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Climate Change and the Allocation of Time

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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. High temperatures also induce substitution toward more sedentary activities indoors, suggesting potentially important implications for population health. Similar relationships arise using cross-sectional models, suggesting little 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. These temperature changes, in turn, are likely to exert profound impacts on the way in which humans interact with the planet. One fundamental aspect of life that may be altered under this new climatic paradigm is the amount of time that individuals allocate to outdoor and indoor activities.¹ These changes are important for at least three reasons. First, people appear to derive tremendous amounts of utility from being outside – nearly \$300B per year is spent on outdoor recreational activities alone (American Recreation Coalition, 2007). Second, outdoor activities are typically less sedentary than indoor ones and thus may have more subtle impacts on population health. Third, time spent outdoors is a direct route through which climate change will affect human health. Therefore, if people self-protect by limiting time outside in response to a change in temperature, this represents a form of short-run adaptation to climate change.²

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 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 that this number will climb to a staggering 16 percent within the coming century.³ Given the

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 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.

³ 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.

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.

In this paper 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.⁴ Based on county of residence and date of survey, these data are linked to daily weather data from the National Climatic Data Center as well as daily pollution levels (a potential confounder) using data from nationwide monitors maintained by the Environmental Protection Agency. 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.

⁴ We focus primarily on time allocated to non-market activities because a long line of literature finds labor supply is highly inelastic in the short run (see, e.g., Card (1994)). Consistent with this, we find little evidence of an association between contemporaneous temperature and time allocated to work.

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 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. 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 also analyze the relationship between temperature and the composition of indoor activities. Our definition of outdoor time includes primarily non-sedentary activities, such as participation in sports and travel, which are generally beneficial to health, so it is important to know what indoor activities serve as replacements. Interestingly, high temperatures lead to more sedentary activities indoors. Television watching climbs dramatically above 105°F, while non-sedentary indoor household activities witness a corresponding drop (similar to outdoor activities). 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 virtually identical to fixed effect estimates, suggesting little scope for longer-run adaptation given the current technology environment.⁵

Given our climate response function and the limited opportunities for adaptation, we conclude our analysis by calculating changes in outdoor 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)⁶, 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 less than fourteen minutes by 2070-2099, which represent a 2-4% increase in an activity that generates a substantial amount of utility. Moreover, there appears to be important variation across states. Texas, the biggest loser, will experience an approximately 35 minute decline in weekly outdoor time – the equivalent of nearly one day’s worth of outdoor time per week. At the other end of the spectrum, Northeastern states will see as much as a 49

⁵Interestingly, these results also imply that individuals do not sort into their current locations based on their tolerance for weather.

⁶ 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.

minute increase in weekly outdoor time, which translates into nearly one additional day's worth of outdoor time per week. While beyond the scope of this paper, these heterogeneous impacts point towards potentially interesting impacts on internal US migration in the future.

This paper is structured as follows. Section 2 describes the data. Section 3 describes our econometric model. Section 4 describes our results and section 5 concludes.

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.

Despite information on where the activity took place, there is no single comprehensive indicator of all 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. 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.

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. 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. Table 1 presents summary statistics for this sample. Based on our definition of outdoor time, individuals average 44 minutes outside per day. Most outdoor time is spent on non-sedentary

activities, with 20 minutes devoted to household activities, 12 minutes to sports, and 4 minutes to travel.

Many demographic variables from the CPS are brought forward to the ATUS, providing a large pool of potential covariates for our analysis. Table 1 also displays the mean and standard deviation for these variables (age, gender, number of children under age 18, earnings, employment status, race, education, and marital status) as well as county level covariates (precipitation, snowfall, humidity, ozone, and carbon monoxide).

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.D. 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. Furthermore, the mean outdoor time per day for those without geographic identifier is 48 minutes, quite close to the value in our final sample.

3. Methods

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

$$(1) \quad Y_{ict} = \sum_j \beta_j \text{temp}_{ct} + \delta_1 Z_{ct} + \delta_2 X_{ic} + DOW_t + f(t) + \alpha_c + \varepsilon_{ict}$$

where Y is the number of minutes spent in a specific activity for individual i in county c on date t . We specify Y in levels rather than logs because individuals can report zero minutes in a particular activity, so we 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 outdoor time, described

below. Z_{ct} are other environmental attributes potentially correlated with temperature and X_{ic} are individual level covariates that capture preferences for outdoor 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. α_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 outdoor time (β_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.⁷

In this specification we model temperature flexibly by including dummy variables for every 5 degrees as displayed in Figure 1.⁸ We omit the 76-80 degree dummy variable, so we interpret our results as the change in minutes spent outside at a certain temperature bin relative to 76-80 degrees.⁹ By modeling temperature flexibly, we are able to capture potentially important nonlinear impacts of temperature on outdoor time.

In modeling temperature flexibly, we also examine implications from different assumptions about the impacts from the upper end of the temperature distribution.¹⁰

Since climate change is expected to result in more days above 105 degrees, and the human body is considered particularly susceptible to the impacts of temperature above

⁷ Since multiple individuals can be observed on the same day within a county, we cluster standard errors on the county-date.

⁸ We also estimate models with 2.5 degree size bins for temperature, shown below, and find this makes little difference.

⁹ 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.

¹⁰ 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.

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.

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. While biological adaptation is unlikely¹¹, technological ones seem more plausible. Just as portable heaters and more advanced clothing can make extreme cold temperature more tolerable, technology may advance to make extreme heat more tolerable. If technology permits greater adaptation to climate, then traditionally warmer areas are more likely to invest in technologies that permit greater adaptation at higher temperatures, and vice-versa for traditionally cooler areas.

While it is not possible to predict the types of technology that will develop in the future, we explore the impacts of current technological differences by examining behavioral response using cross-sectional models. While there is little spatial variation in the most obvious and effective form of available adaptation – air conditioning – there are more subtle ways to adapt, such as installing window films or painting the exterior of a house a lighter color to reflect heat. A cross-sectional analysis allows for individuals to

¹¹ The body's ability to thermo-regulate is limited in nature and based on absolute temperature levels. Although there is some individual level variation based on genetic differences and health status, temperatures above 105 degrees are considered high risk to all. This assertion is also supported by our finding that behavioral responses to temperature are quite comparable in cross-sectional and fixed effects models.

adjust to local conditions through such technological adaptations, providing 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 area, permanent inland water area¹², 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 local 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 outdoors on average. To account for sorting, we include measures of average seasonal temperature for each county from the 1980s.

4. Results

4.A. Outdoor time

Our main results for outdoor time are depicted in Figures 3a and b, which plot the coefficients for the temperature dummy variables (along with 95% confidence intervals) with different cutoffs for the highest temperature bin. Figure 3a, which uses 91+ as the

¹² While we recognize water area could conceivably change because of climate change, our results are insensitive to omitting this variable.

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 significant. These results imply that warmer temperatures will unarguably lead to increased outdoor time.

When we extend the highest temperature bin to 111+ degrees (Figure 3b), however, 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 96-100 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 Figure 3a. Importantly, these results now raise an ambiguity about whether the impact of forecasted temperatures on outdoor time will be positive or negative on net.

We claim an important step in our methodology is to model temperature flexibly. In Table 2, we present estimates from our flexible specification along with estimates under more stringent assumptions on the relationship between temperature and outdoor time. Column (1) repeat the results from Figure 3b, showing an inflection point between 86-90 degrees. Results from column (2), which include a quadratic in temperature, suggest an inflection point of 114 degrees, which would imply unambiguously positive impacts from climate change on outdoor time.

Although the temperature bins add a tremendous amount of flexibility, we are placing the restrictions of uniform responses within a 5 degree interval. In Figure 4 we display results that assess the sensitivity of the temperature bin size by using 2.5 degree bin sizes. The results are nearly identical.

In Figure 5, we display results from models that assess the sensitivity of our results to numerous specification checks. In the first three checks, we assess sampling bias and construct validity by using sampling weights, limiting our sample to individuals where the exact county is known, and excluding activities that we may have erroneously assigned as outdoors. Our results are largely unaffected by these adjustments. 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 all individual level covariates. Our results are again largely unaffected.

4.B. Substitution patterns

Individuals may compensate for changes in temperatures by shifting the time of day they spend time outdoors, such as increases in the morning and evening hours during extremely hot periods. In Figure 6, 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.¹³ We find comparable responses by time of day, suggesting little evidence of intratemporal substitution.

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 have similar issues coding activities as strictly indoors, so we begin by focusing on a

¹³ Results were also comparable when we choose 8 a.m. and 6 p.m. as cutoffs (not shown).

fairly unambiguous indoor activity that consumes nearly 2.5 hours per day of individual's time: television viewing. As expected, we find an asymmetric U-shaped pattern, but one that is even more asymmetric than before, shown in Figure 7. At colder temperatures, television viewing increases by 25-30 minutes (relative to 76-80 degrees), which explains over half of the 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 80 minutes, while outdoor time only decreases by 35 minutes.

Since the increase in television viewing at high temperatures exceeds the decrease in outdoor activities, individuals must be changing the composition of indoor activities as well. We hypothesize that people substitute away from less sedentary indoor activities to television viewing, an extremely sedentary one, for two reasons. One, people may be symptomatic from exposure to heat, so as part of their recuperation they rest by watching television. Two, mitigation from air conditioning may be partial¹⁴, so people engage in more sedentary activities to reduce energy exertion.

To test this, we explore the impact of temperature on indoor household activities, such as housework and interior maintenance, which require more energy than television viewing.¹⁵ The results, shown in Figure 8, support this hypothesis. Indoor household activities are fairly constant over a wide range of temperatures, with a slight increase in temperatures below 50 degrees. At temperatures above 111 degrees, however, household activities show a sharp decline of 35 minutes. Although this estimate is not statistically

¹⁴ For example, if air conditioning is provided by a window unit, the benefits are local to the area in which the unit is installed.

¹⁵ We did not focus explicitly on indoor exercise because people engage in this activity less than 7 minutes per day.

significant, the decrease almost completely explains the gap between the decrease in outdoor activities (35 minutes) and increase in television viewing (81 minutes).

4.C. Technological adaptation

Thus far we have assumed that all individual respond to temperatures in the same way, but there may be technological differences throughout the country that enable people to respond differently to temperature extremes. To assess this, we estimate cross-sectional models of the responses to temperature. The results, shown in Figure 9, indicate nearly identical response functions for the panel and cross-sectional models. Also shown in Figure 9, cross-sectional estimates are also largely insensitive to excluding individual level covariates that may proxy for preferences, supporting our claim that controlling for average seasonal climate accounts for sorting. Cross-sectional estimates for television viewing and indoor household activities (not shown) are also quite similar to fixed effects estimates. These results suggest that, given the current state of technology, there is little scope for adaptation to temperature changes.

4.D. Climate change impacts

As previously mentioned, the inverted U-shaped response function suggests net impacts on outdoor time from forecasted changes in climate could be positive or negative depending on the empirical shift in temperature distribution. We compute this by combining our estimated relationship between temperature and outdoor time with climate change forecasts from the Hadley 3 model. To do so, we multiply our estimated coefficients (β_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 3, we find positive but small net impacts on outdoor activities, with estimates ranging from 1 to 2 minute increases in daily time spent outdoors. 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 (β_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 (Figure 9) suggests these estimates may not differ tremendously. The results, shown in Table 4, indicate that the already mild winters coupled with increases in extremely hot weather in the South will lead to net declines in outdoor time, with Texas witnessing a nearly 5 minute per day drop in time spent outdoors. 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. 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 overall positive impacts in Table 3 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 activities with television watching. In examining the role of technological 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.

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Figure 1. Historical and Forecasted Temperature Distribution

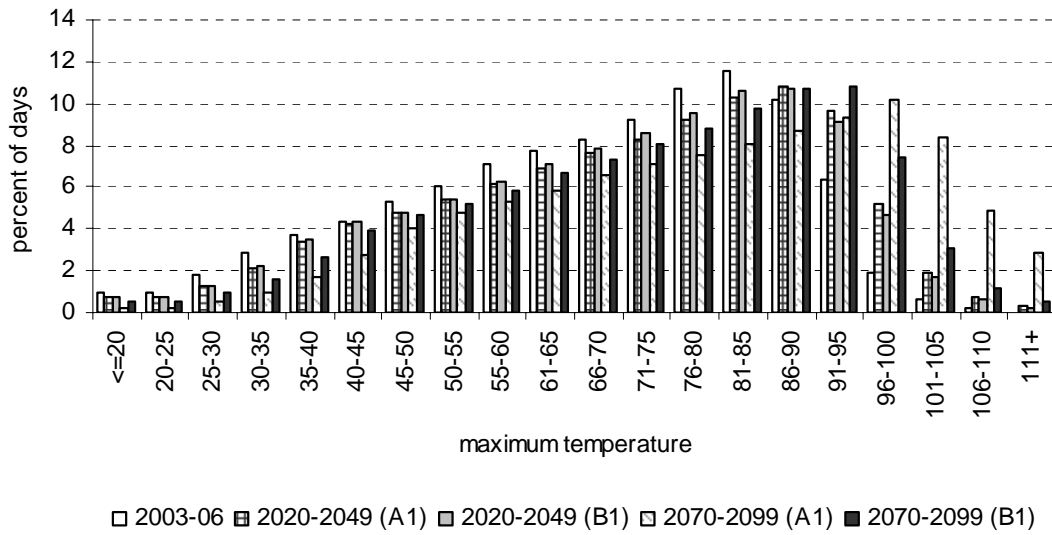
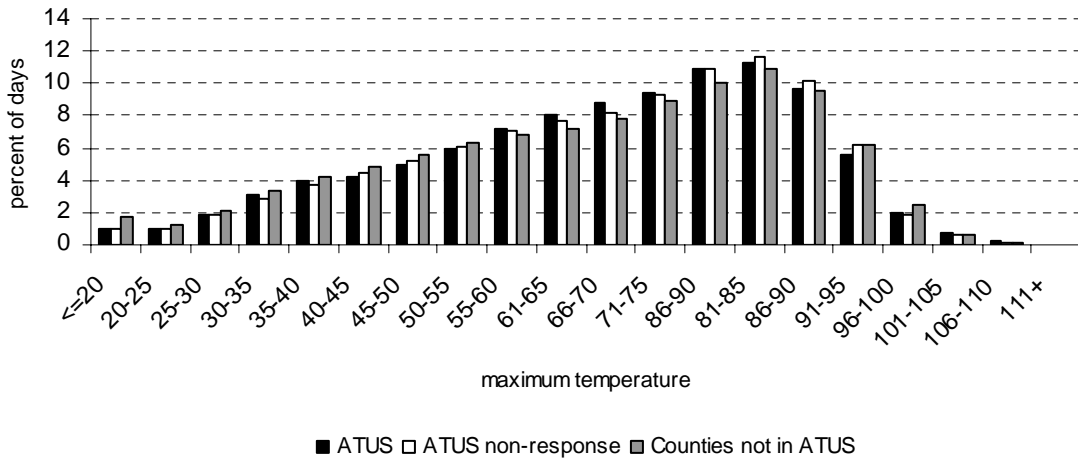
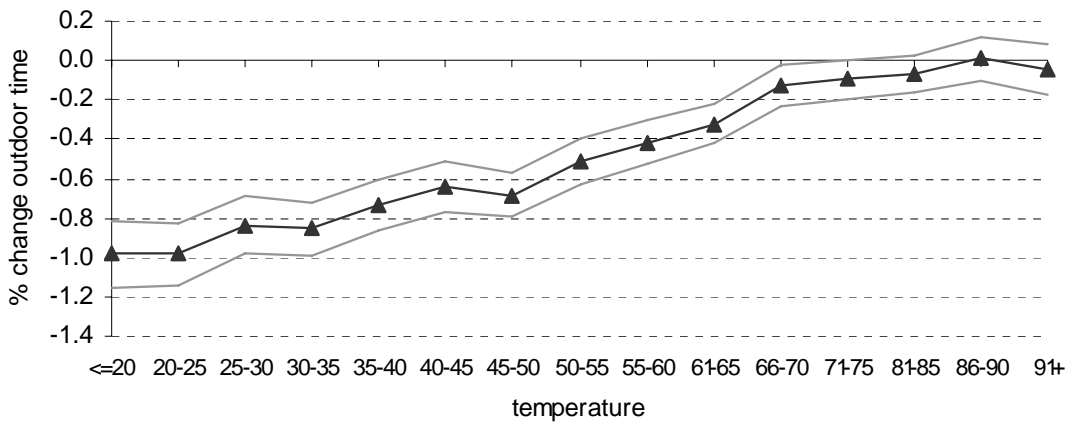


Figure 2: Distribution of observations by temperature for excluded and included sample



**Figure 3a. Relationship between temperature and outdoor time:
Temperature through 91**



**Figure 3b. Relationship between temperature and outdoor time:
Temperature through 111**

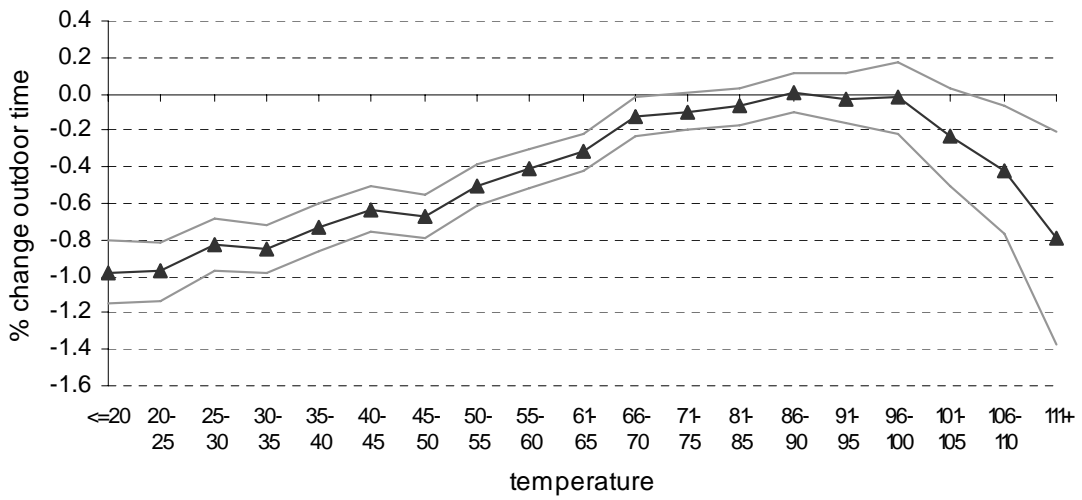


Figure 4. Relationship between temperature and outdoor time: Sensitivity to temperature bin size

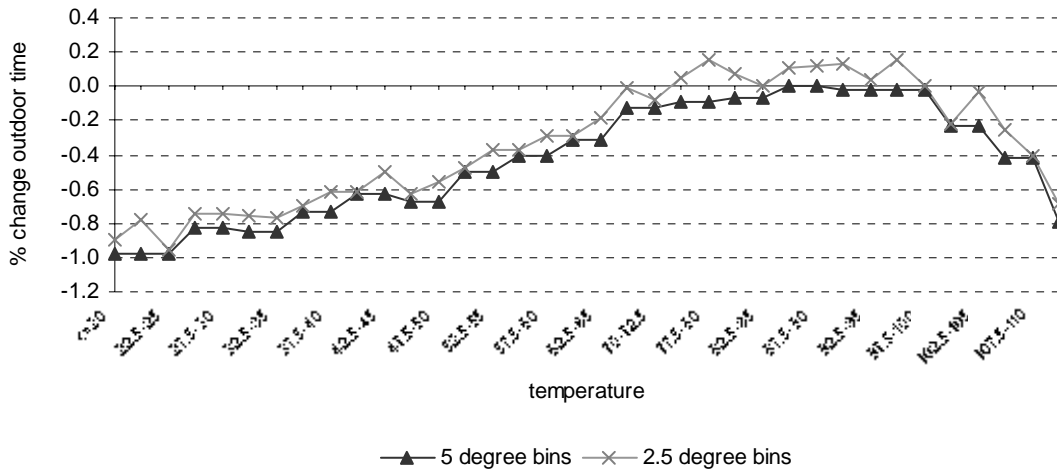


Figure 5. Relationship between temperature and outdoor time: Robustness checks

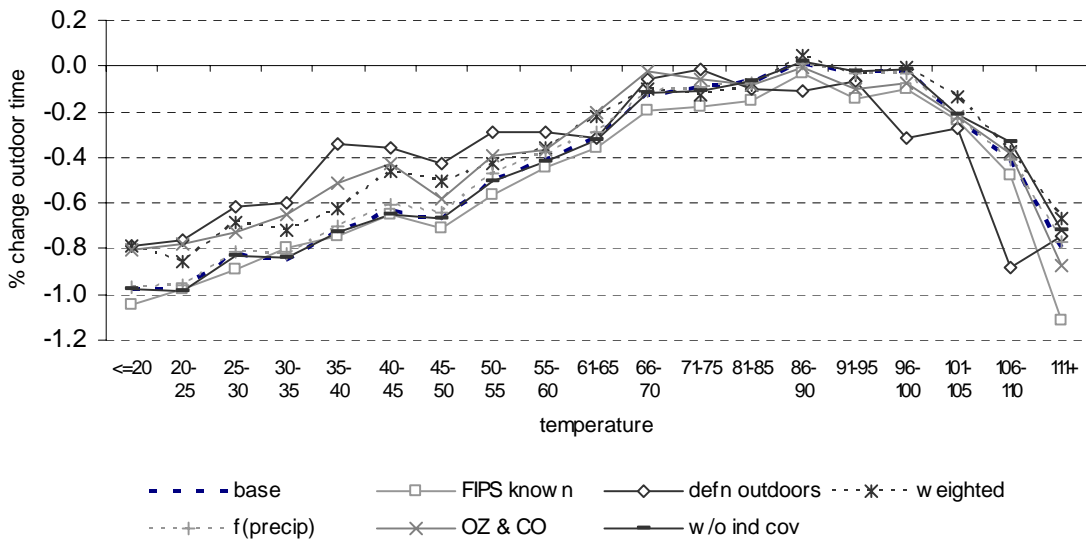


Figure 6. Relationship between temperature and outdoor time by time of day

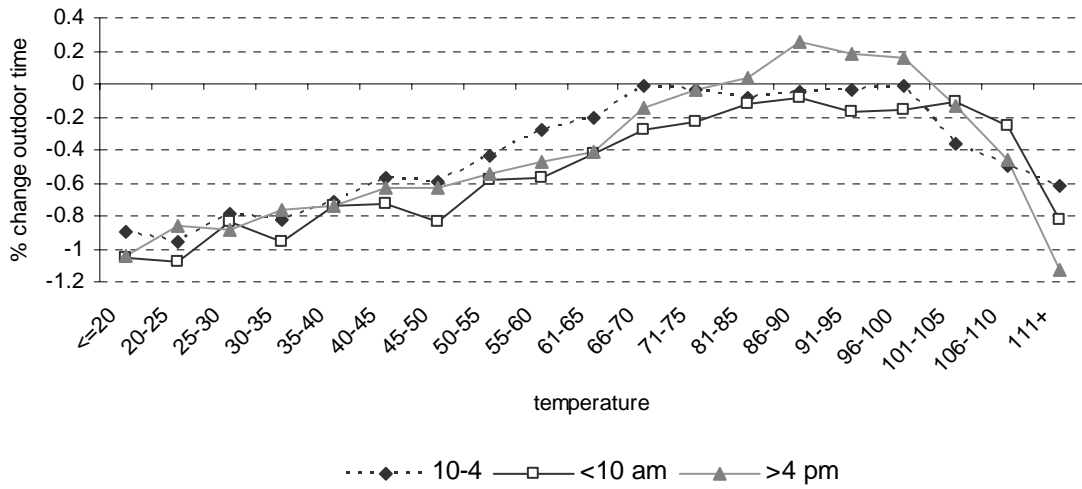


Figure 7. Relationship between temperature and television viewing

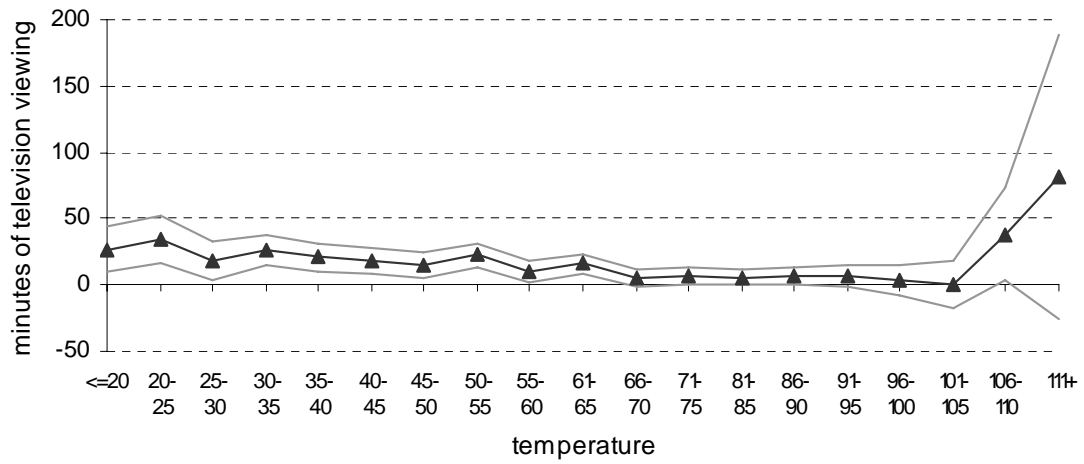


Figure 8. Relationship between temperature and indoor household activities

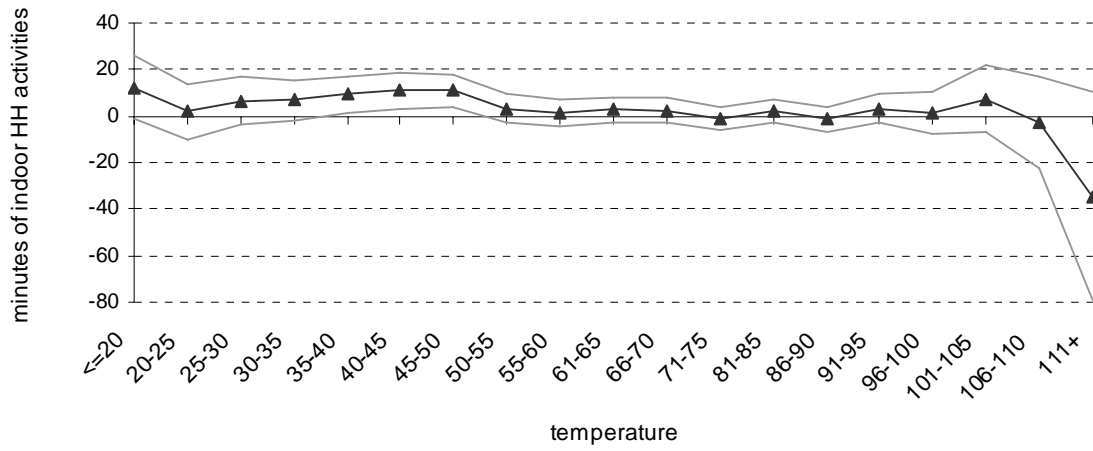


Figure 9. Long and Short-run relationship between temperature and outdoor time

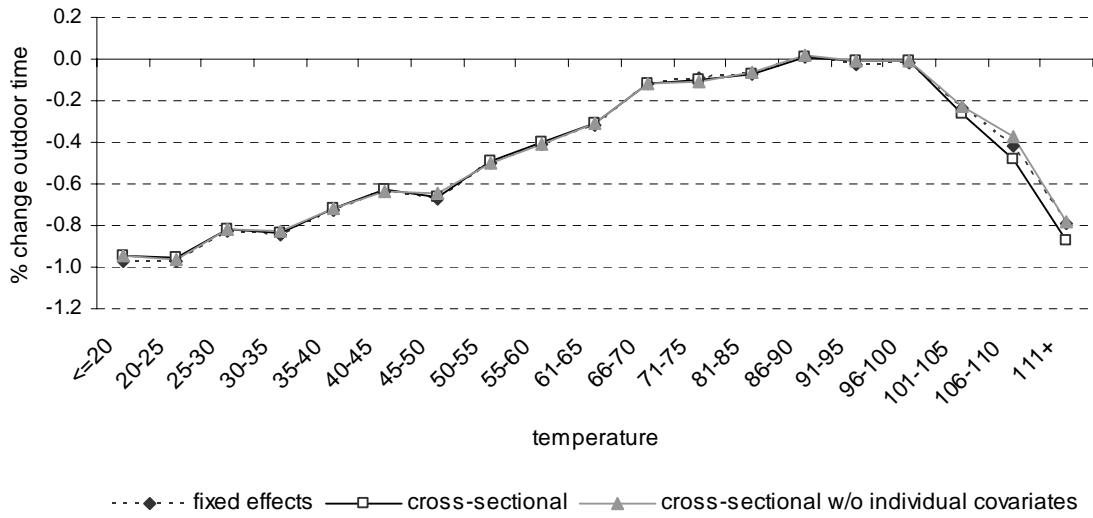


Figure 10. Historical and Forecasted (A1) Temperature Distribution for Maricopa County (Phoenix), AZ, and Suffolk County (Boston), MA

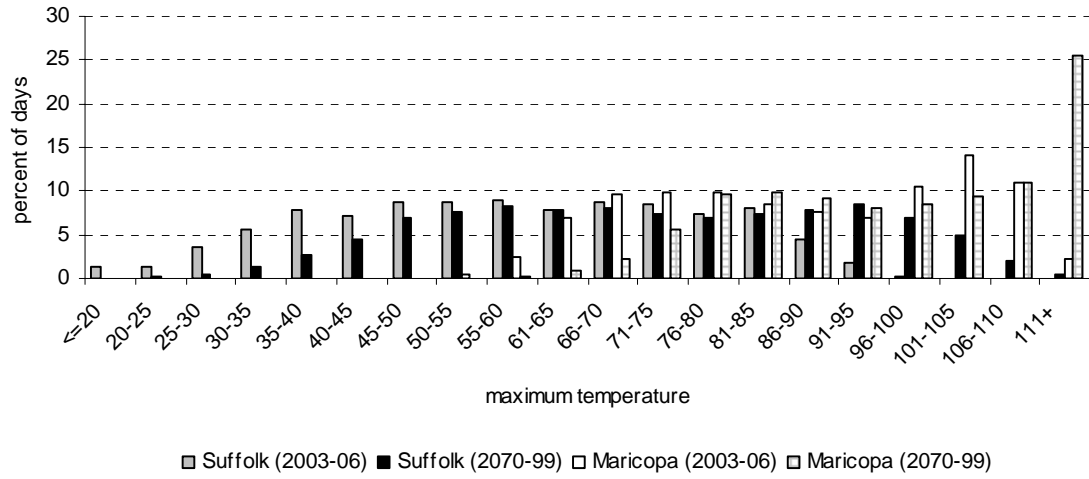


Table 1. Summary statistics

<u>A. Activity time</u> (minutes per day)		
(n=42323)	mean	std. dev.
Outdoor time		
overall	43.78	96.81
<10 am	13.33	54.10
10-4	20.74	59.75
>4 pm	9.72	33.00
household activities	20.14	66.64
sports	12.25	50.41
travel	3.87	15.76
other	7.52	43.97
Indoor time		
television viewing	160.09	165.66
indoor household activities	96.65	122.58
 <u>B. Covariates</u>		
(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. Estimates of relationship between outdoor time and temperature

	1	2
max. temp./100		140.664** [14.146]
(max. temp./100)^2		-61.946** [12.621]
(max. temp./100)^3		
max. temp. <=20	-42.701** [3.755]	
max. temp. 20-25	-42.635** [3.508]	
max. temp. 25-30	-36.170** [3.206]	
max. temp. 30-35	-37.092** [2.921]	
max. temp. 35-40	-31.937** [2.872]	
max. temp. 40-45	-27.701** [2.830]	
max. temp. 45-50	-29.511** [2.586]	
max. temp. 50-55	-21.934** [2.608]	
max. temp. 55-60	-17.898** [2.391]	
max. temp. 61-65	-13.904** [2.301]	
max. temp. 66-70	-5.371* [2.325]	
max. temp. 71-75	-4.124 [2.249]	
max. temp. 81-85	-3.012 [2.189]	
max. temp. 86-90	0.379 [2.475]	
max. temp. 91-95	-1.103 [3.076]	
max. temp. 96-100	-0.93 [4.425]	
max. temp. 101-105	-10.202 [5.986]	
max. temp. 106-110	-18.276* [7.876]	
max. temp. 111+	-34.753** [13.063]	

* significant at 5%; ** significant at 1%. Robust standard errors clustered on county-date in brackets. All regressions also include snow, precipitation, humidity, county FEs, day of week dummies, year-month dummies, and individual covariates listed in Table 1. Max. temp. 76-80 is omitted (reference) category in column (1). N=42,323 in all columns.

Table 3. Net change in activities under various climate change scenarios

	2020-49 (A1)	2020-49 (B1)	2070-99 (A1)	2070-99 (B1)
outdoor time	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

Table 4. Net change in outdoor time by State for 2070-2099 under emissions scenario A1

State	outdoor time	State	outdoor time
Texas	-4.57	Iowa	1.89
Oklahoma	-3.02	North Dakota	2.20
Louisiana	-2.08	Wyoming	2.26
Kansas	-1.70	North Carolina	2.41
Arizona	-1.59	District of Columbia	2.50
Mississippi	-1.36	Indiana	2.65
Arkansas	-1.36	Utah	2.80
Florida	-0.72	Virginia	2.84
Alabama	-0.70	Minnesota	2.90
Nebraska	-0.29	Colorado	3.02
Georgia	-0.28	Maryland	3.33
Missouri	-0.11	West Virginia	3.52
South Dakota	0.48	Ohio	3.70
South Carolina	0.69	Delaware	3.71
California	0.84	New Jersey	4.44
Tennessee	0.95	Michigan	4.58
Montana	1.04	Pennsylvania	4.60
Kentucky	1.16	Rhode Island	5.30
Nevada	1.28	Massachusetts	5.43
Idaho	1.37	New York	5.47
Illinois	1.41	Connecticut	5.50
New Mexico	1.52	Vermont	5.51
Oregon	1.85	New Hampshire	5.52
Washington	1.87	Maine	6.50