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TEMPERATURE AND THE ALLOCATION OF TIME:
IMPLICATIONS FOR CLIMATE CHANGE

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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. We find large reductions in U.S. labor supply in industries with high exposure to climate and similarly large decreases in time allocated to outdoor leisure. We also find suggestive evidence of short-run adaptation through temporal substitutions and acclimatization. Given the industrial composition of the US, the net impacts on total employment are likely to be small, but significant changes in leisure time as well as large scale redistributions of income may be consequential. In developing countries, where the industrial base is more typically concentrated in climate-exposed industries and baseline temperatures are already warmer, employment impacts may be considerably larger.

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1. Introduction

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 important aspect of life that is likely to be transformed under a new climatic paradigm is individual decisions regarding the allocation of their time. Higher temperatures can lead to changes in time allocated to work by altering the marginal productivity of labor (or the marginal cost of supplying labor), especially in climate-exposed industries, such as agriculture, construction, and manufacturing.[2] Higher temperatures may also change the marginal utility of leisure activities,[3] altering the distribution of time allocated to non-work activities. Each of these responses will, in turn, generate indirect impacts through tradeoffs between labor and leisure. Since time is a limited but extremely valuable resource, the welfare implications associated with these climate-induced reallocations of time are potentially quite large.[4]

In this paper we estimate the impacts of climate on the allocation of time to labor as well as leisure activities. Our paper is unique in at least two regards. First, it is the only analysis, to our knowledge, of the impacts of climate on labor supply[5] – the primary source of household income throughout the world. Our understanding of this relationship is also important because it sheds light on the micro-foundations for the macroeconomic literature that has focused on

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[2]The marginal productivity of labor may be influenced through impacts on endurance, fatigue, and cognitive performance. See Gonzalez-Alonso et al., 1999; Galloway and Maughan, 1997; Nielsen et al. 1993 for evidence on endurance and fatigue. See Epstein et al. (1980), Ramsey (1995), Hancock et al. (2007), Pilcher et al. 2002 for evidence on cognitive performance.

[3] See Ma et al., 2006; Pivarnik et al., 2003; U.S. Department of Health and Human Services, 1996; Eisenberg and Okeke, 2008 for evidence on the relationship between temperature and various leisure activities.

[4] Although our paper is concerned with welfare impacts from climate change, the partial equilibrium nature of our analysis precludes us from making welfare calculations. For a more general analysis of welfare impacts at the household level, see Albouy et al. (2009).

[5] Note that while we use the terminology labor supply throughout the paper, we are referring to equilibrium employment levels due to perturbations in supply and demand.

climate and economic growth (Sachs and Warner, 1996; Nordhaus, 2006, Dell et al., 2008). It

also provides a direct test of the exogenous labor supply assumption embedded in most of the

Integrated Assessment Models that are used to simulate the economic impacts of climate change

and that play a prominent role in the design of climate change policies.

Second, individuals' allocation of time in response to temperature represents an avenue

for exploring potential adaptations that may minimize welfare effects from climate change.[6]

Activity choice and location should be viewed as a form of avoidance behavior whereby

individuals protect themselves from the heat by, perhaps, spending more time indoors on hot

days. We further probe short- to medium-run adaptation strategies through an examination of

intra- and inter-temporal reallocations of time as well as through acclimatization, whereby

weather tolerance is altered by prior climate experience such that, for example, Minnesotans may

act more like Floridians once their climate warms. While new climate-neutralizing technologies

will almost certainly be invented in the coming century, these estimates deepen our

understanding about what is possible given the existing technology set and, in turn, the potential

value of innovations that help us to cope with climate change in the future.

We begin our analysis by estimating the impacts of temperature on time allocation using

individual level data from the 2003-2006 American Time Use Surveys (ATUS) linked to daily

weather data from the National Climatic Data Center. Our econometric models include 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.[7] We

flexibly model temperature by including a series of indicator variables for five degree

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[6] Our work could also be viewed as a general equilibrium extension of the numerous studies that have focused on
the impacts of climate change on circumscribed sets of leisure activities (see, for example, Loomis and Crespi, 1999;
Mendelsohn and Markowski, 1999; Englin and Moeltner, 2004).
[7] This identification strategy has also been employed in other studies examining various aspects of climate change
(Schlenker et al., 2005; Deschenes and Greenstone 2007a and 2007b).

temperature bins, with the highest bin for days over 100 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.[8]

In exploring the scope for adaptation, we focus our attention on the high end of the

temperature distribution since our interest in this question is driven by concerns about climate

change under which the low end of the distribution will get warmer and thus easier to manage.

We examine potential short-run compensatory behavior by testing to see whether individuals re-

allocate activities across days by comparing the impacts of lagged temperature to that of

contemporaneous temperature. We complement this analysis with an examination of

intratemporal substitution, i.e. moving climate-exposed activities from daylight to twilight hours.

The role of acclimatization in adaptive strategies is investigated over both the short and medium-

run. The former relies on comparisons of responses at different points in the summer season,

with the notion that hot days may be easier to tolerate in August than in June when they have just

begun to arrive. To analyze the latter, we stratify our model by historical climate to obtain

separate short-run responses for traditionally hotter vs. colder places. It is important to note that,

in general, our tests for adaptation are underpowered. As a result we view this work as

exploratory, but perhaps the best that can be done given pressing concerns about societal

responses to climate change and the limited data availability under current climatic conditions.

Our results reveal impacts on a wide range of activities. While we find suggestive

evidence of a moderate decline in aggregate labor supply response at high temperatures, further

analysis reveals considerable heterogeneity across industry sectors based on their exposure to

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[8] The 2006 heat wave covered most of the U.S. from mid-July through early-August. For example, beginning on July 17, every state except Alaska experienced a high temperature over 90 degrees for three consecutive days based on our weather data (described below).

climatic elements. At temperatures above 85 degrees Fahrenheit, workers in industries with high exposure to climate reduce daily labor supply by as much as one hour. Almost all of the decrease in labor supply happens at the end of the day when fatigue from prolonged exposure to heat has likely set in. We find limited evidence consistent with adaptation to higher temperatures, recognizing demand factors may limit workers discretion in choosing labor supply.

In terms of leisure activities, we generally find an inverted U-shaped relationship with temperature for outdoor leisure and a corresponding U-shaped relationship for indoor leisure. This relationship is most pronounced for those not currently employed, as they have the most flexibility in their scheduling. Overall, these results suggest that protective behavior in response to warmer temperatures may provide an important channel for minimizing the impacts of heat. Temporal substitutions as well as acclimatization also appear to mute the impacts of extreme heat, although these findings are often not significant at conventional levels, in part, because of limited sample size when the data are disaggregated at the high end of the distribution.

The impacts on labor supply are non-trivial. If temperatures were to rise by 5 degrees Celsius in the U.S. by the end of the coming century[9] and no adaptation occurs, U.S. labor supply would fall by roughly 0.6 hours per week in high-exposure industries, representing a 1.7% decrease in hours worked and thus earnings. In developing countries, where industrial composition is generally skewed toward climate-exposed industries and prevailing temperatures are already hotter than those in most of the US, the economic impacts are likely to be much larger.

The remainder of our paper is organized as follows. The next section provides a conceptual framework for the analysis of climate change impacts on time allocation decisions.

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[9] This temperature increase loosely corresponds with the business-as-usual emissions scenario (A2) forecast from the Intergovernmental Panel on Climate Change Fourth Assessment Report (http://www.ipcc.ch/).

Section 3 describes the data and Section 4 details our econometric approach. The results are presented in Section 5. Section 6 concludes.

2. Conceptual Framework

High temperatures cause discomfort, fatigue, and even cognitive impairment depending on the composition of one's activities and the degree to which they are exposed to the elements. For simplicity, we imagine that individuals allocate their total time in a day across three broad activity categories: work, outdoor leisure, and indoor leisure.[10] Since one of our outcomes of interest is the impact of temperature on labor supply, we distinguish between two types of workers based on exposure to climate – those that are generally sheltered from climate and those that are not. We refer to the former as having low risk of exposure to climate ('low-risk') and the latter as having high risk of exposure to climate ('high-risk'). We also separately focus on those not employed where they only allocate their time to outdoor and indoor leisure activities.

We begin with a description of the labor-leisure tradeoff for those in the high-risk sector. As summer temperatures increase for these individuals, the marginal utility from outdoor leisure falls, the marginal productivity of their labor falls, and, given the near-omnipresence of air conditioning in the US[11], the marginal utility from indoor leisure is mostly unchanged. As a result, time is re-allocated from work and outdoor leisure to indoor leisure activities.[12] In

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[10] In our original specification we also included sleep because it may be affected through changes in the marginal utility of labor or leisure (Biddle and Hamermesh, 1990), but since it proved insensitive to temperature we focus on the allocation of time over waking hours.

[11] According to the 2001 American Housing Survey, 79.5% of all household had some form of air conditioning, with the rate of ownership much higher in warmer regions.

[12] Technically, high temperatures could also lead to an increase in work (outdoor leisure) if the marginal utility of the last hour of indoor leisure were smaller than the utility gain from the consumption associated with the first additional hour of work (the first additional hour of outdoor leisure). For this to obtain, the marginal utility of indoor leisure would have to be decreasing at a sharply increasing rate while the other functions remain relatively flat.

contrast, increasing winter temperatures lead to reallocations away from indoor leisure and into work and outdoor activities. These seasonal effects need not be symmetric.

The tradeoff is slightly different for those in the low-risk sector since hotter summers only directly affect the marginal utility they receive from outdoor activities. In this case, time is re-allocated from outdoor leisure to indoor leisure and work. The division between these climate-sheltered activities depends on the relative returns to allocating additional hours to each.[13] As with the high-risk case, the effects in winter work in the opposite direction, potentially yielding reductions in work and indoor leisure time.

For those individuals that are not employed, the tradeoff is much more straightforward. Increased heat in the summer leads to more leisure time spent indoors, while increased heat in other seasons will lead to more leisure time spent outside. Since leisure decisions for this group do not depend on equilibrium outcomes in the labor market, we expect these individuals to be more responsive to changes in temperatures than those who are employed.

The models described above allow for little adaptation to changes in climate, and hence best describe a partial picture of short run behavioral responses to temperature.[14] On hot days, individuals may shift activities to cooler moments within the day (intratemporal substitution) or simply postpone them until cooler days arrive (intertemporal substitution). In addition to adaptation through behavioral changes, individuals may acclimatize (or habituate) to new temperatures.[15] Physiological acclimatization arises through numerous channels, including changes in skin blood flow, metabolic rate, oxygen consumption, and core temperatures

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[13] More formally, the tradeoff will depend on the relative slopes of the marginal utility curve for indoor leisure and the marginal productivity of labor at the old climate equilibrium, i.e. it depends on the second derivatives of the utility and production functions with respect to hours.

[14] While adaptation typically refers to long run changes, we view any action that minimizes the potential welfare impacts from climate change as adaptation.

[15] In the behavioral economics literature this is referred to as reference dependent preferences (see Rabin, 1998)

(Armstrong and Maresh, 1991). It can occur in short periods of time – up to two weeks in healthy individuals under controlled training regimens – but longer for unhealthy individuals or those experiencing passive exposure (Wagner et al., 1972). Over longer periods of time, behavioral acclimatization may also enable individuals to adjust to changes in climate through the adoption of various technologies to cope with unpleasant temperatures.[16] These forms of short- and medium-term adaptation, which are essential for understanding potential individual level adaptations to climate change, are probed further in the analysis that follows.

3. Data

3.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. Each respondent is interviewed the day after the diary date, and is contacted for 8 consecutive weeks to obtain an interview.

We classify individuals into three groups. For the first two groups, we separate workers into high and low risk of exposure to climate based on National Institute of Occupational Safety (NIOSH) definitions of heat-exposed industries (NIOSH, 1986) and industry codes in the ATUS. These include industries where the work is primarily performed outdoors -- agriculture, forestry, fishing, and hunting; construction; mining; and transportation and utilities – as well as

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[16] Acclimatization has an ambiguous effect on responses to temperature. Physiological acclimatization, such as greater tolerance for warmer weather, may increase the demand for outdoor activities, while behavioral changes, such as increased adoption of air conditioning, may increase demand for indoor activities.

manufacturing, where facilities are typically not climate controlled and the production process often generates considerable heat. Individuals from all remaining industries are defined as low-risk. Given potential ambiguities regarding the degree of heat exposure within the manufacturing sector, we also perform sensitivity analyses by classifying these workers as low risk, and find this makes little difference. The third group consists of those currently unemployed or out of the labor force. To measure labor supply, we sum the total number of minutes in which the activity occurred at the respondent's workplace, where this is by definition equal to zero for the non-employed group.

We similarly break leisure into relatively climate sensitive and insensitive categories – outdoor and indoor activities, respectively. Despite information in the ATUS 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 steps to construct a measure of time spent outdoors, with all remaining activities coded as indoor activities. First, we code outdoor time if the respondent reported the activity was "outdoors, away from home" or the respondent was "traveling by foot or bicycle." Second, we include activities that do not fall into these categories but, based on the activity code, were unarguably performed outdoors. For example, if a respondent was "at the home or yard" and conducted "exterior maintenance" or "lawn maintenance," we coded this as an outdoor activity. We classify activities that take place in ambiguous locations, such as "socializing, relaxing and leisure" that occurred at home, as indoors so our measurement of total time spent outdoors understates actual outdoor time. Given this categorization, nearly all outdoor activities are

somewhat physically demanding, while indoor activities are generally lower intensity.[17] While

imperfect, this split is particularly attractive for our purposes, since the marginal utility of

physically active endeavors, especially those outdoors, is expected to be most responsive to

changes in temperature.

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 locations with over 100,000

residents to maintain confidentiality, making geographic identifiers available for 3/4 of the

sample, though we examine the external validity of this limitation 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 assessed the sensitivity of this assumption by limiting analyses

to individuals with exact county identified, and found this had little impact on our estimates.

3.B. Weather

We obtain historical weather data from the 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 has little impact

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[17] We can separately identify high intensity indoor activities that took place at a gym or sports club, but very few activities fell into this category: on average individuals spend 0.9 minutes per day at a gym.

on our results.[18] 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.

3.C. Daylight

Daylight is positively correlated with temperature and is likely to influence time allocation, 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 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 and date in our sample.

3.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. Table 1 presents summary statistics for our final sample. Time allocated to work is just under 3 hours per day, but this includes individuals who report zero hours of work because they are not employed or are interviewed on a day-off. Conditional on working, labor supply is 7 hours a day overall, but closer to 8 for high-risk laborers.[19] In terms of leisure activities, individuals spend just under ¾ of an hour a day in the defined outdoor activities, recalling that we are likely to understate total outdoor time. Many individuals are identified as spending zero minutes outside; conditional on spending time outside individuals allocate roughly two hours to outdoor leisure. Outdoor leisure is highest for high-risk workers, but comparable across the three other groups. Most of the day is

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[18] Unfortunately this limits our ability to explore the joint impacts of heat and humidity, which may also be relevant for affecting time allocation.
[19] We also present results from analyses below that explicitly accounts for the excess zeros.

spent in indoor activities – nearly 12 hours a day – and nearly everyone spends at least 1 minute

a day inside. The non-employed spend the most time indoors, followed by low-risk workers and

then high-risk workers. The remaining 7.5 hours per day is spent sleeping (not shown).[20]

Many demographic variables from the CPS are brought forward to the ATUS, providing

a large pool of potential covariates for our analysis, also shown in Table 1. Nearly all

demographics are comparable across groups with one notable exception. The mean age of the

non-employed is 52, compared to 42 and 41 for high- and low-risk workers, respectively. This

difference is not surprising given that many non-employed are retired. This difference is

important to keep in mind when analyzing responses across groups because while the non-

employed may have more flexibility in their scheduling, they may also be more sensitive to

extreme temperatures because of their age (Wagner et al., 1972).

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 2070-2099 based on the Hadley 3 climate forecast model under the business-as-

usual emissions scenario (A1) for the same counties in our final sample.[21] The distribution is

predicted 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 exceed 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.

Since these days are 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.

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[20] As previously mentioned, we did not find evidence of a relationship between temperature and sleep.
[21] These forecasts were a major input into the Intergovernmental Panel on Climate Change 3rd assessment report.
Daily values were assigned to counties as described in Schlenker and Roberts (2009).

3.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), a particularly relevant concern in this context 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 Appendix Figure 1, the distribution of temperature across the two groups is nearly identical, suggesting non-response bias due to temperature is likely to be minimal in our analysis.

An additional concern is that the external validity of our sample is compromised by only focusing on more urban areas where geographic residence is obtained. 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 Appendix Figure 1, we find little difference between the two distributions, suggesting external validity is unlikely to be compromised.

4. Econometric Model

4.A. Baseline model

To examine the relationship between temperature and time allocation, we estimate the following econometric model:

(1) $plabor_{ict} = \sum_j \beta_{1j}\, temp_{ct} + \delta_1 Z_{ct} + \gamma_1 X_{ic} + DOW_{1t} + f_1(t) + \alpha_{1c} + \varepsilon_{1ict}$

(2) $poutdoor_{ict} = \sum_j \beta_{2j}\, temp_{ct} + \delta_2 Z_{ct} + \gamma_2 X_{ic} + DOW_{2t} + f_2(t) + \alpha_{2c} + \varepsilon_{2ict}$

(3) $pindoor_{ict} = \sum_j \beta_{3j}\, temp_{ct} + \delta_3 Z_{ct} + \gamma_3 X_{ic} + DOW_{3t} + f_3(t) + \alpha_{3c} + \varepsilon_{3ict}$

(4) $\beta_{1j} + \beta_{2j} + \beta_{3j} = 0$ for all j

where *plabor* is the percent of time allocated to labor market activities for individual i in county

c on date t, *poutdoor* is the percent of time allocated to outdoor leisure activities, and *pindoor* is

the percent of time allocation to indoor leisure activities.[22] *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, precipitation, humidity, and minimum temperature) and X_{ic} are individual level

covariates meant to capture preferences for particular activities, listed in Table 1. DOW_t are day

of week dummy variables to account for differences in schedules throughout the week. $f(t)$ are

year-month dummy variables to control for seasonal and annual time trends in activity choice. α_c

are county fixed effects that capture all time invariant observable and unobservable attributes

that affect time allocation decisions. Therefore, our parameters of interest that relate temperature

to time (β_j) are identified from daily variations in weather within a county. We demonstrate

below that our results are insensitive to numerous robustness checks, supporting the validity of

our model.[23]

We estimate equations (1)-(3) via seemingly unrelated regression, imposing constraint

(4), which limits the net effect from a temperature change on total time to sum to zero.[24] For

ease of interpretation, we multiply all coefficients by the total number of minutes in a day (1440)

to obtain the change in minutes allocated to each activity. We estimate these models for all

individuals, and then separately for those employed in high-risk industries and those employed in

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[22] Note that we do not distinguish between home production and leisure.
[23] Since multiple individuals can be observed on the same day within a county, we cluster standard errors on the county-date.
[24] We assess the impact of this restriction below.

low-risk industries. For those not currently employed, we estimate equations (2)-(3), modifying the constraints accordingly.

To examine the impacts of temperatures, it is essential that we flexibly model the relationship between temperature and time spent in certain activities given the expected nonlinear relationship: increases in temperature may lead to increases in outdoor leisure at colder temperatures, but beyond a certain point may lead to decreases (Galloway and Maughan, 1997). Our model includes separate indicator variables for every 5-degree temperature increment (as displayed in Figure 1), which allows differential shifts in activities for each temperature bin.[25] We omit the 76-80 degree indicator variable, so we interpret our estimates as the change in minutes allocated to that activity at a certain temperature range relative to 76-80 degrees.

4.B. Exploring adaptation

We estimate several alternative models to explore the scope for behavioral substitutions and acclimatization, with the mean of the dependent variables for these alternative models shown in Table 2. To assess intertemporal substitution, we include lagged temperature in equations (1)-(3) in addition to contemporaneous temperature, and also place a comparable constraint on lagged temperatures that the net effect on total time sums to zero. We also flexibly model lagged temperature using the same indicator variables. 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. If individuals substitute activities across days, then we expect unpleasant lagged temperatures to increase the demand for current activities.

By aggregating responses within a day, any estimated effects are net of intratemporal substitutions whereby individuals reschedule activities to more pleasant times of the day. To

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[25] Models with 2.5 degree size bins for temperature yield strikingly similar results. We also estimated models with higher order polynomials in temperature. Our results were sensitive to the polynomial degree (results available upon request), thus persuading us to use a more flexible approach.

assess intratemporal substitution, we split the dependent variables in equations (1)-(3) into time spent during daylight vs. twilight hours and estimate separate models for each. To define time allocation during twilight, we include activities that began less than two hours after sunrise or less than two hours before sunset, where sunrise and sunset values vary over both space and time. Since we are interested in comparing daylight vs. twilight responses and the mean level of each variable differs (as shown in Table 2), we present these results as the percentage change in time allocation by dividing the change in minutes by the mean of the dependent variable. If unpleasantly warm days are cooler during the evening or the morning, then we expect smaller responses to temperatures during twilight hours as compared to daylight hours.

The impacts of short-run acclimatization are assessed by estimating separate temperature responses for June and August. Since hot days are a relatively new phenomenon in June but quite common by August, a diminished response to high temperatures in August should be viewed as evidence of acclimatization.[26] Since this test greatly reduces our sample size and power to detect differential effects, we modify the minimum temperature bin to under 65 degrees, a reasonably innocuous change given the months of our focus.

By including county fixed effects, the econometric model identifies short run behavioral responses to temperature. Although most physiological acclimatization occurs within a short period of time, behavioral acclimatization may require more time to take effect. To assess longer run adjustments, we explore the impacts of temperature separately for historically warmer and cooler areas. In particular, we compare the response function for people that live in places with the warmest third of average July-August temperatures during the 1980s to those that lived in the

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[26] We do not want to conduct this test by comparing the impact of temperature across seasons for at least two reasons. One, this only identifies impacts where there is sufficient temperature overlap across seasons, making it unlikely to identify the impact from very hot weather. Two, marginal utility from pleasant weather may diminish at different rates depending on how often such weather is experienced.

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coldest third.[27] The presumption is that those that live in hotter climates have had longer periods

of time to adapt to warmer conditions, through more complete physiological adaptation as well

as investments in technologies that make it easier to cope with high temperatures. If people

adapt to changes in climate, people in cooler places would show comparable adaptations as they

become warmer, suggesting that the short run response curve of colder places will eventually

become like the short-run response curve of hotter places.

5. Results

    5.A. Baseline results

      We begin with a focus on the impacts of temperature on time allocation for all

individuals, and then focus on the impacts for the groups defined in Table 1. In Figure 2, we find

some evidence of a downward trend in labor supply from higher temperatures, shown in the first

panel. The estimates, however, are not large in magnitude – the response at 100+ degrees is 19

minutes – and are not statistically significant at conventional levels. This suggests that,

consistent with recent findings (Connolly, 2008), labor supply on net is not responsive to

changes in temperature.

      Turning to leisure time, we find an asymmetric relationship between temperature and

outdoor leisure. Time outside at 25 degrees is 37 minutes less than at 76-80 degrees, and

steadily climbs until 76-80 degrees. It remains fairly stable until 100 degrees, and falls after that,

though the impact at the highest temperature bin is not statistically significant. While this pattern

is consistent with physiological evidence suggesting fatigue from exposure at temperature

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[27] The colder places predominantly consist of counties in the Northeast and upper Midwest; warmer places in the Southeast and Southwest; and omitted places in the mid-Atlantic, mountain states, and lower Midwest. California was almost evenly split amongst the three categories. We also perform this analysis for those in the warmest/coldest quartile or quintile, and found comparable results.

extremes (Galloway and Maughan (1997), the lack of significance at high temperatures and the high inflection point suggests external factors may play an important role in individuals responses.

Indoor leisure shows a highly asymmetric U-shaped pattern. Indoor leisure increases by roughly 30 minutes at 25 degrees compared to 76-80 degrees, and then steadily decreases until 76-80 degrees. It remains stable until roughly 95 degrees, and then increases considerably after that. At temperatures over 100 degrees, indoor leisure increases by 27 minutes relative to 76-80 degrees, with this estimate statistically significant at conventional levels.

The analysis in Figure 2, however, masks potentially important heterogeneity due to differential occupational exposure to temperature. In Figure 3, we focus on time allocations for individuals employed in industries with a high risk of climate exposure. For labor supply, we continue to find little response to temperatures below 80 degrees, but monotonic declines in labor supply above 85 degrees. At temperatures over 100 degrees, labor supply drops by a statistically significant 59 minutes as compared to 76-80 degrees. Thus, as hypothesized, the marginal productivity of labor for these workers appears to be significantly impacted by temperatures at the high end of the climate spectrum.

In terms of leisure activities, the results are comparable to the patterns found for all workers, with a slightly higher increase in indoor leisure to accommodate the decrease in labor supply at higher temperatures. At high temperatures, workers appear to substitute their labor supply for indoor leisure, with surprisingly no decline in outdoor leisure. This suggests that, while the marginal utility from outdoor leisure may be declining, the marginal utility of indoor leisure is decreasing at a faster rate over this temperature range.

In Figure 4, we focus on time allocations for those in low-risk industries. For labor supply, we again see little response to colder temperature. While we see a decrease in labor supply at temperatures above 95 degrees, this effect is modest and not statistically significant. The high fraction of workers in these industries explains why we see no net effect on labor supply from higher temperatures. In terms of leisure activities, we see comparable responses as above for colder temperatures, but more muted responses at hotter temperatures which is consistent with the smaller labor supply response for this group.

In Figure 5, we present results for those not employed. Consistent with expectations, we find outdoor and indoor leisure more responsive to temperature changes, particularly at hotter temperatures. Outdoor leisure begins decreasing at lower temperatures when compared to employed individuals, with declines beginning around 90 degrees. Furthermore, the impacts at higher temperatures are larger and statistically significant. Temperatures over 100 degrees lead to a statistically significant decrease in outdoor leisure of 22 minutes compared to 76-80 degrees. Consistent with Deschenes and Greenstone (2007b), such responses at high temperatures are supportive of short-run adaptation whereby individuals protect themselves from the heat by spending more time inside, which may lessen the health impacts from higher temperatures (Alberini et al., 2008).

5.B. Robustness checks

In Figure 6, we display results from models that assess the sensitivity of our results to several specification checks, though our results are robust to additional checks not shown. We focus solely on labor supply for high-rsk workers and outdoor leisure for non-employed because this is where we find the largest and most significant effects, though results are similar for the other activities and groups shown in Figures 2-5. We include in this figure the confidence

intervals from our baseline results to facilitate interpretation, though as we demonstrate below our estimates are highly insensitive to these alternate specifications.

Since those employed in the manufacturing industry may in fact work in low risk industries if the manufacturing plant is climate controlled, we may have erroneously classified exposure risk for some workers. Our first robustness check shifts individuals from the manufacturing industry into low risk.[28] Despite the nearly 50% decrease in sample size in the high risk group, our estimates are largely unaffected by this change. If anything, we find a slightly larger reduction in labor supply at higher temperatures, which is consistent with this misclassification, though the difference is minimal.

In the next two checks we assess potential omitted variable bias. First, we exclude all individual level covariates to assess whether county fixed effects capture sorting into locations based on temperature. Second, we include county-season fixed effects to allow for seasonal shocks specific to each county. Figure 6 confirms that these modifications have minimal impact on our estimates, suggesting confounding is unlikely to be a major concern.

As previously mentioned, we have a large mass of observations at zero. Since these zeros represent corner solutions rather than a negative latent value, linear models should produce consistent estimates of the partial effects of interest near its mean value. To further assess this, we estimate two-part models that separately model the extensive and intensive margins.[29] In estimating this model, we also relax the constraint that the coefficients across activities sum to zero, so it also tests this restriction. Shown in this Figure, the results from the two-part model

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[28] This test is irrelevant for the non-employed group.
[29] More specifically, based on laws of probability, $E(y|x) = P(y>0|x) * E(y|y>0,x)$. We estimate $P(y>0|x)$ using a probit model and $E(y|y>0,x)$ by OLS, and compute marginal effects by taking the derivative of $P(y>0|x) * E(y|y>0,x)$.

are quite comparable to the linear estimates. Taken together, the results from Figure 6 document a robust relationship between temperature and time allocation.

        5.C. Adaptation

        Our static, short-run model may conceal important responses that minimize the impact of climate shocks. In this section, we probe potential behavioral substitutions and acclimatization as described in the econometric section. As with the robustness checks, we focus solely on labor supply for high-risk workers and outdoor leisure for non-employed because this is where we find the largest effects and hence have the largest scope for adaptation. It is important to keep in mind that these tests rely on considerably smaller sample sizes, particularly at the upper tail of the distribution, and thus are underpowered to produce statistical significance at conventional levels. Given the importance of this topic and the inherently limited data availability under current climatic conditions, these results should be viewed as suggestive of the types of adaptation we may see in the future.

        We begin by exploring the intertemporal effects of temperature whereby individuals may compensate for unpleasant weather by shifting their activities across days, suggesting that the estimates we have shown thus far may overstate the impacts from warmer temperatures. In Figure 7 we present estimates from regressions that includes the same indicator variables for lagged temperature (in addition to indicators for current temperature). Given that we find a decrease in labor supply for high-risk workers, if intertemporal substitution exists we expect to see an increase in labor supply from high lagged temperatures. This does not appear to be the case, suggesting little or no role for intertemporal substitution in the workplace. In contrast, outdoor leisure for the non-employed appears responsive to rescheduling. The two highest

temperature bins for lagged temperature are positive, with the estimate of an increase of 15 minutes at 100+ degrees (compared to 76-80 degrees) statistically significant at the 10% level.

In Figure 8, we present results exploring the potential for intratemporal substitution by estimating whether individuals shift the timing of activities within the day. For labor supply, we find that hours worked during daylight is largely unaffected by warmer temperatures. However, hours worked during twilight is highly responsive to warmer temperatures, and hence appears to be the driving force behind the labor supply response found in our base analyses. Furthermore, the difference in responses for temperatures above 85 degrees is statistically significant at conventional levels. If we separate twilight time into the beginning vs. end of the day (not shown), we also find that nearly all of the decrease during twilight hours comes from the end of the day. This pattern is consistent with the idea that workers have little discretion over labor supply during core business hours, but as fatigue sets in from accumulated exposure to higher temperatures and marginal productivity declines, labor supply becomes responsive.

Turning to outdoor leisure for the non-employed, we find patterns consistent with individuals shifting activities to more favorable times of the day, though the differences are not statistically significant. For example, we find the turning point for twilight activities occurs at higher temperatures. Furthermore, the drop off from temperatures above 100 degrees is smaller during twilight hours, representing a 26 percent decrease as opposed to a 58 percent decrease during daylight hours (compared to 76-80 degrees).

As a test of short-run acclimatization, we explore whether individuals are less sensitive to warmer temperatures as they become more common by estimating the impact of temperatures separately in June vs. August. While our estimate for the highest temperature bin is consistent with acclimatization for labor supply, the overall pattern is less well-behaved. For outdoor

leisure, we find a pattern highly consistent with short-run acclimatization. Responses in August compared to June are smaller at high temperatures but larger at unseasonably cold temperatures. Given the dramatic drop in sample size, it is unsurprising that these differences are not statistically significant. The differences at high temperatures, however, are large in magnitude. For example, at days over 100 degrees, the non-employed spend 30 more minutes outside in August than in June.

Thus far we have assumed that all individuals respond to temperatures in the same way. Our final test for adaptation allows for heterogeneous responses to temperature based on historical climates by grouping counties into those in the highest third of historical July-August temperatures and the coldest third. Shown in Figure 10, although we continue to see declines in both labor supply and outdoor leisure at high temperatures in the historically warmer places, the response to high temperatures, particularly for outdoor leisure, is noticeably smaller than the response in colder places. Here again the difference in estimates is not statistically significant but the point estimates are quite large.

6. Conclusion

The warmer temperatures that are projected to spread across the planet 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 policies. In this paper, we examine the impacts of climate on individual's allocation of time within the US. We find large reductions in labor supply in climate-exposed industries as temperatures increase beyond 85 degrees. We also find large decreases in outdoor leisure activities at higher temperatures, but only for those who are not employed.

Our labor results imply a substantial transfer of income from mostly blue-collar sectors of the economy to more white-collar sectors, which may have important regional and political consequences. Moreover, the restructuring of leisure time in response to climate change carries with it substantial welfare implications. Nearly $300B per year is spent on outdoor recreational activities alone (American Recreation Coalition, 2007), so summer reductions in outdoor time represent a direct and potentially large loss of utility while winter increases could bring gains. Similarly, substitution toward or away from sedentary activities as seasonal temperatures move in and out of the comfortable range could have profound impacts on population health through changes in the incidence of obesity, diabetes, and cardiovascular disease.[30]

It is also important to note that while the net employment impacts in the US may be small, they may be considerably larger in developing countries, where the industrial base is more typically concentrated in climate-exposed industries and baseline temperatures are already warmer. In middle-income countries like Mexico, for example, back-of-the-envelope calculations suggest a 2.0% drop in overall employment at the end of this century.[31] In poorer regions like sub-Saharan Africa, where nearly all labor is in climate-exposed industries, the consequences may be devastating. Such a pattern of results is strikingly consistent with the emerging literature on climate change and macroeconomic growth (Dell et al., 2008).

While we find suggestive evidence of adaptation through temporal substitutions and acclimatization, it is likely that adaptation will become more substantial in the future. Better technologies to cope with the elements will be invented and firms may find their adoption

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[30] See, for example, Veerman et al., 2007, Li et al., 2006, and Laaksonen et al., 2005.

[31] We compute these numbers by assuming the labor supply response in Mexico is the same as the US, using Texas baseline temperatures for Mexico, imposing a uniform warming of 5 degrees Celsius, and assuming 49.7% are employed in exposed industries (Hanson, 2003). Clearly labor supply responses may differ, especially if the rate of substitution between capital and labor differs and/or capital is differentially affected by climate change. While a time use survey for Mexico is available (Encuesta Nacional sobre Trabajo, Aportaciones y Uso del Tiempo), it does not include the necessary variables to permit such an analysis.

increasingly attractive as the costs associated with lost labor productivity become larger.

Adaptation may also take the form of re-location if individuals and firms move from the

currently warm regions of the South to the historically cooler North.[32] Similar changes may take

place on a global scale. Exploring the scope for longer-run adaptation is essential for policy

making and a fruitful area for future research.

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[32] Previous research examining climate and migration have typically focused on moving away from colder weather (e.g., Cragg and Kahn, 1997; Deschenes and Moretti, 2009), which 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.

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Figure 1. Historical and forecasted temperature distribution
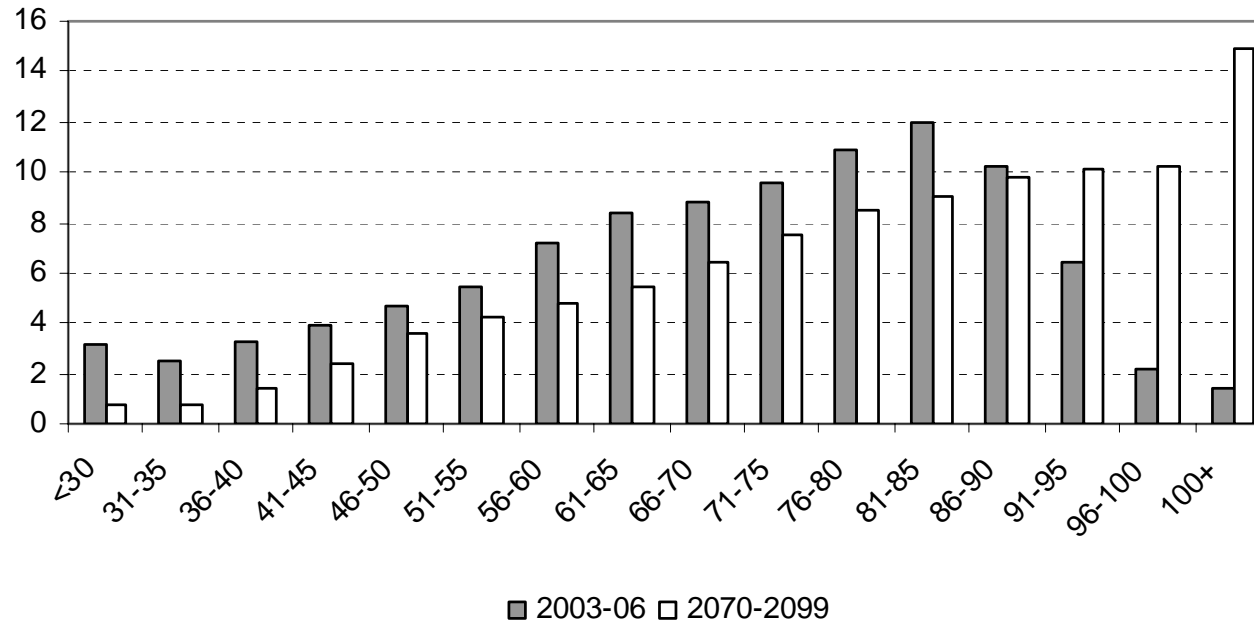
Notes: This figure is based on daily observations for each county included in the final ATUS sample for the years indicated. 2070-2099 forecasted temperatures are based on the Hadley 3 climate model under the highest warming scenario (A1).

Figure 2. Relationship between temperature and time allocation for all individuals
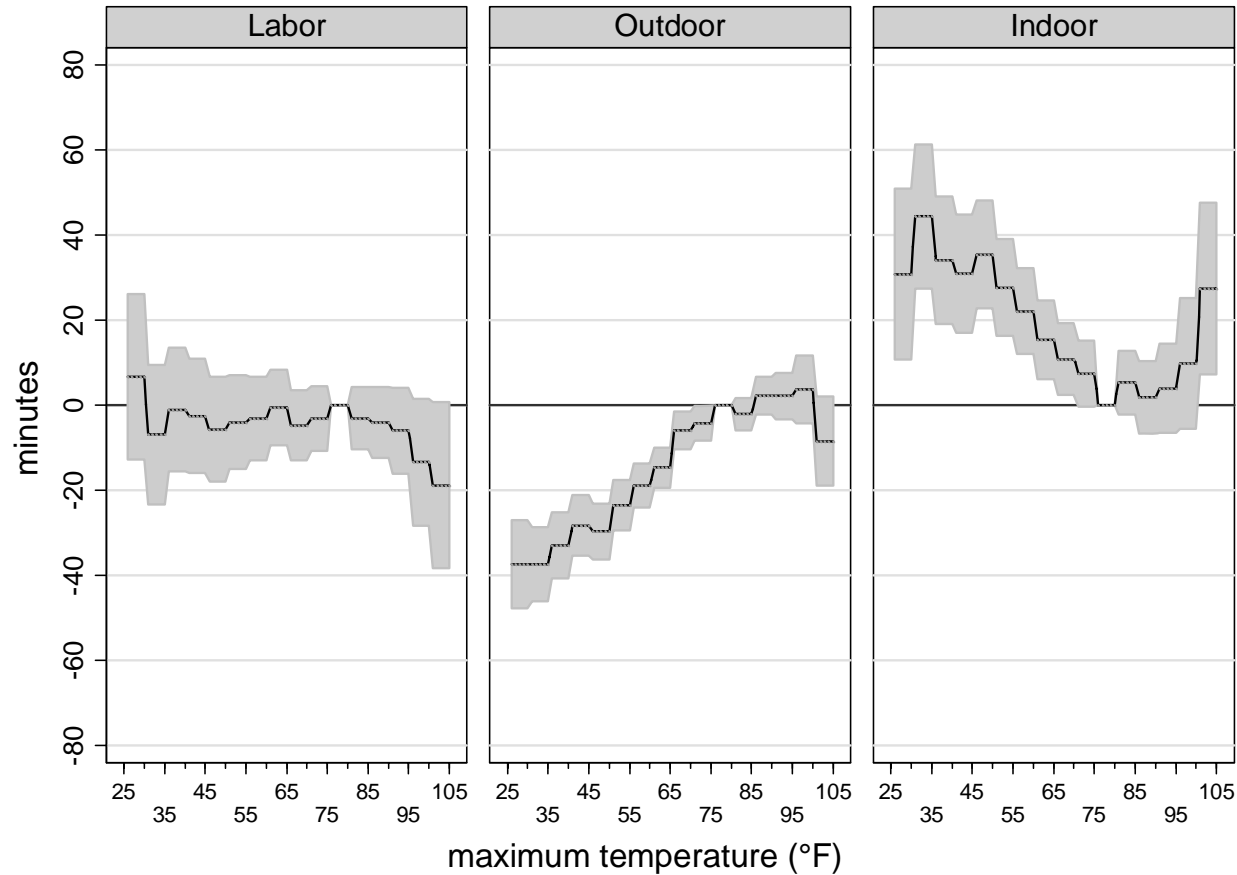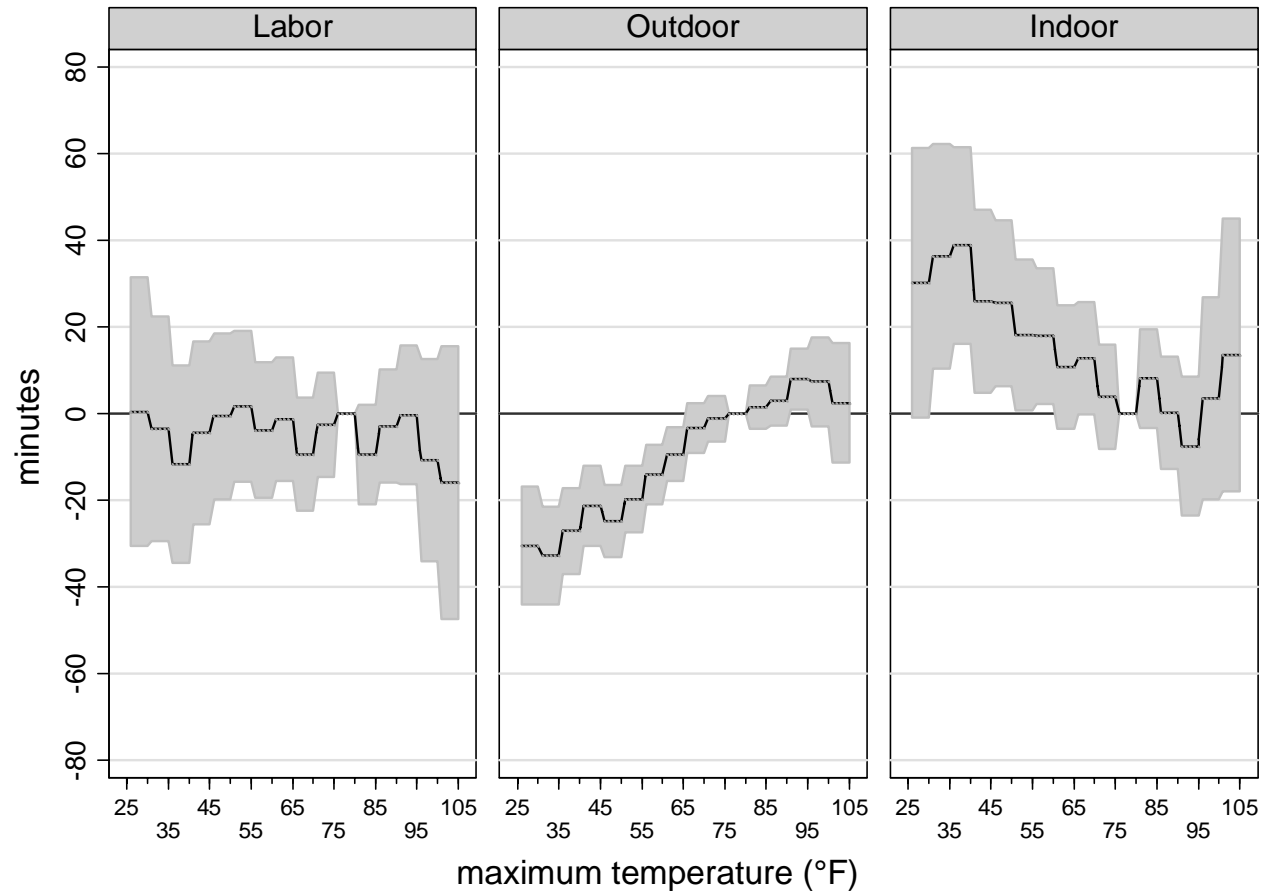

Notes: N=42,280 in all regressions. 95% confidence interval shaded in gray. Each figure displays the estimated impact of temperature on time allocation based on equations (1)-(4) in the text. Covariates include age, gender, # of children, earnings, employment status, race, education, marital status, family income, day of week dummies, minimum temperature, precipitation, humidity, sunrise, sunset, year-month dummies, and county fixed effects.

Figure 3. Relationship between temperature and time allocation for high risk industries
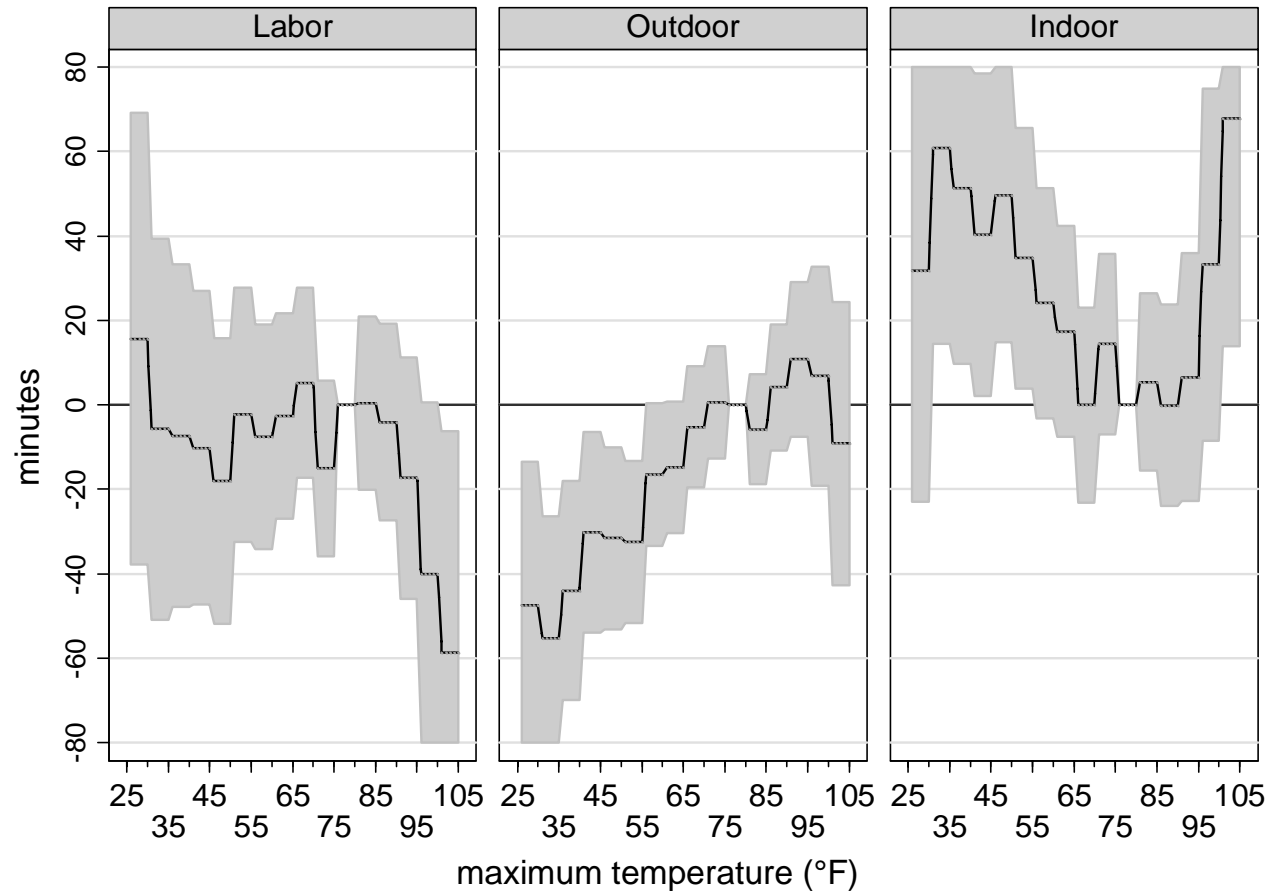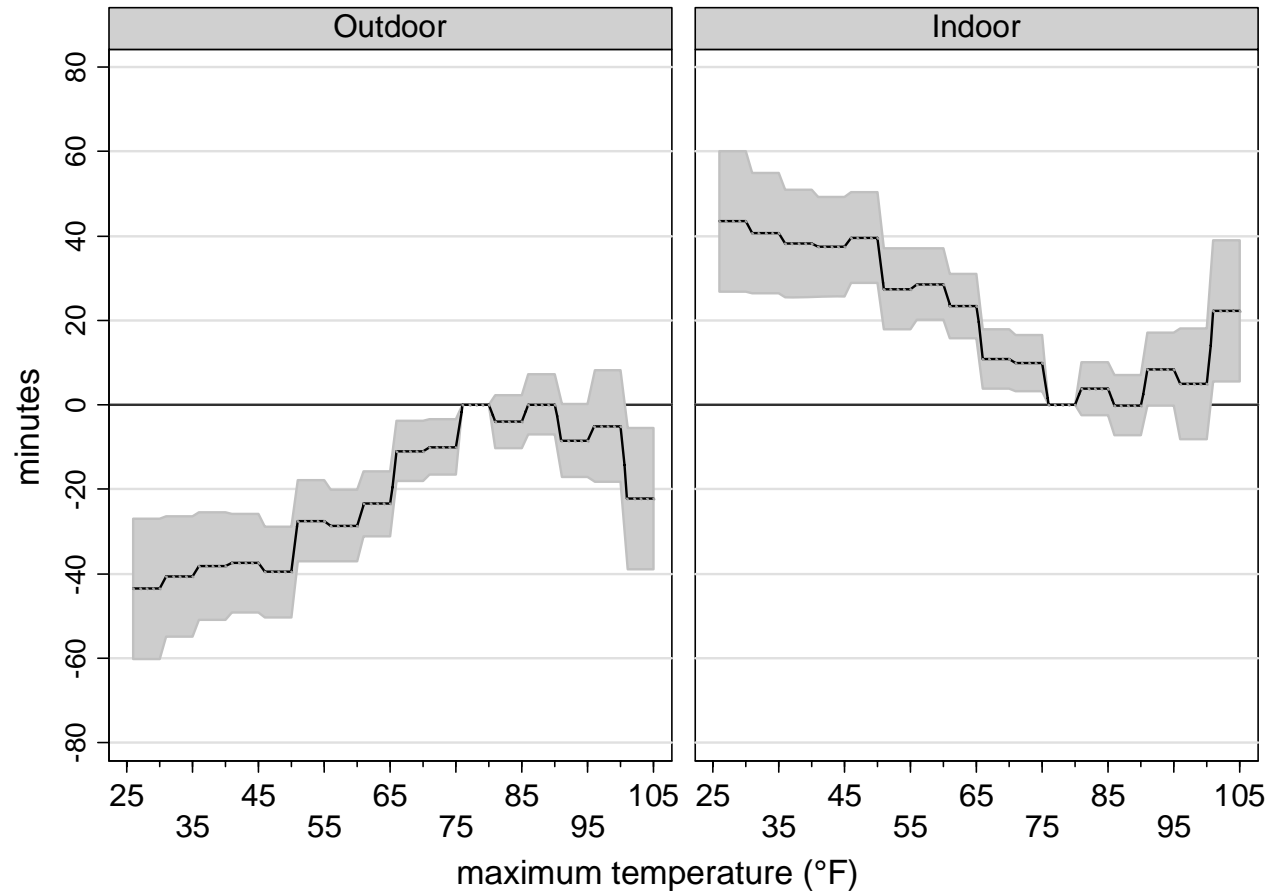

See notes to Figure 2. N=6,246 in all regressions. 95% confidence interval shaded in gray. 'High risk' defined as agriculture, forestry, fishing, and hunting, mining, construction, manufacturing, and transportation and utilities industries.

Figure 4. Relationship between temperature and time allocation for low risk industries


See notes to Figure 2. N=21,151 in all regressions. 95% confidence interval shaded in gray. 'Low risk' defined as remaining industries not listed in Figure 3.

Figure 5. Relationship between temperature and time allocation for non-employed


See notes to Figure 2. N=14,883 in all regressions. 95% confidence interval shaded in gray. 'Non-employed' defined as unemployed or out of labor force.

Figure 6. Robustness checks
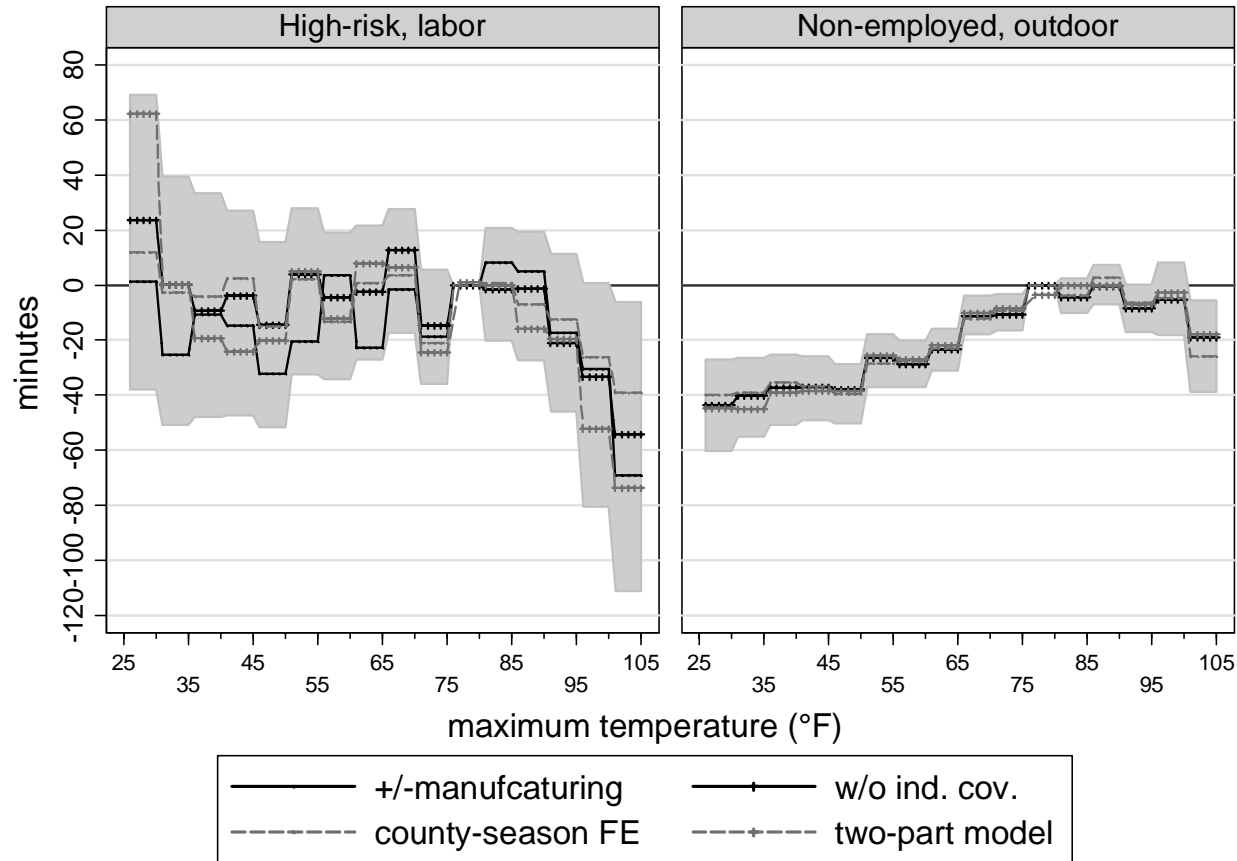
See notes to Figure 2. 95% confidence interval for baseline estimates shaded in gray. '+/- manufacturing' moves those employed in the manufacturing industry from high to low risk. 'w/o ind. cov.' excludes all individual level covariates. 'county-season FE' includes a county-season fixed effect. 'two-part model' presents marginal effects from models that separately estimate the extensive and intensive margins to account for excess zeros and does not constrain coefficients across activities to sum to zero.

Figure 7. Intertemporal substitution
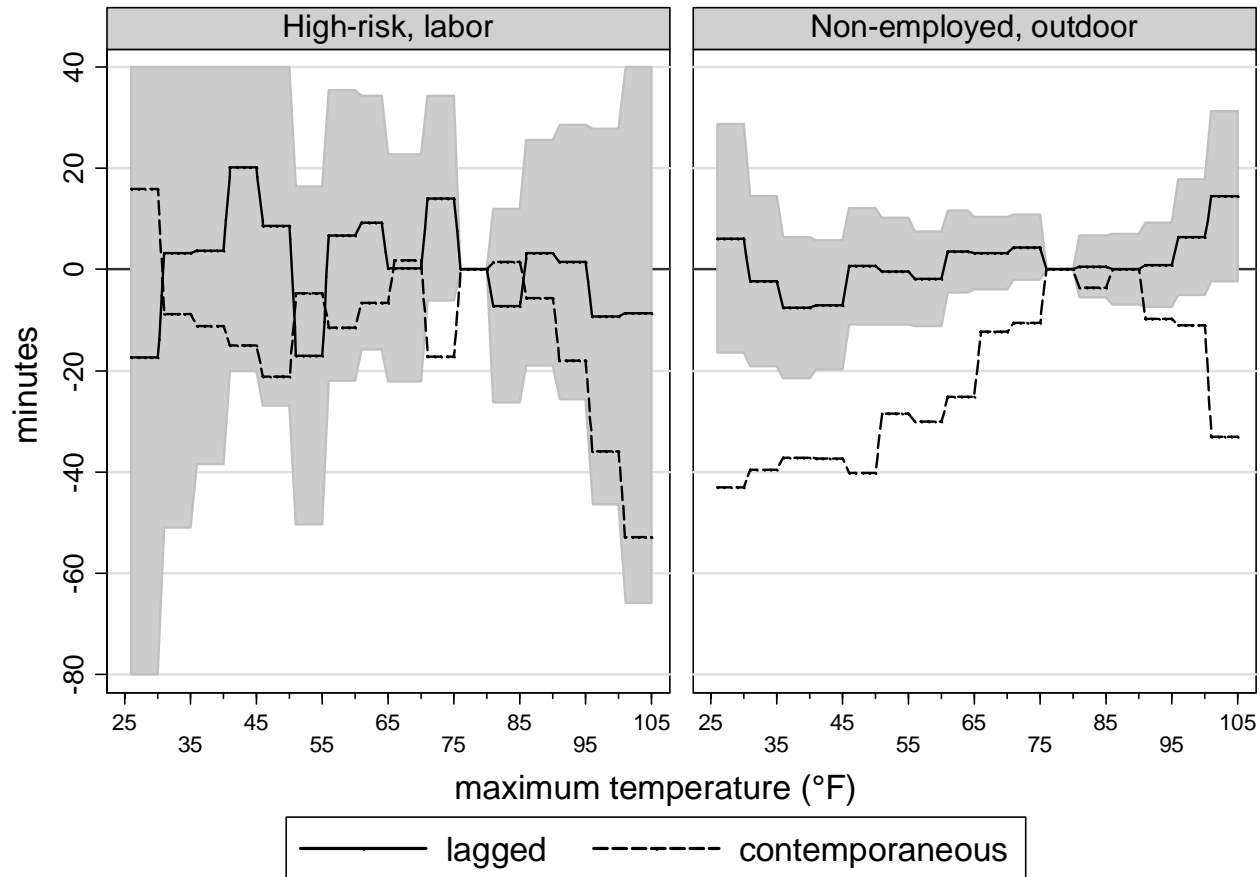
See notes to Figure 2. Estimates include indicator variables for both contemporaneous temperature and lagged temperature, where lagged temperature is defined as the maximum of the 6 previous days' temperature. 95% confidence interval for lagged estimates shaded in gray.

Figure 8. Intratemporal substitution
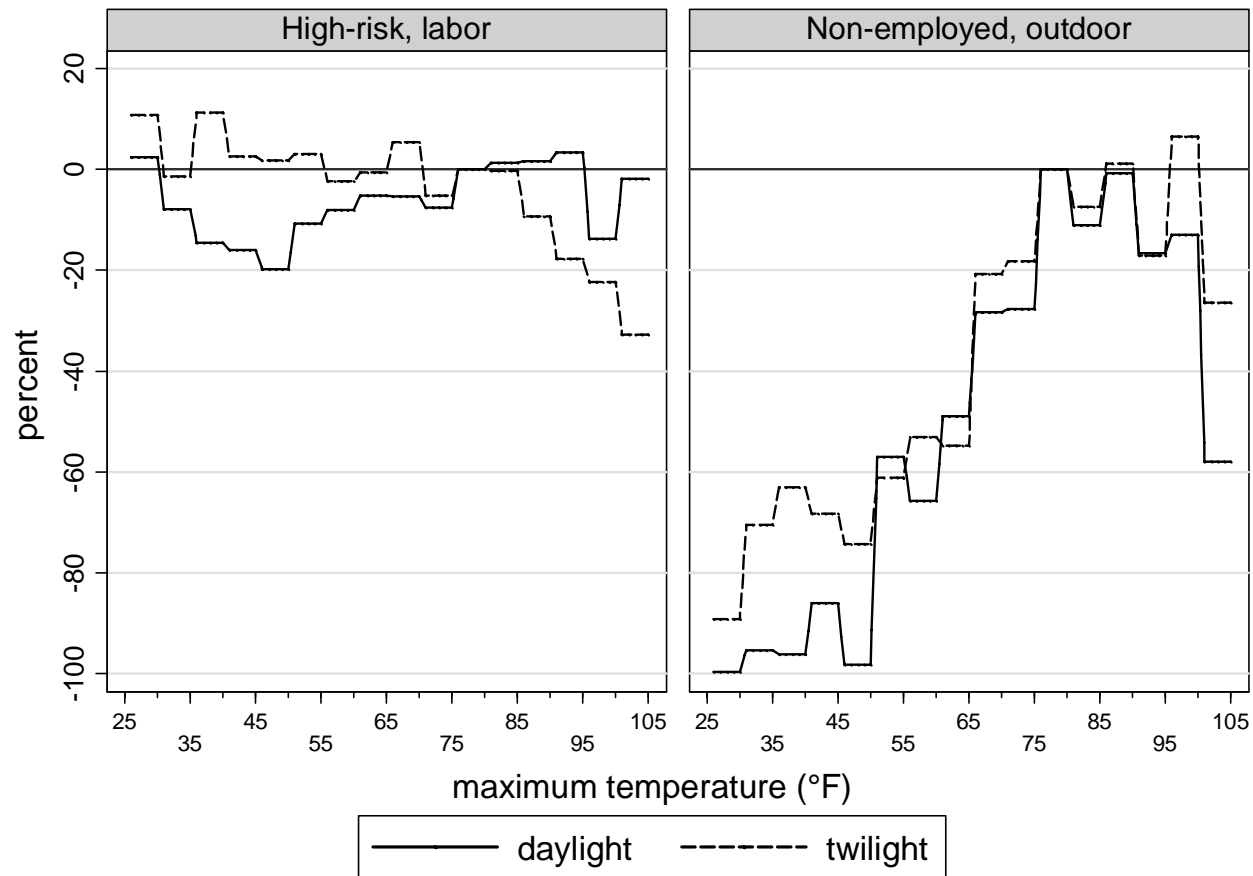
See notes to Figure 2. "Daylight" is defined as the time from 2 hours after sunrise until 2 hours before sunset. "Twilight" is defined as before 2 hours after sunrise or after 2 hours before sunset.

Figure 9. Short-run acclimatization
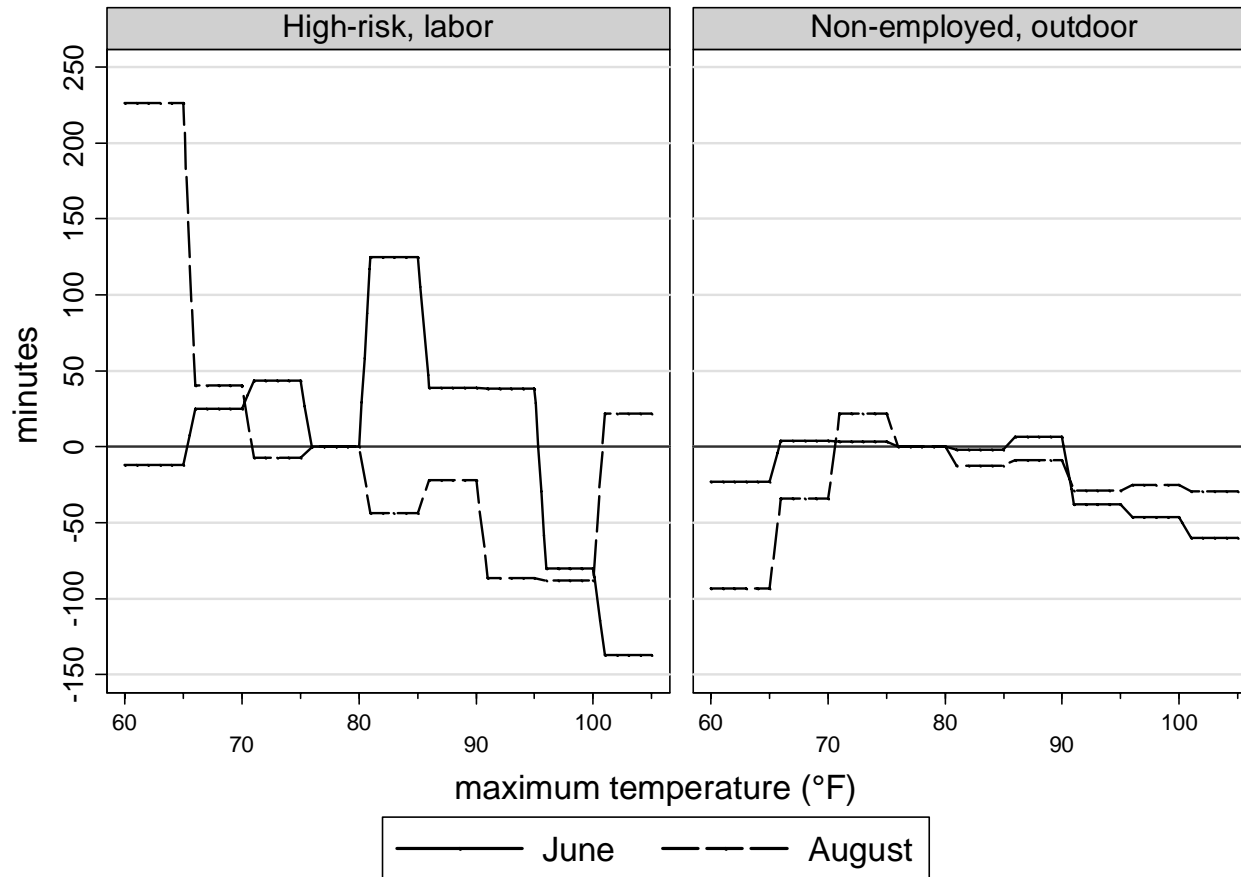
See notes to Figure 2. Results from this figure are based on regressions stratified by month. N=483 for "June" estimates and N=477 for "August" estimates for high risk. N=1173 for "June" estimates and N=1228 for "August" estimates for non-employed.

Figure 10. Medium-run acclimatization
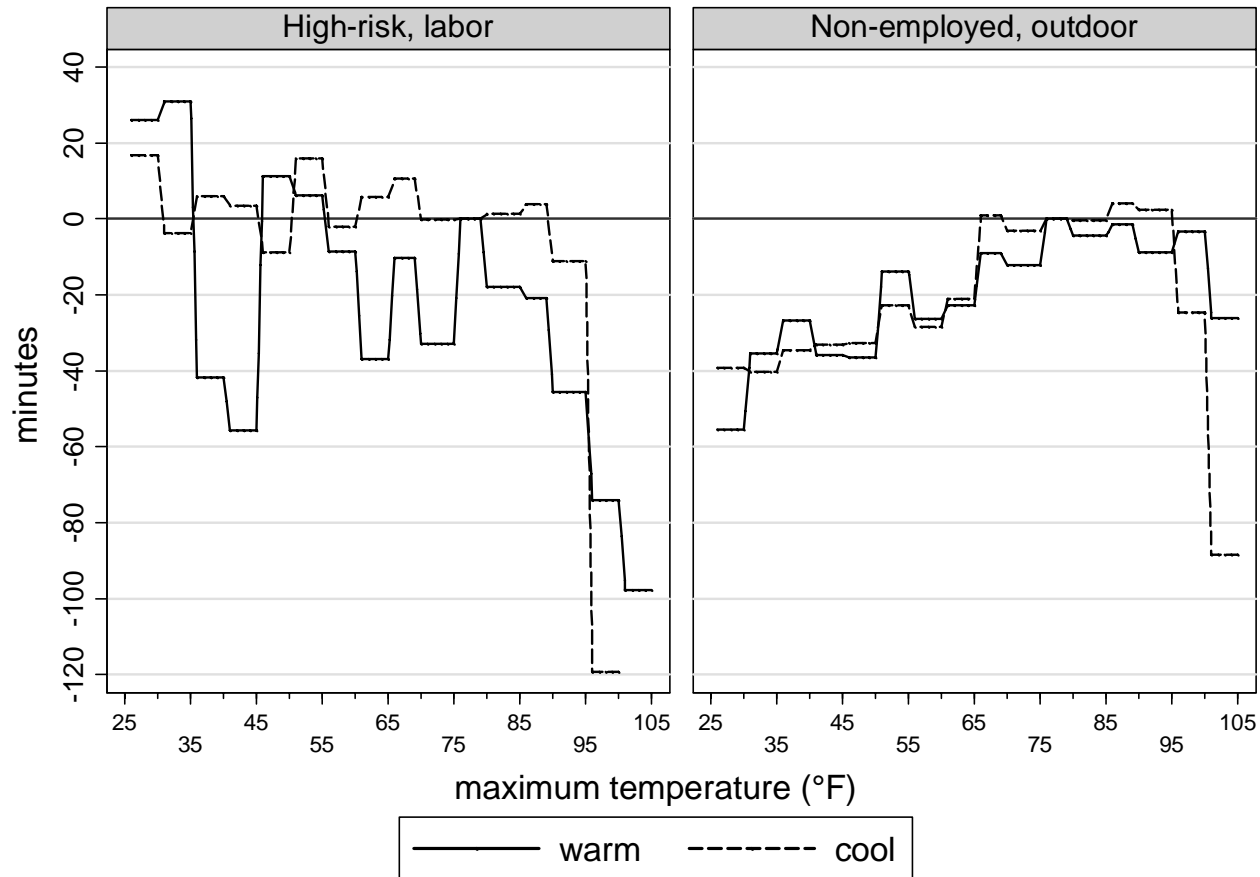
Notes: See notes to Figure 2. Results from this figure are based on regressions stratified by historical climate. Warm (cool) is defined as counties in the top (bottom) third of the 1980-1989 July-August temperature distribution. N=2066 (2364) for warm (cool) July-August in high risk industries. N=5365 (5102) for warm (cool) July-August non-employed.

Table 1. Summary statistics

|	All (N=42280)		High-risk (N=6246)		Low-risk (N=21151)		Non-employed (N=14883)	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
A. Time allocation								
Labor								
hours	2.71	4.05	4.38	4.58	4.06	4.34	-	-
percent hours = 0	0.61	0.49	0.43	0.5	0.42	0.49	-	-
hours | hours > 0	7.01	3.51	7.76	3.3	6.99	3.46	-	-
Outdoor leisure								
hours	0.73	1.61	0.99	2.09	0.65	1.48	0.73	1.55
percent hours = 0	0.6	0.49	0.6	0.49	0.61	0.49	0.58	0.49
hours | hours > 0	1.82	2.12	2.47	2.7	1.67	1.99	1.75	1.98
Indoor leisure hours	11.72	3.86	10.13	3.82	10.7	3.83	13.80	2.82
B. Covariates								
max. temperature (˚F)	67.48	19.04	67.01	18.92	67.31	19.18	67.91	18.88
min. temperature (˚F)	47.16	17.57	46.52	17.24	47.03	17.73	47.61	17.47
precip. (in./100)	11.17	30.23	11.09	28.95	10.83	29.5	11.70	31.77
snowfall (in./10)	0.66	5.17	0.69	4.88	0.64	4.87	0.67	5.66
max. rel. humidity	84.68	14.22	84.9	13.93	84.67	14.2	84.60	14.38
age	45.29	17.25	42.32	11.47	41.34	13.39	52.16	21.50
male	0.43	0.5	0.74	0.44	0.41	0.49	0.34	0.47
# children < 18	0.92	1.16	1.03	1.17	0.98	1.13	0.79	1.19
annual earnings ($1k)	46.0	61.2	80.3	62.2	68.2	63.3	-	-
diary day a holiday	0.02	0.13	0.02	0.14	0.02	0.13	0.02	0.13
employed	0.65	0.48	-	-	-	-	-	-
absent from work	0.03	0.17	0.04	0.2	0.04	0.21	-	-
out of labor force	0.31	0.46	-	-	-	-	0.88	0.33
employed full time	0.51	0.5	0.91	0.29	0.75	0.43	-	-
white non-Hispanic	0.68	0.47	0.69	0.46	0.7	0.46	0.66	0.47
HS dropout	0.17	0.38	0.13	0.34	0.1	0.3	0.29	0.45
HS graduate	0.25	0.43	0.33	0.47	0.2	0.4	0.29	0.45
some college	0.26	0.44	0.28	0.45	0.28	0.45	0.22	0.42
spouse/partner in HH	0.55	0.5	0.68	0.47	0.57	0.49	0.47	0.50

Notes: All statistics at the daily level. 'High risk' defined as those employed in agriculture, forestry, fishing, and hunting, mining, construction, manufacturing, and transportation and utilities industries. 'Low risk' consists of remaining industries. 'Non-employed' defined as unemployed or out of labor force.

Table 2. Various labor and outdoor leisure measures

	All	High risk	Low risk	Non-employed
Intratemporal substitution				
Labor: twilight	1.31	2.25	1.92	-
Labor: daylight	1.38	2.08	2.10	-
Outdoor leisure: twilight	0.24	0.36	0.22	0.23
Outdoor leisure: daylight	0.48	0.63	0.43	0.51
N	42280	6246	21151	14883
By historical July-August temperature				
Labor: warm	2.68	4.49	4.14	0.08
Outdoor leisure: warm	0.71	0.98	0.61	0.74
Labor: cold	2.72	4.20	4.01	0.10
Outdoor leisure: cold	0.76	1.02	0.69	0.74
N	15058	2364	7592	5102
By month				
Labor: June	2.69	4.58	3.94	0.13
Outdoor leisure: June	1.00	1.24	0.91	1.03
Labor: August	2.75	4.25	4.16	0.08
Outdoor leisure: August	0.94	1.19	0.86	0.98
N	3527	477	1822	1228

Note: All numbers represent the mean value of each variable for each group. "Daylight" is defined as the time from 2 hours after sunrise until 2 hours before sunset. "Twilight" is defined as before 2 hours after sunrise or after 2 hours before sunset. Warm (cool) is defined as counties in the top (bottom) third of the 1980-1989 July-August temperature distribution.

Appendix Figure 1: Distribution of observations by temperature for excluded and included sample
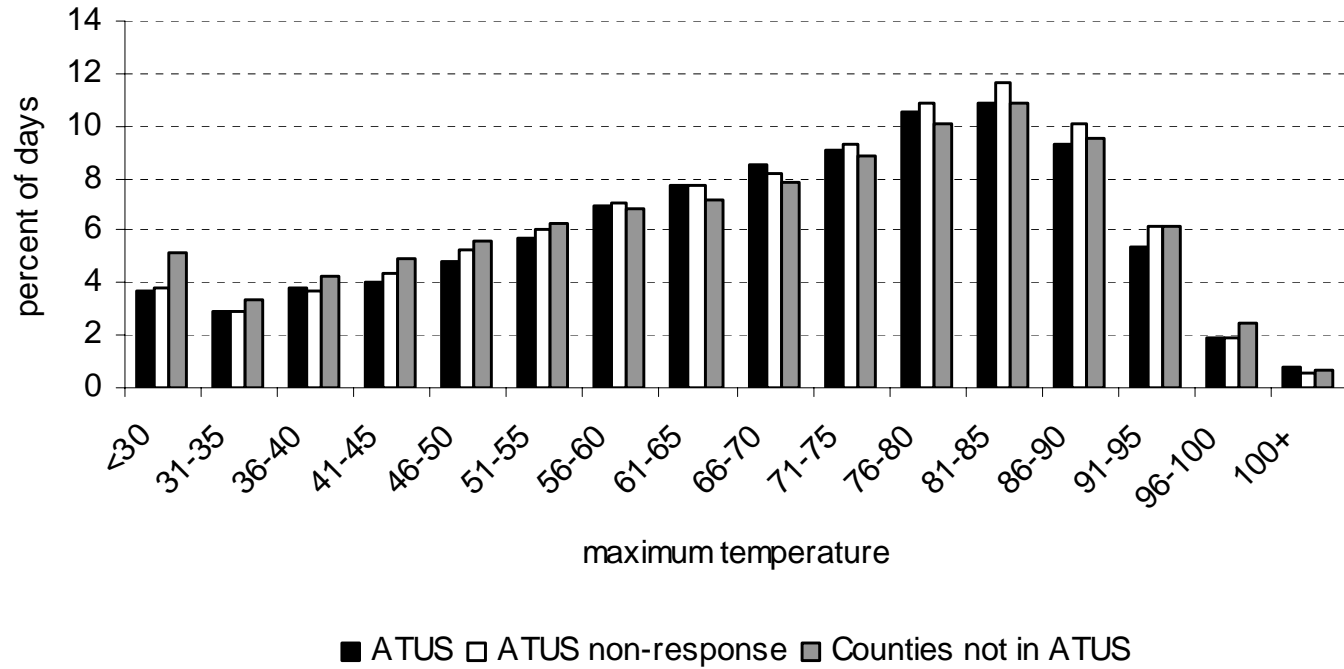
Notes: 'ATUS' is the final sample used in the analysis. 'ATUS non-response' is the same counties as the final sample but on dates without time diaries. 'Counties not in ATUS' is all dates from counties not included in the ATUS sample.