between temperature and mortality (Alberini et al., 2008).

Our results also suggest more subtle health impacts from temperature increases. As temperatures rise beyond 100 degrees, individuals shift away from less sedentary activities, both outdoors and indoors. These activities are largely replaced with the sedentary activity of television viewing. This decrease in physical activity suggests climate change may impact health through means other than heat-specific illnesses.

Our evidence of heterogeneous net impacts by State suggests considerable migration within the country may occur. Previous research examining climate and migration have typically focused on moving away from colder weather (e.g., Cragg and Kahn, 1997; Deschenes and Moretti, forthcoming). This is sensible given historical patterns in climate and the gradual shifting of population towards the South and Southwestern regions of the US. But we could conceivably begin to see reverse patterns as people seek to avoid heat, especially as the colder winters in Northern regions becomes milder.  This is a fruitful area for future research.

## References

Abrams, Katharine, Aaron Maitland, and Suzanne Bianchi (2006). "Nonresponse in the American time use survey: Who is missing from the data and how much does it matter?" *Public Opinion Quarterly* 70(5): 676–703.

Alberini, Anna, Erin Mastrangelo and Hugh Pitcher (2008). "Climate Change and Human Health: Assessing the Effectiveness of Adaptation to Heat Waves." Mimeograph, University of Maryland

American Recreation Coalition (2007). "Outdoor recreation outlook 2008." Prepared for the 2007 Marketing Outlook Forum.

Card, David (1994). "Intertemporal labour supply: An assessment." In Advances in Econometrics, ed. Christopher A. Sims. Cambridge: Cambridge University Press.

Cragg, Michael and Matthew Kahn (1997). "New Estimates of Climate Demand: Evidence from Location Choice." *Journal of Urban Economics* 42: 261-284.

Deschenes, Olivier and Michael Greenstone (2007a), "The Economic Impacts of Climate Change: Evidence from Agricultural Output and Random Fluctuations in Weather," *American Economic Review*, 97(1): 354-385.

Deschenes, Olivier and Michael Greenstone (2007b). "Climate Change, Mortality, and Adaptation: Evidence from Annual Fluctuations in Weather in the US." MIT Department of Economics Working Paper 07-19.

Deschenes, Olivier and Enrico Moretti (forthcoming). "Extreme Weather Events, Mortality and Migration." *Review of Economics and Statistics*.

Englin, Jeffrey, and Klaus Moeltner (2004). "The Value of Snowfall to Skiers and Boarders," Environmental and Resource Economics 29:123-136.

Galloway SD, Maughan RJ (1997). "Effects of ambient temperature on the capacity to perform prolonged cycle exercise in man." Med Sci Sports Exerc. 29(9): 1240-9.
González-Alonso, José, Christina Teller, Signe L. Andersen, Frank B. Jensen, Tino Hyldig, and Bodil Nielsen (1999). "Influence of body temperature on the development of fatigue during prolonged exercise in the heat." J Appl Physiol 86: 1032-1039.

Loomis, John and John Crespi (1999). “Estimated Effects of Climate Change on Selected Outdoor Recreation Activities in the United States,” Chapter 11 in The Impact of Climate Change on the United States Economy, Cambridge University Press, pp. 289-314.

Ma, Y, BC Olendzki, W Li, AR Hafner, D Chiriboga, JR Hebert, M Campbell, M Sarnie and IS Ockene (2006). “Seasonal variation in food intake, physical activity, and body weight in a predominantly overweight population.” European Journal of Clinical Nutrition 60: 519–528.

Pivarnik, J. M., Reeves, M. J., Rafferty, A. P. (2003). “Seasonal variation in adult leisure-time physical activity.” Med Sci Sports Exerc 35: 1004–1008.

Mansfield, Carol, F. Reed Johnson, and George Van Houtven (2006). “The missing piece: Valuing averting behavior for children's ozone exposures.” *Resource and Energy Economics* 28(3): 215-28.

Mendelsohn, Robert and Marla Markowski (1999). “The Impact of Climate Change on Outdoor Recreation,” Chapter 10 in The Impact of Climate Change on the United States Economy, Cambridge University Press, pp. 267-288.

Neidell, Matthew (2009). “Information, Avoidance Behavior, and Health: The Effect of Ozone on Asthma Hospitalizations.” Journal of Human Resources 44(2): 450-478.

Nielsen, B, J R Hales, S Strange, N J Christensen, J Warberg and B Saltin (1993). “Human circulatory and thermoregulatory adaptations with heat acclimation and exercise in a hot, dry environment.” J Physiol Vol 460: 467-485.

Richardson, Robert, and John Loomis, “Adaptive Recreation Planning and Climate Change: A Contingent Visitation Approach,” Ecological Economics 50(83-99): 2004.

Schlenker, Wolfram, W. Michael Hanemann, and Anthony Fisher (2005), “Will U.S. Agriculture Really Benefit from Global Warming? Accounting for Irrigation in the Hedonic Approach,” *American Economic Review*, 95(1), pp. 395-406.

Schlenker, Wolfram, and Michael Roberts (2008). “Estimating the Impact of Climate Change on Crop Yields: The Importance of Nonlinear Temperature Effects.” NBER working paper 13799.

Whitehead, John, Ben Poulter, Christopher Dumas, and Okymung Bin (2008). “Measuring the Impacts of Sea-Level Rise on Marine Recreational Shore Fishing in North Carolina.” Department of Economics, Appalachian State University, Working Paper 08-09.

Figure 1. Historical and forecasted temperature distribution

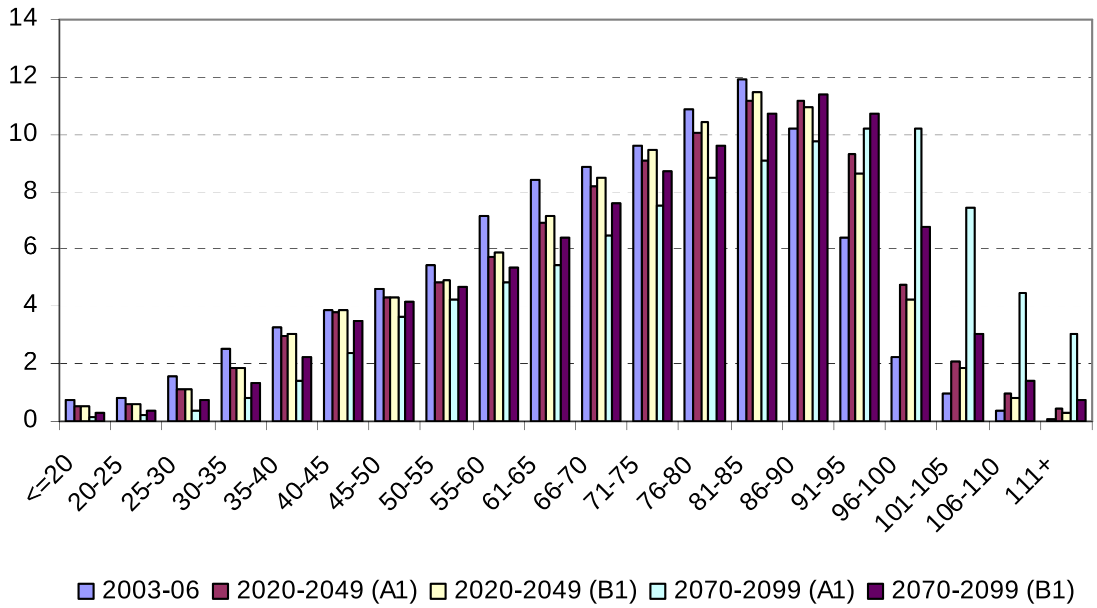


Figure 2: Distribution of observations by temperature for excluded and included sample

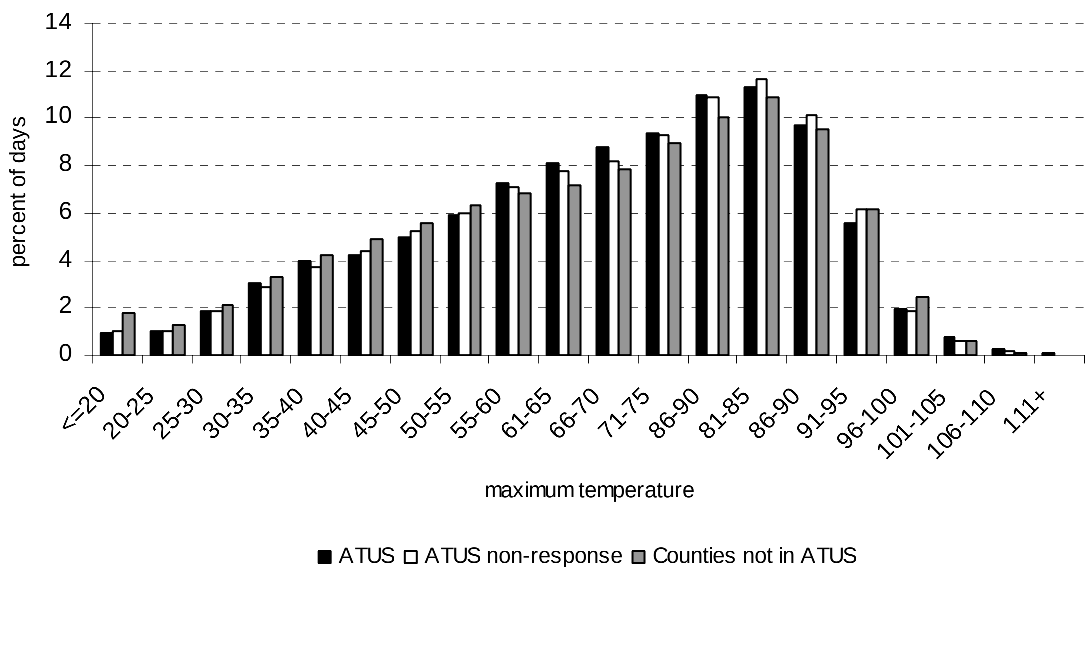

Figure 3. Estimates of relationship between temperature and total outdoor time: sensitivity to functional form

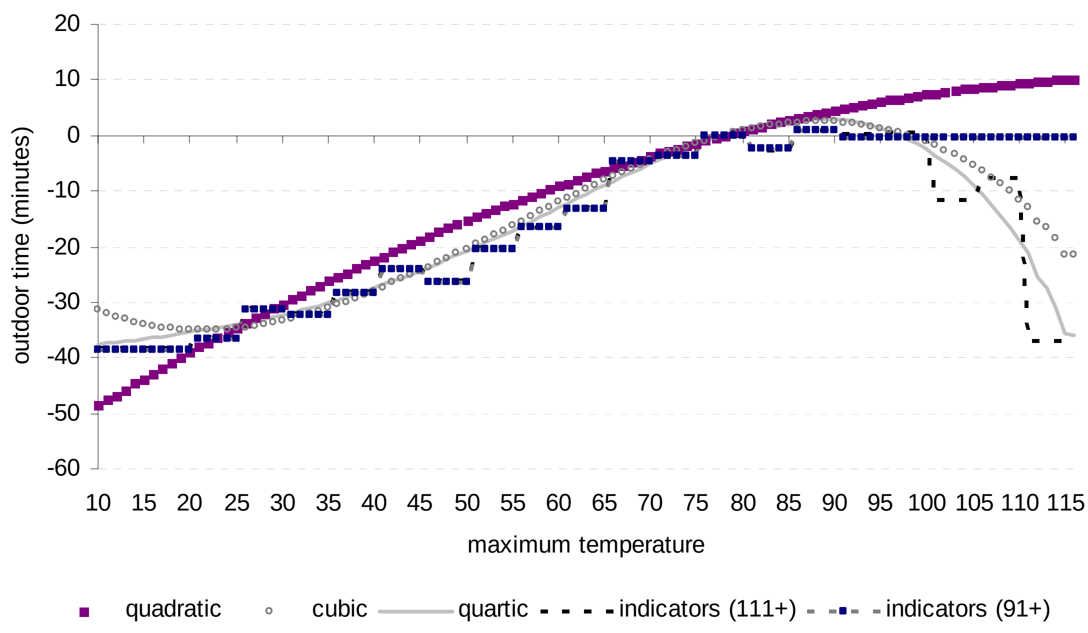


Figure 4. Estimates of relationship between temperature and total outdoor time: robustness checks

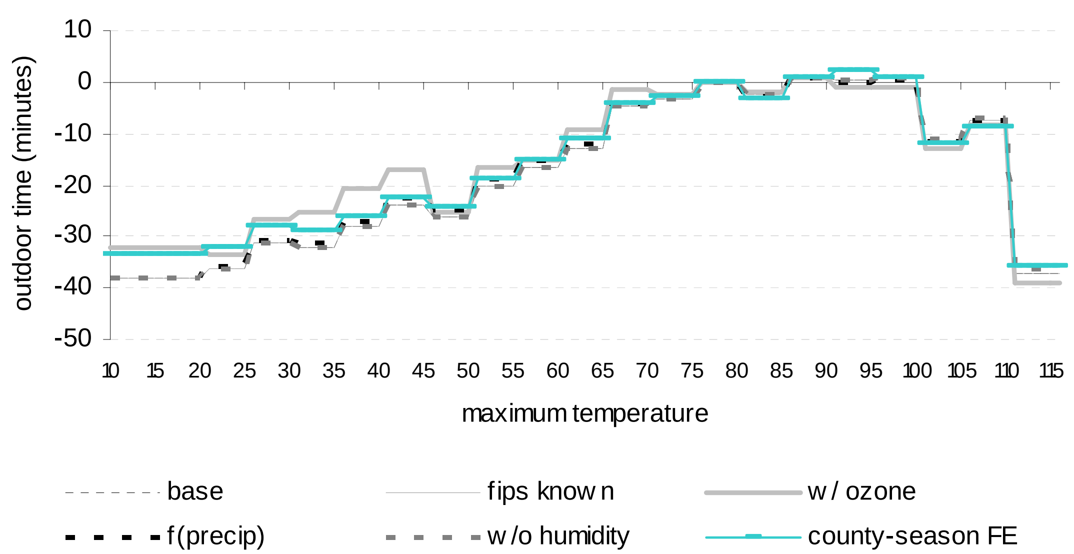

Figure 5. Estimates of relationship between temperature and activity intensity

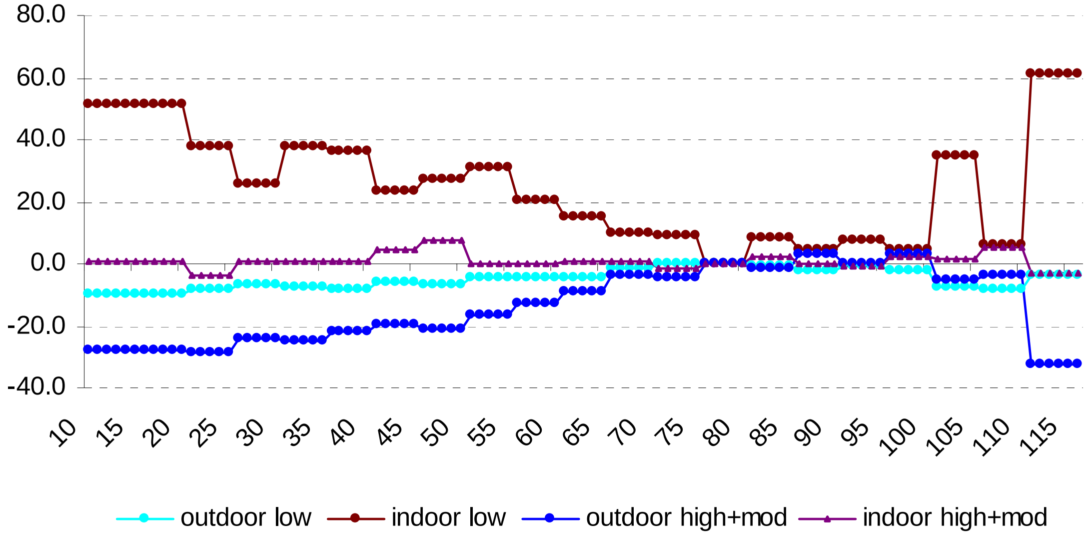


Figure 6. Estimates of relationship between temperature and specific activities

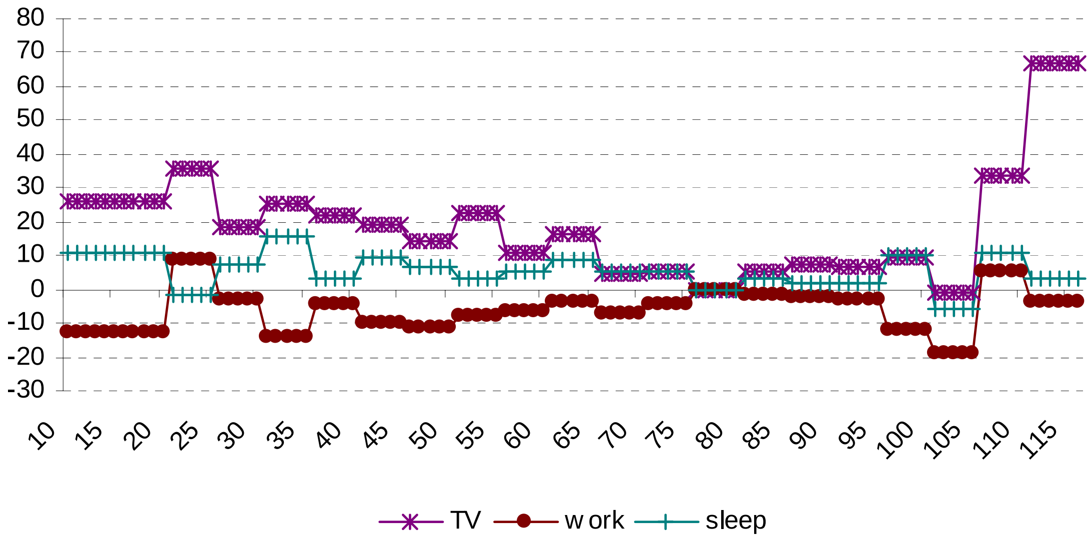

Figure 7. Estimates of relationship between temperature and total outdoor time by time of day

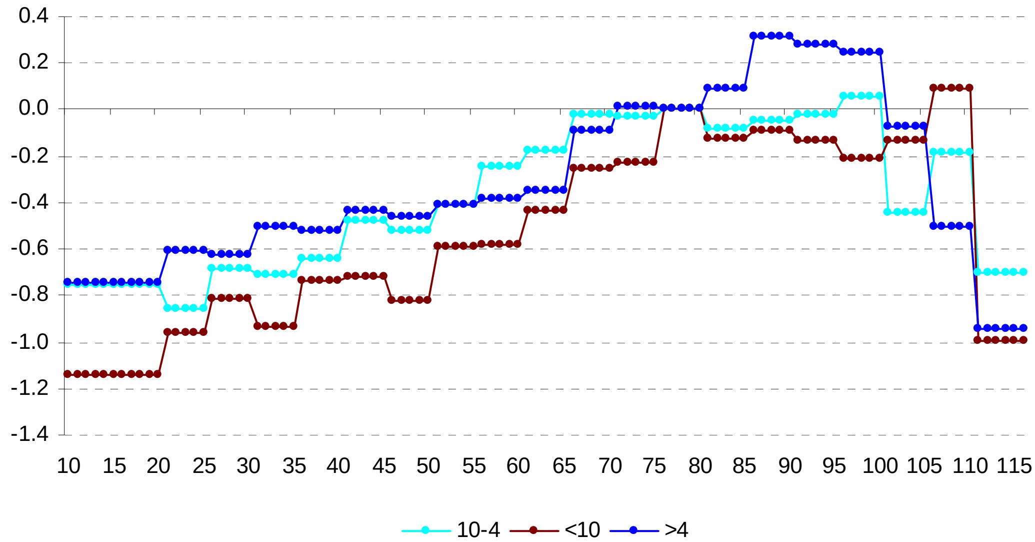


Figure 8. Estimates of relationship between temperature and total outdoor time, dynamic specification

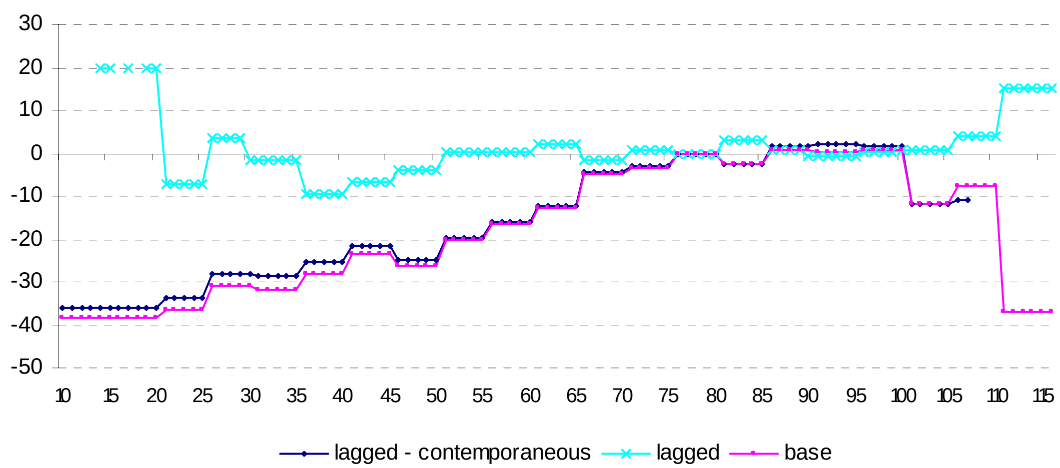

Figure 9. Cross-sectional and fixed estimates of relationship between temperature and total outdoor time, sensitivity to individual level covariates

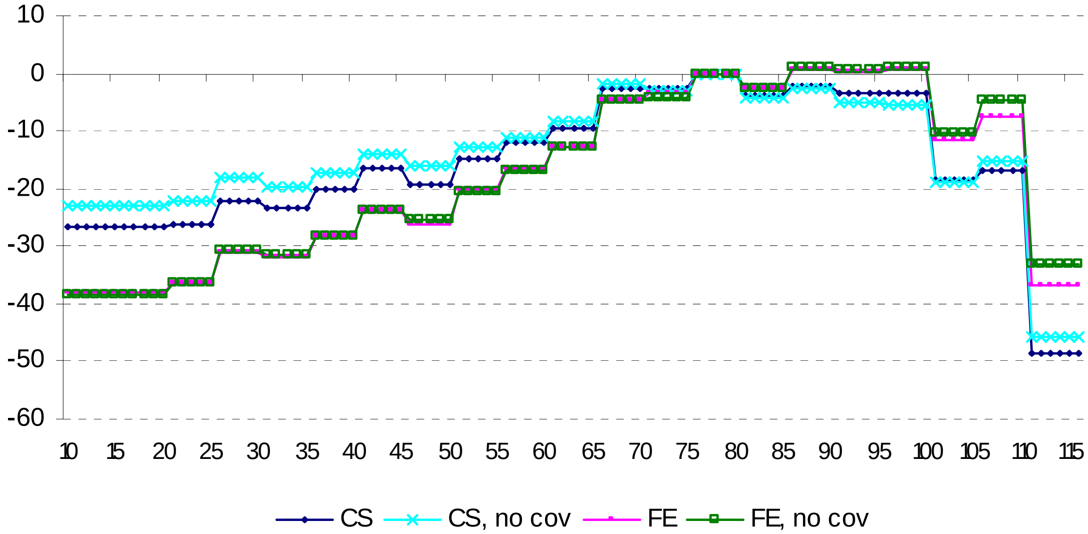


Figure 10. Historical and forecasted (A1) temperature distribution for Maricopa County (Phoenix), AZ and Suffolk County (Boston), MA

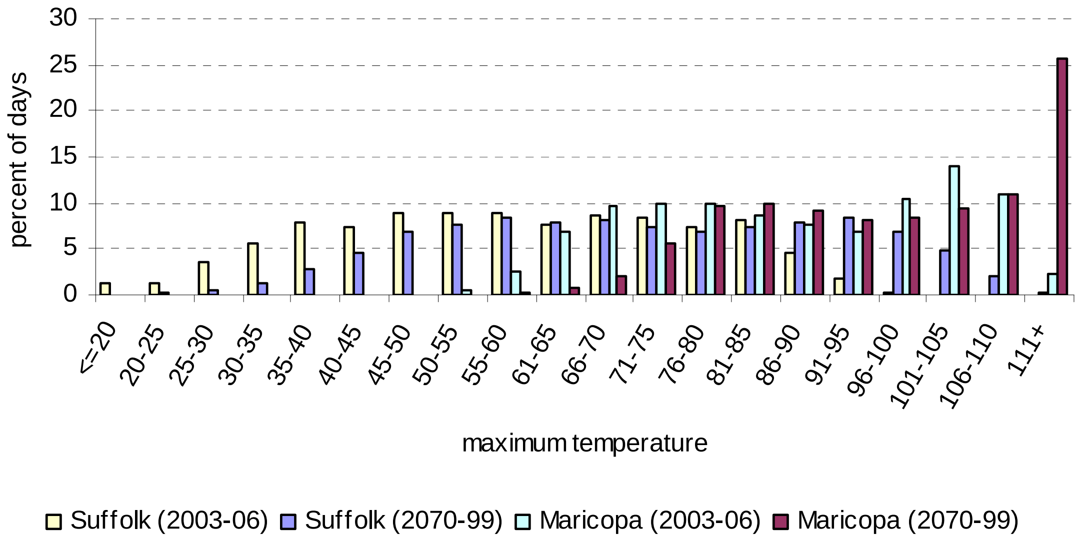

Table 1. Summary statistics

| A. Time allocation (minutes per day) (n=42323) | mean | std. dev. |
|---|---|---|
| **Outdoor time** | | |
| overall | 43.78 | 96.81 |
| high intensity (>6 METs) | 2.17 | 17.60 |
| moderate intensity (3-6 METs) | 26.69 | 77.26 |
| low intensity (<3 METs) | 13.81 | 48.81 |
| <10 am | 13.33 | 54.10 |
| 10-4 | 20.74 | 59.75 |
| >4 pm | 9.72 | 33.00 |
| **Indoor time** | | |
| high intensity (>6 METs) | 2.25 | 15.97 |
| moderate intensity (3-6 METs) | 45.56 | 88.14 |
| low intensity (<3 METs) | 608.92 | 226.99 |
| television viewing | 160.09 | 165.66 |
| Average METs | 1.91 | 0.41 |
| Work | 162.84 | 243.22 |
| Work\|>0 | 420.47 | 210.75 |
| Sleep (not truncated at 4 am) | 690.68 | 188.03 |

| B. Covariates (n=42323 except last 5 variables) | mean | std. dev. |
|---|---|---|
| Age | 45.29 | 17.25 |
| male | 0.43 | 0.50 |
| # children < 18 | 0.92 | 1.16 |
| annual earnings | 45990 | 61203 |
| diary day a holiday | 0.02 | 0.13 |
| employed | 0.65 | 0.48 |
| absent from work | 0.03 | 0.17 |
| out of labor force | 0.31 | 0.46 |
| employed FT | 0.51 | 0.50 |
| white non-Hispanic | 0.68 | 0.47 |
| HS dropout | 0.17 | 0.38 |
| HS graduate | 0.25 | 0.43 |
| some college | 0.26 | 0.44 |
| spouse or unmarried partner in HH | 0.55 | 0.50 |
| precipitation (in./100) | 11.17 | 30.23 |
| snowfall (in./10) | 0.66 | 5.17 |
| maximum relative humidity (imputed) | 84.68 | 14.22 |
| maximum relative humidity (n=27940) | 83.77 | 17.12 |
| mean 8-hour ozone (ppm) (n=30838) | 0.04 | 0.02 |
| mean 8-hour CO (ppm) (n=30909) | 0.79 | 0.50 |
| max 8-hour ozone (ppm) (n=30838) | 0.05 | 0.02 |
| max 8-hour CO (ppm) (n=30909) | 1.03 | 0.78 |

Table 2. Net change in time allocation under various climate change scenarios

| | 2020-49 (A1) | 2020-49 (B1) | 2070-99 (A1) | 2070-99 (B1) |
|---|---|---|---|---|
| outdoor time – all | 1.02 | 0.97 | 1.64 | 1.88 |
| lower 95% CI | 0.59 | 0.65 | -0.42 | 1.18 |
| upper 95% CI | 1.45 | 1.30 | 3.70 | 2.59 |
| indoor time - low intensity | -0.26 | -0.32 | 1.30 | -0.55 |
| lower 95% CI | -1.00 | -0.83 | -3.90 | -1.80 |
| upper 95% CI | 0.49 | 0.19 | 6.49 | 0.70 |

Table 3. Net change in time allocation by State for 2070-2099 under emissions scenario A1

| State | outdoor time - all | indoor time - low intensity | calories burned (155 lbs.) | annual weight change |
|---|---|---|---|---|
| Texas | -4.57 | 11.70 | -19.52 | 2.04 |
| Oklahoma | -3.02 | 11.23 | -9.69 | 1.01 |
| Louisiana | -2.08 | 4.13 | -9.98 | 1.04 |
| Kansas | -1.70 | 10.11 | -1.87 | 0.19 |
| Arizona | -1.59 | 7.24 | -3.86 | 0.40 |
| Mississippi | -1.36 | 4.23 | -5.11 | 0.53 |
| Arkansas | -1.36 | 6.47 | -3.01 | 0.31 |
| Florida | -0.72 | 0.22 | -4.58 | 0.48 |
| Alabama | -0.70 | 2.78 | -2.10 | 0.22 |
| Nebraska | -0.29 | 6.97 | 4.57 | -0.48 |
| Geogia | -0.28 | 2.09 | 0.06 | -0.01 |
| Missouri | -0.11 | 5.98 | 4.82 | -0.50 |
| South Dakota | 0.48 | 5.39 | 8.23 | -0.86 |
| South Carolina | 0.69 | 0.76 | 5.33 | -0.56 |
| California | 0.84 | 4.69 | 9.99 | -1.04 |
| Tennessee | 0.95 | 1.87 | 8.10 | -0.84 |
| Montana | 1.04 | 3.00 | 9.76 | -1.02 |
| Kentucky | 1.16 | 1.55 | 9.19 | -0.96 |
| Nevada | 1.28 | 4.45 | 12.67 | -1.32 |
| Idaho | 1.37 | 2.40 | 11.37 | -1.19 |
| Illinois | 1.41 | 2.37 | 11.64 | -1.21 |
| New Mexico | 1.52 | 1.19 | 11.26 | -1.17 |
| Oregon | 1.85 | 2.35 | 14.52 | -1.51 |
| Washington | 1.87 | 2.23 | 14.52 | -1.51 |
| Iowa | 1.89 | 2.36 | 14.78 | -1.54 |
| North Dakota | 2.20 | 1.50 | 16.04 | -1.67 |
| Wyoming | 2.26 | 1.19 | 16.18 | -1.69 |
| North Carolina | 2.41 | -0.79 | 15.35 | -1.60 |

| | | | | |
|---|---|---|---|---|
| District of Columbia | 2.50 | -1.00 | 15.70 | -1.64 |
| Indiana | 2.65 | 0.26 | 17.90 | -1.87 |
| Utah | 2.80 | 0.07 | 18.73 | -1.95 |
| Virginia | 2.84 | -0.80 | 18.22 | -1.90 |
| Minnesota | 2.90 | 0.07 | 19.37 | -2.02 |
| Colorado | 3.02 | 0.42 | 20.51 | -2.14 |
| Maryland | 3.33 | -1.55 | 20.77 | -2.17 |
| West Virginia | 3.52 | -1.28 | 22.26 | -2.32 |
| Ohio | 3.70 | -1.14 | 23.64 | -2.47 |
| Delaware | 3.71 | -1.67 | 23.20 | -2.42 |
| New Jersey | 4.44 | -1.95 | 27.76 | -2.90 |
| Michigan | 4.58 | -2.10 | 28.57 | -2.98 |
| Pennsylvania | 4.60 | -2.07 | 28.72 | -3.00 |
| Rhode Island | 5.30 | -2.55 | 32.98 | -3.44 |
| Massachusetts | 5.43 | -2.58 | 33.82 | -3.53 |
| New York | 5.47 | -2.60 | 34.02 | -3.55 |
| Connecticut | 5.50 | -2.60 | 34.21 | -3.57 |
| Vermont | 5.51 | -2.75 | 34.20 | -3.57 |
| New Hampshire | 5.52 | -2.75 | 34.22 | -3.57 |
| Maine | 6.50 | -3.11 | 40.42 | -4.22 |