EFFECTS OF TEMPERATURE ON THE ALLOCATION OF TIME DURING THE GREAT RECESSION OF 2008-2009

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Abstract

Due to global warming, humans have changed their behavior. In this paper, I will specifically address reallocation of time spent by human beings performing activities due to global warming. Since the 2006 heatwave, we have observed much hotter temperatures, especially the highest records for temperature in 2012 and 2016. This paper tests the robustness of Graff Zivin and Neidell's results on reallocation of time spent by humans doing activities due to global warming by using a finer resolution weather data set at the county level from the PRISM Climate Data and the American Time Use Survey (ATUS) in the period of 2007-2016. I also examined whether the Great Recession has effects on the relationship between temperature and time allocation. I found that the relationship between time allocation and temperature is sensitive to temperature measurement. Time allocated to leisure activities is responsive in the cold weather but not in the warm weather. Time allocated to working is not significantly responsive to temperature changes, neither in cold nor warm weather. In addition, although the unemployment rates increased remarkably during the Great Recession, there is no statistically significant effects of the recession on the relationship between temperature and time allocation.

Keywords

Time allocation, leisure, labor, temperature, climate change

1. Introduction

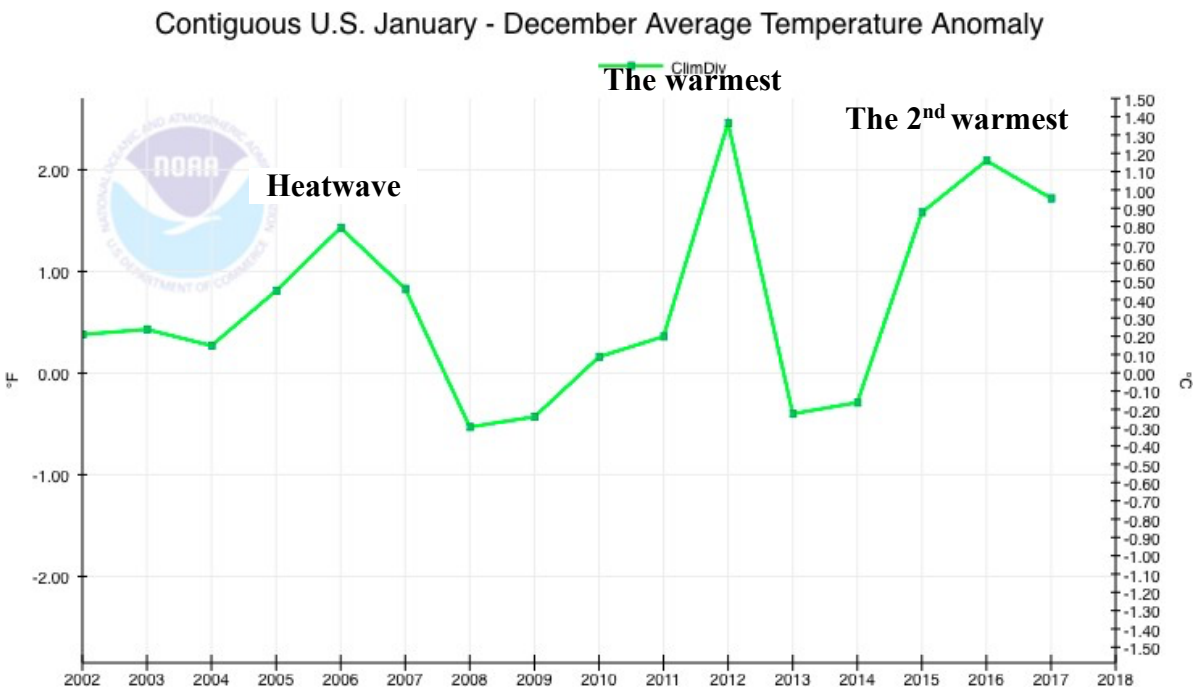
Climate change has already had considerable effects on the environment and everyday life. Adaptation to these impacts is being observed in human adjustments, one of which is the reallocation of time. Recent studies report the effect of the weather on time use; Huysmans (2002), which uses the Netherland's Time Budget Survey, finds that the weather has a significant effect on the time spent sleeping, watching television, reading, participating in sports, walking and cycling outside, using transportation of various forms, as well as on spending leisure time spent outside the home. Conolly (2008) exploits daily weather data and the American Time Use Survey (ATUS) 2003-2004 data and shows that American labor supply is intertemporally elastic to rainfall. On rainy days, men shift 30 minutes on average from leisure to work. Using the same data sets for the period 2003-2006, Graff Zivin and Neidell (2014, hereafter referred to as GZN) also find a large impact of temperature on individual's allocation of time to labor as well as leisure activities within the United States.

GZN use individual-level data from the ATUS 2003–2006 linked to weather data from the National Climatic Data Center. To constrain the net effect from a temperature change on total time to sum to zero, they propose a generalized method of moment systems of equations, including year-month and county fixed effects, to identify the effects of daily temperature using the plausibly exogenous variation in temperature over time within counties and seasons. They flexibly model temperature by including a series of indicator variables for 5-degree temperature bins, with the highest bin for days over 100 degrees Fahrenheit (°F). They find large reductions in the time allocated to labor in climate-exposed industries as daily maximum temperatures increase beyond 85°F, most of which is reallocated to indoor leisure. At the lower end of the distribution, time allocated to labor is nonresponsive to temperature increases, but as the temperature warms, outdoor leisure increases and indoor leisure decreases. Their results are in line with the findings in Galloway and Maughan (1997) and Ramsey (1995) on the effect of heat on task performance. Pilcher et al. (2010) conducted a meta-analysis and indicated that not only hot temperature but also cold temperature has a negative impact on performance. Hot temperatures of 90°F Web Bulb Globe Temperature Index or above and cold temperatures of 50°F or less resulted in the greatest decrement in performance when compared with neutral temperature conditions. Also, the duration of exposure to the experimental temperature prior to the task onset, the type of task, and the duration of the task had differential effects on performance. Heat exposure of over 80°F had the

most negative effect on attentional, perceptual and mathematical processing tasks. Cold exposure of less than 65ºF had the most negative effect on reasoning, learning, and memory tasks. Seppänen, Fisk, and Faulkner (2003) also find temperature effects on labor productivity only beyond specific thresholds.

Drawing from research by GZN, this paper examines the robustness of changes in time allocation as a short-run adaption to a higher temperature, particularly given that 2012 and 2016 were, respectively, the warmest and second-warmest years on average for the US in 122 years of record-keeping (Vose et. al., 2017). The year 2017 is the 21st consecutive year the annual average temperature exceeded the average, which was experienced by every state in the contiguous U.S. and Alaska. The annual average temperature in these recent years is much higher than that of the 2006 heatwave (Figure 1-1.) Casual observation suggests that individuals might further modify their work and leisure schedule as the marginal productivity of labor and the marginal utility of leisure activities changes due to higher temperatures.

Figure 1-1. The annual average temperature in Contiguous US 2002-2017



Source: NOAA (2018)

In this paper, firstly, I test the robustness of Graff Zivin and Neidell's model in the 2003-2006 period by using an alternate weather data set and attentively construct the temperature bins before

aggregating the daily maximum temperature data across areas within a county to avoid averaging away extreme temperature realizations. This is important to reveal the non-linear impact of temperature on time allocation. Secondly, I examine a new trend of time allocation in response to the higher temperature, using the American Time Use Survey (ATUS) data and daily weather data at the county level from the PRISM Climate Data in the period of 2007-2016. The 2003-2016 period covers different phases of the business cycle, including the pre-recession period with almost full employment, the Great Recession with a very high unemployment rate, and the recovery period. The changes in determinants of labor market success may impact on the time use behaviors of individuals. Therefore, thirdly, I examine whether the Great Recession has effects on the relationship between temperature and time allocation, expecting that the time allocation will become less responsive during the Great Recession due to a tight labor market.

Comparing GZN's results and my results, I found that the estimation of the relationship between the allocation of time and temperature is sensitive to temperature measurement. While we use the same time use data but different weather data, GZN finds time allocated to labor and indoor leisure activities is responsive at the temperature over 100oF, my result is insignificant. My regression results for each of the periods 2003 – 2006 and 2007 – 2016 shows that the pattern of changes in time allocation due to changes in temperature is stable over the years. In which, individual responses more to temperature changes in the cold weather rather than in the warm weather. Particularly, a day with temperature below 65oF leads to decreases in the time allocated to outdoor leisure, relative to a day with the temperature in the 76-80oF range. This amount of time is reallocated to indoor leisure activities. I found no evidence of changes in the time allocation when temperature increased over 80oF. The lack of significance in the relationship between time allocation and daily maximum temperature at high temperatures (over 80oF) suggest that external factors, such as the development of cooling technology, may play an important role in individual responses. Interestingly, the time allocated to labor is not responsive to changes in temperature, neither in cold or warm weather, in contraction or expansion periods. Generally, although the unemployment rates increased remarkably during the Great Recession, I find no statistically significant effects of the recession on the relationship between temperature and time allocation.

The paper proceeds as follows. Section 2 briefly describes the data sources and reports summary statistics. Section 3 provides the empirical framework which indeed is the GZN model. Section 4 describes the results, including (i) robustness testing of GZN model, (ii) examination of

changes in the time allocation - temperature relationship in the period of 2007-2016, and (iii) effects of the Great Recession on the responsiveness of time allocation to temperature changes. Section 5 concludes the paper.

2. Data

2.1. The American Time Use Survey

The American Time Use Survey (ATUS) provides nationally representative estimates of how, where, and with whom Americans spend their time. This cross-sectional survey was conducted from 2003 to 2016. Respondents are individuals over age 15 randomly selected from households that 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 of time engaged in the activity, and where the activity took place. Each respondent is interviewed the day after the diary date, for 8 consecutive weeks.

Following GZN, I categorize time allocated throughout the day into three broad activity categories: work, outdoor leisure, and indoor leisure[1] . Time allocated to labor is the sum of the number of minutes in which the activity occurred at the respondent's workplace. Outdoor leisure activities included activities that were outdoors or away from home, or activities wherein the respondent was "traveling by foot or bicycle" and activities not falling into these categories but that were unarguably performed outdoors. Activities that took place in ambiguous locations, such as "socializing, relaxing, and leisure" that occurred at home, are categorized as indoor activities, so the measurement of total time spent outdoors understates actual outdoor time. Time allocated on indoor activities is simply the remains of 24 hours after subtracted by time allocated on labor, sleep, and outdoor activities. Given this categorization, nearly all outdoor activities are somewhat physically demanding, while indoor activities are generally of lower intensity. This is appropriate to the research purpose since the marginal utility of physically active endeavors, especially those outdoor activities, is expected to be most responsive to changes in temperature.

Like GZN, I define three groups of individuals based on climate exposure and activity choices: those who are generally sheltered from climate (low-risk), those who are not (high-risk), and those

[1] Sleep is not included since in the GZN's original specification, they proved that it is insensitive to temperature. I checked the responsiveness of sleeping time to changes in temperature and obtained the same results (shown in Appendix A1). For simplicity, home production activities are referred to as leisure.

who are non-employed. These risk categories are based on the National Institute for Occupational Safety and Health (NIOSH) definitions of heat-exposed industries (NIOSH 1986) and industry codes in the ATUS. The high-risk group includes industries where the work is primarily performed outdoors - agriculture, forestry, fishing, and hunting; construction; mining; and transportation and utilities - as well as 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. The third group consists of those currently unemployed or out of the labor force. Those who are on a day off are considered employed, and their work hours are recorded as zero for that day.

To link with weather data at the county level, I match respondents in the ATUS with their records in the CPS to obtain information on their county of residence. In the CPS data set, geographic data below the state level will not be disclosed for geographic divisions with fewer than 100,000 people to maintain confidentiality. For those respondents whose county is not identified but metropolitan area (CBSA, or commonly referred to as MSA), I assign them to the county with the highest population within the CBSA. This was done by using CBSA – county crosswalk files from the MABBLE Geocorr[2]. The process provides me with county identifiers for three-quarters of the ATUS sample. In detail, for the period of 2007-2016, the ATUS-CPS consists of 120,661 respondents, in which 54,917 individuals have a county identifier and 42,004 individuals only have a metropolitan area reported. As a result, I obtain 96,921 observations in the ATUS with county identified. This number reduces to 91,572 observations in the final sample after merging with valid weather data.

2.2. Weather

I obtain daily weather observations from the PRISM Spatial Climate Datasets, which provides daily max, min temperature, and daily precipitation readings for a 2km x 2km grid of the contiguous United States. To obtain daily weather data at the county level, I first match the PRISM grid cells to each census tract within a county using spatial mapping. Matches are based on the exact longitude and latitude of the PRISM grid centroid and the spatial polygon of all US census tracts. For daily maximum temperature, I bin each grid cell into different temperature bands (5°F

[2] Master Area Block Level Equivalency - Geographic Correspondence Engine, provided by Missouri Census Data Center.

temperature increment) at which the temperature realizations fall into. This fine binning of the data preserves the daily variation in temperatures. I then take simple average of the maximum temperature bins and other weather elements at all PRISM grid cells matched to each census tract to obtain the daily data at the census tract level. Finally, I calculate a weighted average of these weather elements based on the proportion of county population in each census tract (2010 Census data) to produce a single, county-level daily weather data. Since PRISM Climate Data does not cover Alaska and Hawaii and does not provide snow records, I subset this data from Global Historical Climatology Network - Daily Database (GHCN– Daily, Version 3.24).

2.3. Merged Data

I merge the ATUS and PRISM weather data by the county and date to obtain a final sample of over 83,600 and 43,600 individuals with valid weather data in the periods of 2007-2016 and 2003-2006, respectively (from more than 120,000 and 60,000 individuals in the ATUS with county identified). Table 2-1 presents summary statistics for my final sample from 2007-2016, which covers 49 US states[3] with 447 counties.

Among those who are working, time allocated to work is 7 hours a day overall on average, and is higher for the high-risk industries (nearly 8 hours a day). Looking at leisure activities, individuals spend just under 2 hours a day overall on outdoor activities. Outdoor leisure is highest for the high- risk group but it is not significantly different across groups. On average, nearly 12 hours were spent on indoor activities. Non-employed individuals spent the most time indoors with nearly 14 hours while both high-risk and low- risk groups spent more than 10 hours a day on indoor activities. Individuals who were working in the high-risk industrial sector, on average, are older, more often are male, and have more kids, lower education but higher annual earning compared to those in the low-risk group.

[3]Alaska and Wyoming are missing.

Table 2-1. Summary Statistics, 2007 – 2016

	All N = 83,666		High risk N = 11,418		Low risk N = 40,741		Non-employed N = 31,507	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Labor (Hours)	2.672	4.009	4.392	4.535	4.167	4.318	.115	.788
Percent hours=0	.615	.487	.427	.495	.402	.49	.959	.199
Hours|hours>0	6.94	3.482	7.667	3.286	6.966	3.415	2.788	2.759
Outdoor (Hours)	.673	1.528	.823	1.851	.608	1.435	.703	1.512
Percent hours=0	.617	.486	.629	.483	.629	.483	.596	.491
Hours|hours>0	1.757	2.048	2.22	2.477	1.639	1.965	1.742	1.963
Indoor leisure	11.82	3.854	10.247	3.918	10.64	3.841	13.916	2.776
Sleep	8.836	2.267	8.538	2.215	8.586	2.15	9.266	2.365
Max temperature (°F)	67.667	19.379	67.32	19.531	67.465	19.41	68.054	19.276
Min temperature (°F)	46.644	17.668	46.249	17.718	46.49	17.746	46.988	17.541
Precipitation (inches/100)	10.386	25.395	10.707	26.59	10.516	25.486	10.103	24.826
Snowfall (inches/10)	.75	5.473	.727	5.764	.771	5.53	.73	5.288
Demographics								
Age	47.121	17.676	44.062	12.15	42.72	13.61	53.92	21.496
%> age 65	.187	.39	.043	.202	.059	.235	.406	.491
Male	.442	.497	.747	.435	.421	.494	.359	.48
# children <age 18	.859	1.143	.988	1.177	.935	1.119	.715	1.148
Annual earnings ($1000)	29739.9	35424.39	52921.07	33054.79	46242.5	34116.28	0	0
Diary day a holiday	.015	.123	.015	.122	.015	.122	.016	.124
Employed	.623	.485	1	0	1	0	0	0
Absent from work	.027	.161	.038	.191	.044	.205	0	0
Out of labor force	.324	.468	0	0	0	0	.861	.346
Employed full-time	.492	.5	.895	.307	.76	.427	0	0
White non_Hispanic	.636	.481	.639	.48	.656	.475	.608	.488
High school dropout	.145	.352	.115	.32	.076	.266	.244	.429
Some college	.268	.443	.288	.453	.275	.447	.25	.433
Spouse/partner in HH	.516	.5	.633	.482	.555	.497	.422	.494

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

A comparison between the periods of 2007 - 2016 and 2003-2006 (Table 2-2) shows that time allocated on working and max temperature remains statistically unchanged. However, the differences in time allocations between leisure activities and other weather elements in the two samples are statistically significant. On average, individuals in 2007-2016 spent less time on outdoor leisure and more time on indoor leisure and sleep than the 2003-2006 period, although this difference is, on average, just less than ten minutes a day. Over the period of 2007-2016, the weather was colder, there was more snow, and there was less rain than the period of 2003-2006 , but these variations are minimal.

Table 2-2. Time allocations and weather elements 2003-2006 vs. 2007 – 2016

		2003-2006 (1) N = 43,613 **Mean**	**2007-2016 (2)** N= 83,666 **Mean**	**Different (2)-(1)**
Labor	Hours	2.686	2.672	-.014
	% hours=0	.613	.615	.002
	Hours |hrs>0	6.935	6.94	.005
Outdoor	Hours	.726	.673	-.053***
	%hours=0	.601	.617	.016***
	Hours |hrs>0	1.818	1.757	-.062***
Indoor leisure (hours)		11.701	11.82	.118***
Sleep (hours)		8.731	8.836	.104***
Max temperature (°F)		67.59	67.667	.077
Min temperature (°F)		46.978	46.644	-.333***
Precipitation (inches/100)		11.163	10.386	-.776***
Snowfall (inches/10)		.673	.75	.077**

Notes: All statistics are at the daily level. *, **, *** denote significance at the 10%, 5%, and 1% level, respectively.

3. Econometrics Model

In this paper, I use the model proposed by GZN to examine the relationship between temperature and time allocation. Their model is as following:

$$labor_i = f_1(temp_{c(i),t(i)}) + \delta_1 Z_{c(i),t(i)} + \gamma_1 Xi + g_1(t(i)) + \alpha_{1c(i)} + \varepsilon_{1i}, \quad (1)$$

$$outdoor_i = f_2(temp_{c(i),t(i)}) + \delta_2 Z_{c(i),t(i)} + \gamma_2 Xi + g_2(t(i)) + \alpha_{2c(i)} + \varepsilon_{2i}, \quad (2)$$

$$indoor_i = f_3(temp_{c(i),t(i)}) + \delta_3 Z_{c(i),t(i)} + \gamma_3 Xi + g_3(t(i)) + \alpha_{3c(i)} + \varepsilon_{3i}, \quad (3)$$

where the variable labor is the amount of time allocated to labor activities for individual i, the variable outdoor is the amount of time allocated to outdoor leisure activities, and the variable indoor is the amount of time allocation to indoor leisure activities. Let t(i) represent the date individual i is observed and c(i) represent the county in which individual i resides.

Many recent studies (eg. Seppänen, Fisk, and Faulkner (2003), Seppänen, Fisk, and Lei (2006), Schlenker and Roberts (2009), Dell, Jones, and Olken (2009), and Pilcher et al. (2010)) found a nonlinear effect of temperature on economic outcomes and labor productivity. The function f(temp) is to allow for a nonlinear relationship between daily maximum temperature and time allocation since increases in temperature may lead to increases in outdoor leisure at colder temperatures, but beyond a certain point, they may lead to decreases. To reveal nonlinear effects, this model considers separate indicator variables for different bins (5°F temperature increment) at which the weather realizations fall into. This fine binning of the data preserves the daily variation in temperatures. The 76°F–80°F indicator variable is omitted, so the estimates are interpreted as the change in the time allocated to that activity at a certain temperature range relative to 76°F–80°F. Deschênes and Greenstone (2011) is an early example of this common approach. The key advantage lies in avoiding functional form specifications, since this method is relatively nonparametric. The weakness is that this approach demands high-resolution data: if aggregates across either space or time before constructing the bins, extreme days could be averaged away, and if nonlinearities are important, this smoothing of the data may produce misleading estimates (Dell, Jones and Olken, 2014). To avoid that problem, I obtain daily maximum temperature from a 4km spatial climate data and construct the 5°F temperature bins before computing the population weighted average to obtain the daily weather data at county level.

In terms of control variables, $Z_{c(i)t(i)}$ are other county-level environmental attributes potentially correlated with temperature (daylight, precipitation, humidity, and minimum temperature). The X_i are individual-level covariates meant to capture preferences for particular activities, listed in Table 2-1. The g(t(i)) includes day-of-week dummy variables to account for differences in schedules throughout the week and year-month dummy variables to control for seasonal and annual time trends in activity choice. The $\alpha_{c(i)}$ are county fixed effects that capture all time-invariant observable and unobservable attributes that affect time allocation decisions. Therefore, parameters of interest

that relate temperature to time are identified from daily variations in weather within a county. In their paper, GZN display numerous robustness checks to support the validity of the model.

Equations (1) - (3) are simultaneously estimated as a generalized method of the moment system of equations in order to constrain the net effect from a temperature change on total time to sum to zero. This procedure also allows addressing autocorrelation and spatial correlation in temperature by clustering standard errors at the state-month level. Following GZN, I estimate these models for all individuals and then separately for those employed in high-risk industries and those employed in low-risk industries. For those not currently employed, I estimate equations (2) - (3), modifying the constraints accordingly.

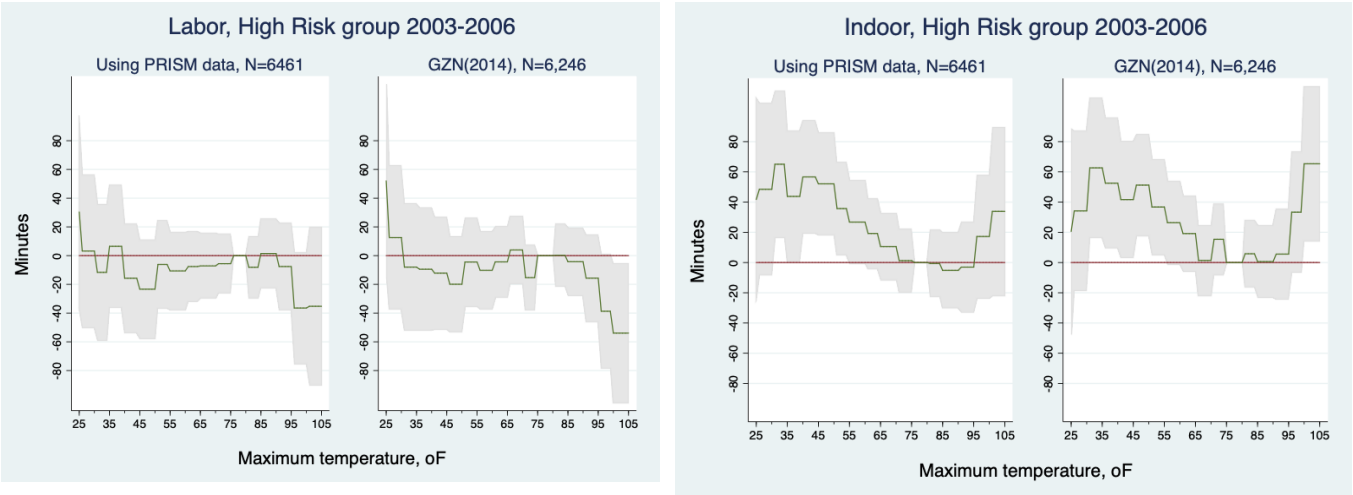
4. Results

4.1. Robustness testing of the GZN model

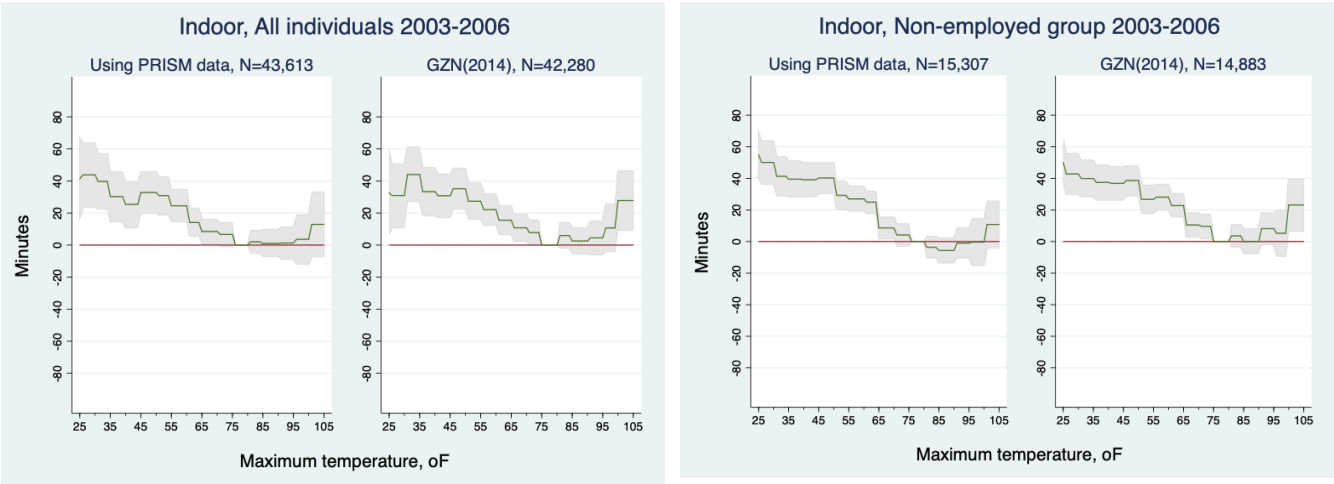
Generally, my replication results are similar to GZN, except for the changes in working hours of individuals who worked in industries with high exposure to climate and indoor activities in the extremely high temperature (Figure 4-1). GZN finds that temperature increases at the higher end of the temperature distribution – above 100°F – would significantly reduce hours worked by nearly one hour for the high-risk group, with this time reallocated to indoor leisure. The same regressions conducted with my final sample indicate that when the temperature is above 100°F, time spent laboring decreases by less than 20 minutes, which is statistically insignificant (Figure 4-1A). Similarly, GZN also shows that time spent on indoor leisure for all individuals significantly increases when temperature increases above 100°F. My results are similar but not statistically significant (Figure 4-1B).

Figure 4-1. Differences in Results between Zivin and Neidell (2014) and the Replication

(A) - High-Risk group



(B) - Indoor activities for All individuals and Non-employed groups



Notes: The 95% confidence interval for regressions is shaded in gray. Each figure displays the estimated impact of temperature on time allocation based on equations (1) – (3) in the text. Covariates include age, gender, number of children, earnings, employment status, race, education, marital status, family income, day-of-week dummies, minimum temperature, precipitation, year-month dummies, and county fixed effects.

As previously mentioned, I obtain insignificant results when I conduct the replication of GZN. ATUS data set is used in both GZN and this study, yet the weather data that was used differed. While I use PRISM weather data, GZN used historical weather data from the NCDC-TD3200/3210 "Surface Summary of the Day" files. Linked to ATUS 2003 – 2006 data, the PRISM provides me with weather data for 413 counties while GZN was able to obtain observations with 406 unique counties. Excluding observations with missing weather data results in 43,613 observations in the

final sample. My data set has 1,333 more observations than that of GZN's. Those added observations occur most frequently in January, when temperature is relatively lower than other months, and in the states of Colorado, Virginia, and New Jersey (Figure 4-2).

Figure 4-2. Observations Added to Zivin and Neidel's (2014) Sample

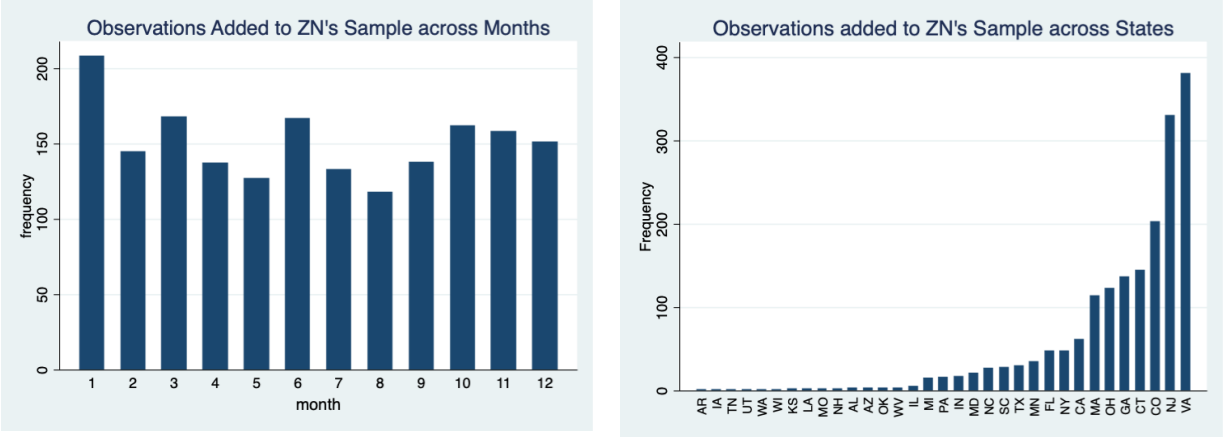
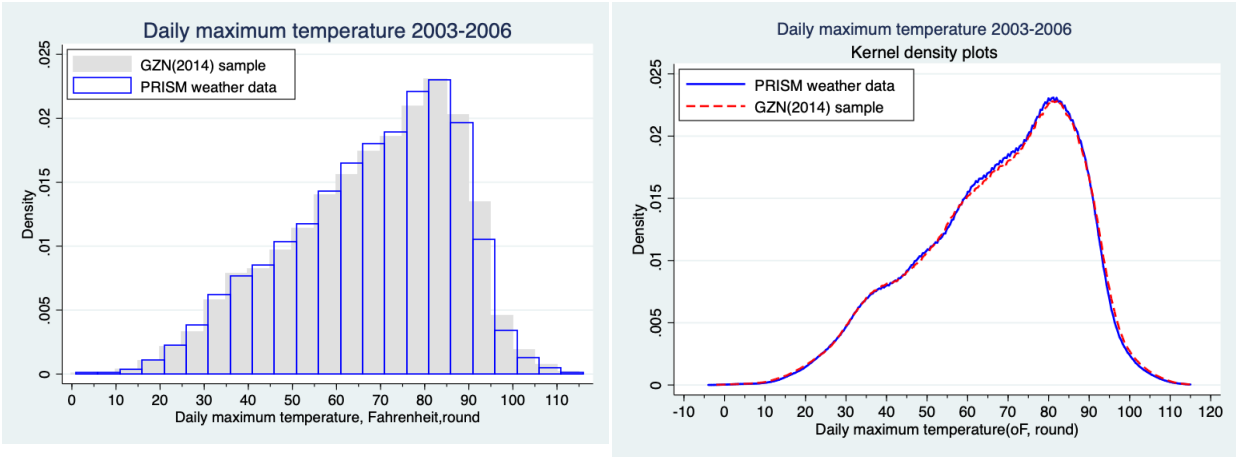


Figure 4-3 shows a comparison between distributions of daily maximum temperature during period 2003-2006 in GZN's dataset and my dataset. Comparing the distributions indicates there are more warm days (over 85ºF) in GZN's sample. However, on average, the daily minimum temperature in GZN is statistically higher than that of my sample, with a 10% level of significance, but the tangible difference is minimal (47.178ºF in GZN's sample versus 46.978ºF in mine). Despite the minimum temperature difference, all other variables of weather – including maximum temperature, rainfall, time allocation, and demographics – are not significantly different between datasets. However, the number of observations with maximum temperature equal or above 100ºF in my final sample is fewer than those in GZN's (513 versus 575). Therefore, the statistic insignificance of my result at the 100+ºF is potentially caused by lack of observations at extremely high temperatures. To check if this is true, I replicate the estimates with GHCN-Daily data, in which I obtained more observations in the temperature bins above 100ºF than in GZN's (709 vs. 530). Nevertheless, the responsiveness of working time to temperature above 100ºF is still insignificant. This indicates that the impact of temperature on time allocation might be sensitive with daily maximum temperature measurement.

Figure 4-3 Distributions of Daily Maximum Temperature 2003-2006 in this paper and GZN (2014)



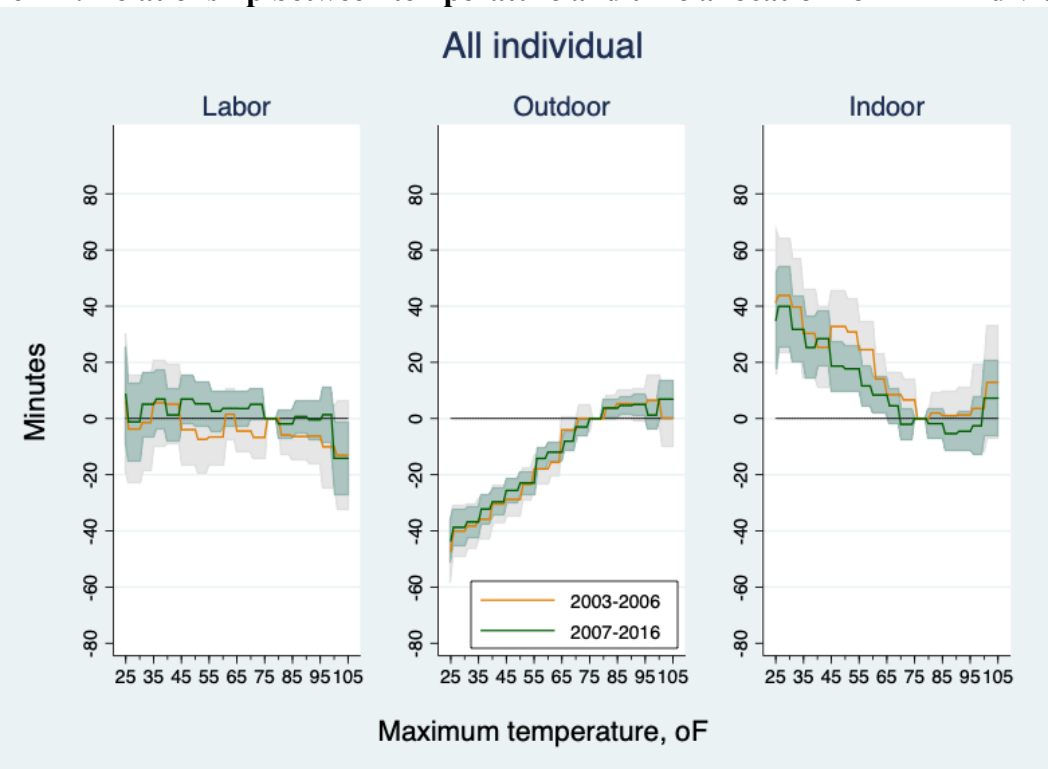
4.2. Examination of changes in time allocation - temperature relationship 2007 - 2016

Regression results based on equations (1) – (3) estimating the relationship between daily maximum temperature and time allocation are shown in Figures from (4-4) to (4-7) for all individuals and three labor groups (high-risk industries, low- risk industries, and non-employed). I split the data into two groups based on the time periods (period 2007-2016 and period 2003-2006) for comparison. This model includes separate indicator variables for every 5°F temperature increment, and the 76°F–80°F indicator variable is omitted. Thus, the estimates are interpreted as the change in the time allocated to each activity at a certain temperature range in comparison to 76°F–80°F. Also note that, in most of the following results, the standard deviation in both tails of temperature distribution (lower than 35ºF and higher than 100ºF) are large, which might be because of too few observations at these bins of temperature.

In the second and last panel of Figure 4-4, as compared to the temperature 76-80ºF, I found a decrease in the time allocated to outdoor leisure and an increase in the time allocated on indoor leisure activities when the daily maximum temperature is at 35ºF in the period 2007-2016. Individuals shift around 30 minutes from outdoor activities to indoor activities when daily maximum temperature declines from 76-80ºF to 25-35ºF. Meanwhile, at the higher end of the distribution (above 75ºF), individuals do not change their time allocation in response to warmer weather. The time spent on working is not responsive to the temperature changes in both cold and warm weather (shown in the first panel).

Comparing the two periods 2007-2016 and 2003-2006, the pattern of change in time allocation across various temperature bins are similar. The 2007-2016 prediction line is closer to zero than that of 2003-2006 prediction line in each panel of Figure 4-4, but the size of the changes is minimal. This indicates that responsiveness of the reallocation of time to daily maximum temperature changes is stable during the whole period of 2003-2016. In the 2007-2016 time period, I find a slight decline (around 15 minutes) in time allocated to labor at temperature over 100ºF as compared to 76-80ºF. Outdoor leisure time at 25ºF is 40 minutes less than 76-80ºF and steadily increases until 76-80ºF, then remains stable until temperatures of over 100ºF. The time decreased in outdoor leisure at temperatures below 76-80ºF is substituted by indoor leisure time. The lack of significance in relationship between time allocation and daily maximum temperature at high temperatures (over 80ºF) suggest that external factors, such as the development of cooling technology, may play an important role in individual responses.

Figure 4-4. Relationship between temperature and time allocation for ALL individuals

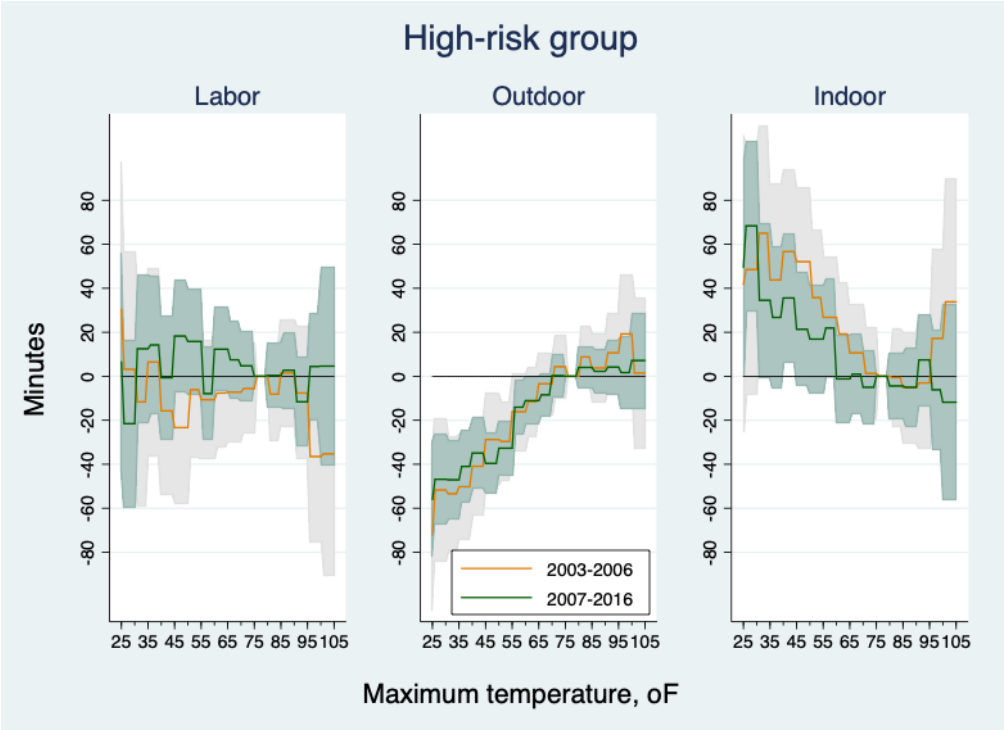


Notes: The 95% confidence interval for regressions in 2007-2016 and 2003-2006 periods is shaded in green and gray, respectively. Each figure displays the estimated impact of temperature on time allocation based on equations (1) – (3) in the text. Covariates include age, gender, number of children, annual earnings, employment status, race, education,

marital status, family income, day-of-week dummies, minimum temperature, precipitation, year-month dummies, and county fixed effects.

Figure 4-5 shows the change in time allocations for those who are working in industries with a high risk of climate exposure. Time allocated to labor is not responsive to change in temperatures. For outdoor leisure activities, the results are similar to that found for all individuals. A day with a maximum temperature below 55ºF is associated with a decrease in time spent on outdoor leisure significantly of 30-45 minutes when compared to a day in the 76-80ºF range. Indoor leisure time is insignificantly responsive to changes in temperature, except at the 25-30ºF and 40-45ºF temperature bins. When comparing all individuals, the impact of temperature on time allocation for the high-risk group during 2007-2016 follows the same pattern as in the 2003-2006 time period.

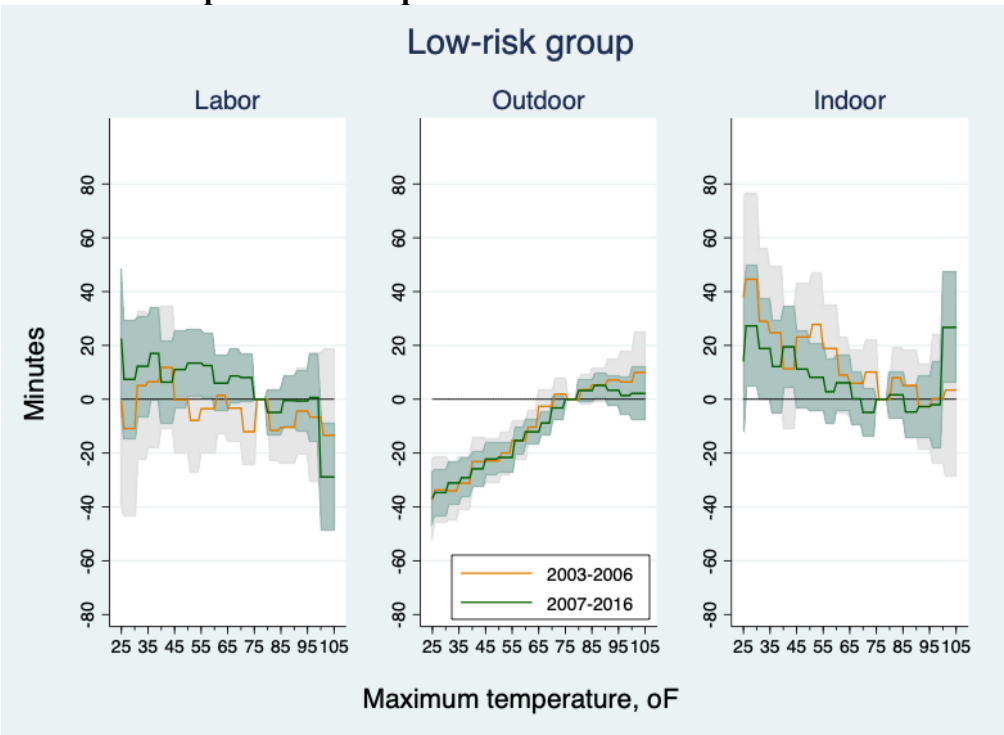
Figure 4-5. Relationship between temperature and time allocation for High-risk industries



Notes: The 95% confidence interval for regressions in 2007-2016 and 2003-2006 periods is shaded in green and gray, respectively. Each figure displays the estimated impact of temperature on time allocation based on equations (1) – (3) in the text. Covariates include age, gender, number of children, earnings, employment status, race, education, marital status, family income, day-of-week dummies, minimum temperature, precipitation, year-month dummies, and county fixed effects.

The impact of temperature on time allocations for low-risk industrial group is presented in Figure 4-6. The trend in time allocation is quite similar to what was found for all individuals (shown in Figure 4-4), except for the indoor leisure time at temperatures below 75ºF and over 100ºF. Compared to general results for all individuals, the impact of lower temperature between 30-60ºF on time allocated to indoor leisure activities for the low-risk group is weaker and only significant within the bins 25-30ºF and 40-45ºF. In contrast, at the temperatures over 100ºF, indoor leisure significantly increased for workers in the low-risk group - by 30 minutes on average, although this amount of time is insignificant for all individuals. Again, time allocation of workers in the low-risk group responds in the same fashion to changes in temperature in 2007-2016 as compare to 2003-2006, especially for time allocated to labor and outdoor leisure activities.

Figure 4-6. Relationship between temperature and time allocation for Low-risk industries

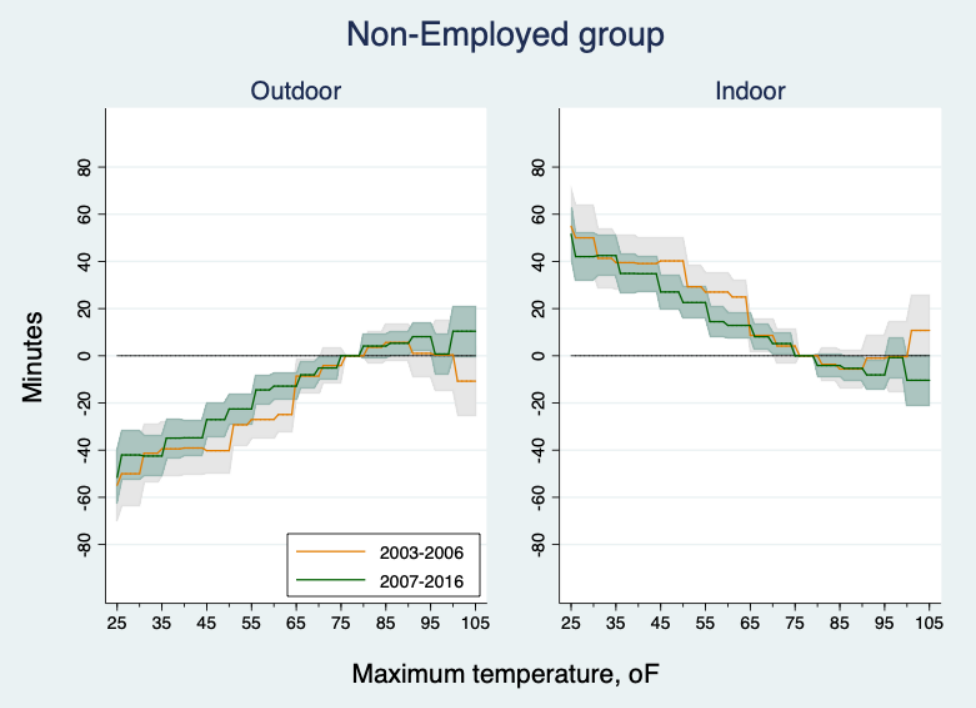


Notes: The 95% confidence interval for regressions in 2007-2016 and 2003-2006 periods is shaded in green and gray, respectively. Each figure displays the estimated impact of temperature on time allocation based on equations (1) – (3) in the text. Covariates include age, gender, number of children, earnings, employment status, race, education, marital status, family income, day-of-week dummies, minimum temperature, precipitation, year-month dummies, and county fixed effects.

Figure 4-7 presents the relationship between daily maximum temperature and time allocation for those who are not employed. For the temperature under 76-80ºF, the impact of temperature on

time allocation is the same for the two periods 2003-2006 and 2007-2016. At temperatures below 76-80ºF, outdoor leisure time decreases by a statistically significant amount and is substituted with indoor leisure (roughly 40 minutes at the temperatures 25-40ºF). Again, time allocated to leisure activities is not responsive to changes in temperature over 80ºF. Figure 4-7 also confirms that the allocation of time in 2007-2016 for the non-employed group, as same as for the high-risk and low-risk groups, responds to temperature changes in the same manner as in the period of 2003-2006.

Figure 4-7. Relationship between temperature and time allocation for Non-employed

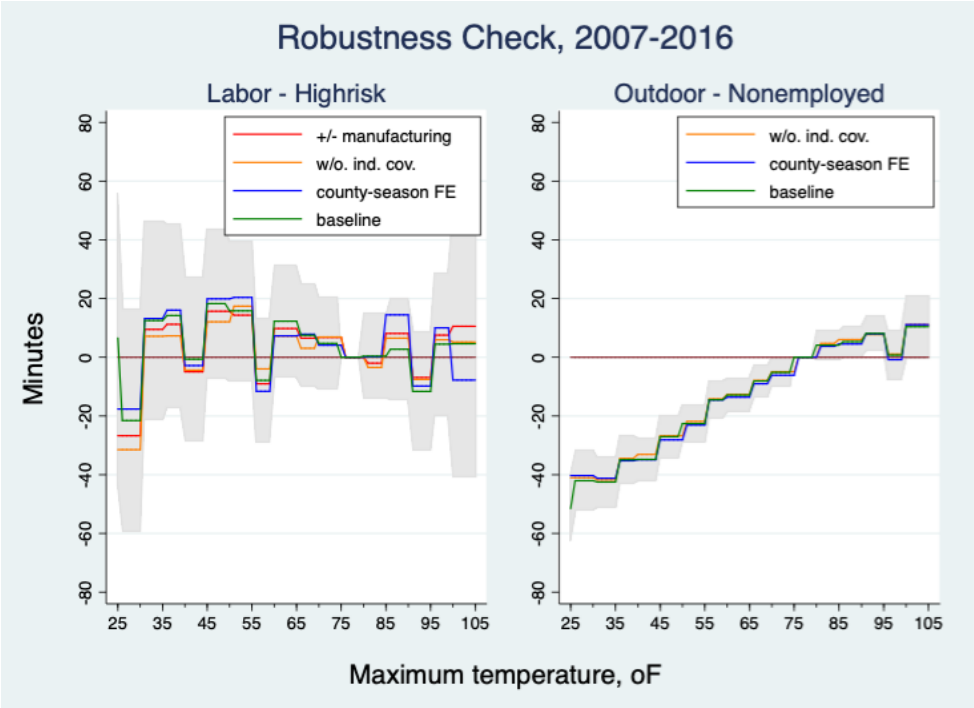


Notes: The 95% confidence interval for regressions in 2007-2016 and 2003-2006 periods is shaded in green and gray, respectively. Each figure displays the estimated impact of temperature on time allocation based on equations (2) – (3) in the text. Covariates include age, gender, number of children, earnings, employment status, race, education, marital status, family income, day-of-week dummies, minimum temperature, precipitation, year-month dummies, and county fixed effects.

To check for the robustness of the result, I move the manufacturing industry from the high-risk group to the low-risk group. Among those in the high risk of climate exposure industries, manufacturing is ambiguous, and the working activities may be either take place in outdoor or indoor condition. There are two other modifications to check for potential omitted-variable bias. In one estimation, I remove all individual covariates to check if county fix effects capture information related to locations based on temperature. In another estimation, I include county-

season fixed effects allowing for seasonal factors specific to each county. The results (Figure 4-8) show that changes in impact of temperature on time allocation across estimations are minimal, indicating the robustness of the results in the baseline model.

Figure 4-8. Robustness Check, 2007-2016



Notes: The 95% confidence interval for the baseline model is shaded in gray. "+/- manufacturing" moves those who were employed in the manufacturing industry from high to low risk; "w/o ind. cov." excludes individual-level covariates; "county-season FE" includes a county-season fixed effect.

Recalling that for those respondents whose county is not identified in the ATUS-CPS, I assign them to the county with the highest population in the CBSA where available in order to link them with weather data at the county level. This might lead to misleading estimates since the comparison between GZN and my replication (section 4.1) suggests that the result is sensitive to the daily maximum temperature measurement. To assess the impact of this CBSA – county matching process, I restrict my estimations to respondents with exact county identified (54,917 observation) in the ATUS-CPS. After merging with valid weather data, I obtain a final sample with 51,582 observations with county exactly identified. I find that the results are very close to those I found in the baseline estimates (Appendix A2), showing the reliability of my results.

Other than the development of cooling technology, an explanation for the decreased responsiveness of time allocation to temperature changes at the temperature over 80ºF could be that laborers have become used to the warm weather and learned strategies to cope with the heat. Furthermore, the relationship between temperature and time allocation might be affected by other variables, such as the Great Recession (December 2007 – June 2009), in which the unemployment rate increased remarkably. This might be the reason why time allocated on working is less responsive to changes in daily maximum temperature. Regardless of weather conditions, laborers need to work to keep their jobs and maintain their income levels. In the following section, I will exploit the variation across counties in timing and severity of the recession to check whether the relationship between time allocation and temperatures is affected by the recession.

4.3. Effects of the Great Recession

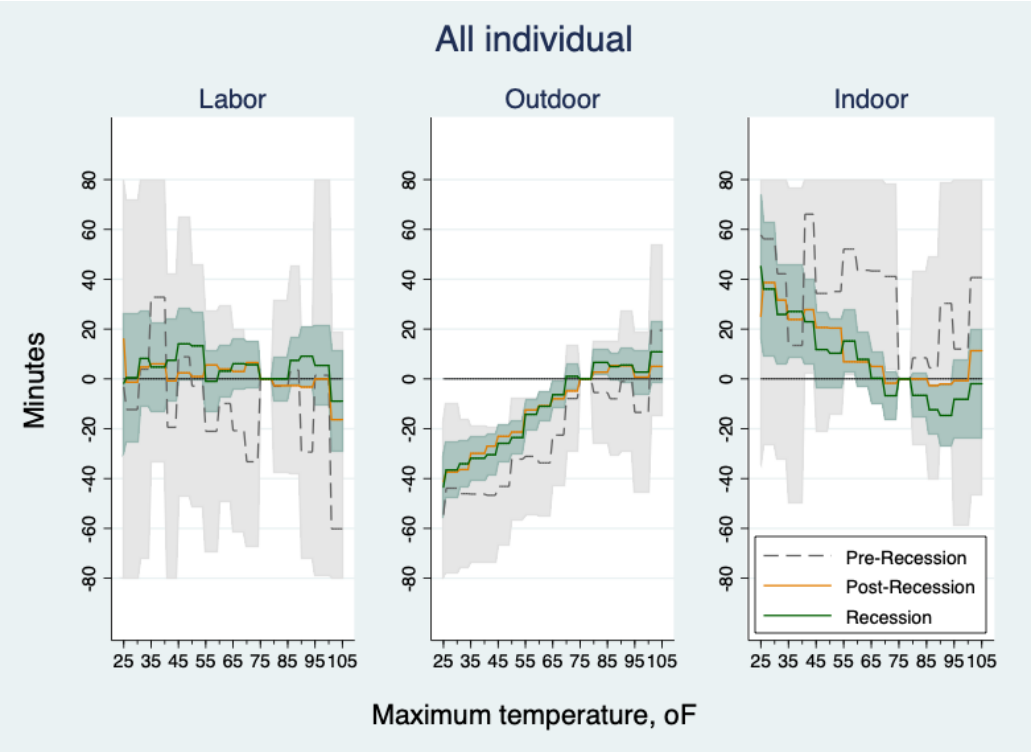
The recession that started in December 2007 was severe according to many measures, but for this paper, I am interested in its effect on the time allocation of laborers. The labor market indicator that I use as the main measure of cycle for this paper is the unemployment rate. From the U.S. Bureau of Labor Statistics' Local Area Unemployment Statistics, I obtain monthly unemployment rates for all counties of 50 U.S. states plus the District of Columbia. After adjusting for seasonality, I link the unemployment rate data to the ATUS data by the county in which ATUS respondents reside. Instead of using the national NBER dates of business cycles, I use the timing of the recession at the county level. Specifically, I assign cycle peak and trough for each of counties by examining the local minimums and maximums in the county level unemployment rates. When the unemployment rate rises quarter to quarter, the economy has most likely entered a recession phase. When the unemployment rate bottoms out, a trough has likely occurred. Despite labor market outcomes being subject to more influence by local variables, using data at the county level is limiting due to the possibility of measurement error in the unemployment rate. I then use the differences in the recession timing and intensity of county-level movement in unemployment rates to estimate how different individuals are affected by business cycle swings.

For this purpose, I employ the same estimations as in the equations (1) – (3) and run parallel regression for each of different time periods. The time periods cover the pre-recession, the 2007 recession, and the post-recession periods. Because equations (1) – (3) include county fixed effects, the coefficients on the set of temperature indicators for each time periods are only identified up to

a common effect caused by variations of recession timing at the county level. Since the time dummies may remove a large portion of the business cycle, I estimate the model without the year-month dummies.

Figure 4-9 depicts results from these estimations with the outcomes for each time period. The pattern and statistical significance of the outcomes are similar for the recession and post-recession time periods. For clarity, I show prediction lines and confidence intervals for the pre-recession and recession periods, while for the post-recession I show only the predictions. Full results are provided in the Appendix. When compared with the recession and post-recession periods, time allocated to labor seems to be more responsive to changes in temperature during the pre-recession period, but this is not statistically significant. For leisure activities, time spent outdoors decreases and is substituted by indoor leisure time at temperatures below 76-80oF. This pattern is similar for all periods, except for insignificant changes in time allocated to indoor activities during the pre-recession period. Overall, the individual time use behavior in response to temperature changes does not seem to vary over the business cycle.

Figure 4-9 . Variations of Relationship between temperature and time allocation over recession time periods for ALL individuals



Notes: The 95% confidence interval for regressions in Pre-recession and Recession periods is shaded in gray and green, respectively. Each figure displays the estimated impact of temperature on time allocation based on equations (4) – (6) in the text. Covariates include age, gender, number of children, annual earnings, employment status, race, education, marital status, family income, day-of-week dummies, minimum temperature, precipitation, and county fixed effects.

The severity of the Great Recession not only varies between counties but also between industries within a county. To examine whether the great recession has no effect on the relationship of individuals' time allocation and temperatures or only affects individuals in some specific industries, I reexamine the above estimations separately on different industrial groups. Instead of categorizing industries based on levels of risk to climate exposure as in the previous section, I separate the employed sample into three main industrial groups[4]: most-affected group (including construction and manufacturing), least-affected group (services and public administration, education and health services), and average - affected group (all other industries, except real estate and rental/leasing industry since this is the source of the recession). This categorization is based on findings of Hoynes, Miller, and Schaller (2012), Şahin, Song, and Hobijn (2009) and information from multiple presses. These papers show that, by the measure of unemployment rate, construction and manufacturing have stood out as the industries most affected by the downturn. In contrast, services and public administration, education and health services seem to have been most sheltered during this recession with the unemployment rate remained well below the aggregate long-term average unemployment rate.

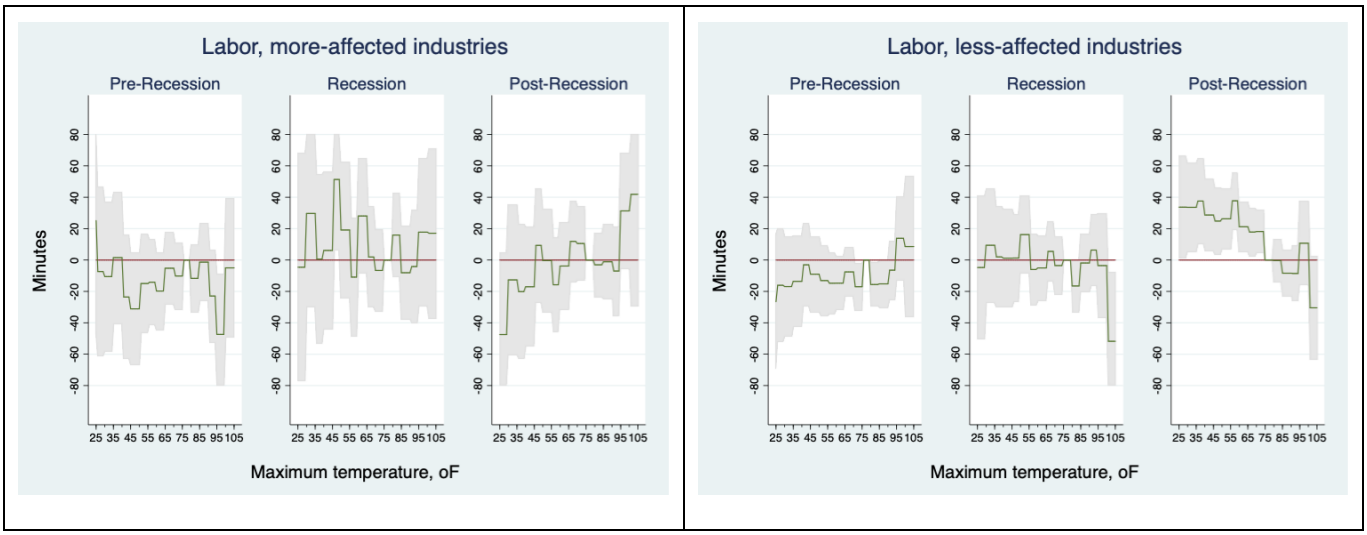
Figure 4-10 shows the differences in responsiveness of workers' time allocation to changes in temperature under different levels of recession severity. Workers in the less - affected industrial group are more flexible in the reallocation of their time in response to temperature changes over the business cycle, especially on time for leisure activities. For time allocated to labor, the more-affected group remains irresponsive to temperature changes either in or out of the recession period. Meanwhile, laborers in the less-affected group significantly increase their time spent on working at the lower temperature compared to the 76-80ºF bin. For leisure time, all groups reduce their time outdoors at the temperatures below 60ºF but while the estimates are mostly insignificant for the more-affected group during the pre-recession and recession periods, they are strongly

[4] I did not consider variation of recession impacts on different demographic groups since Hoynes, Miller, and Schaller (2015), Şahin, Song, and Hobijn (2009) also concluded that the source of this variation can be traced back to variation in severity of recession impact on different industry where those different demographic groups were mainly employed.

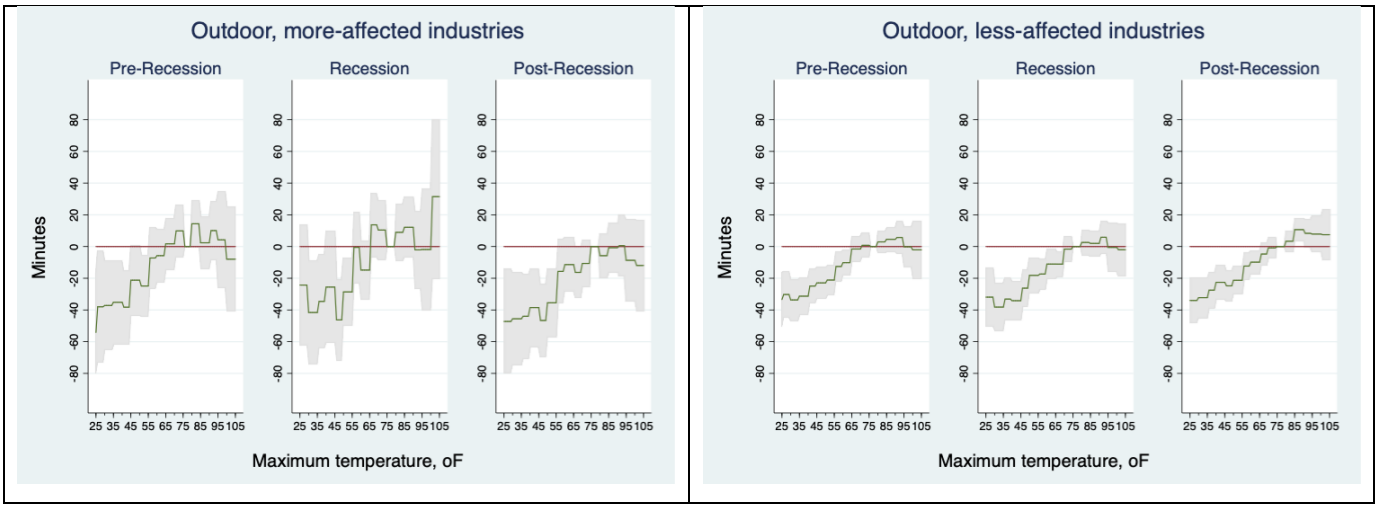
significant for the less-affected group. However, within each industrial group, the pattern is similar over the business cycle. The differences in responsiveness between less-affected and more-affected groups are not due to the recession effect but likely by the characteristics of each specific industry.

Figure 4-10. Variations of Relationship between temperature and time allocation over recession periods by groups of recession affected – level

(A) Labor



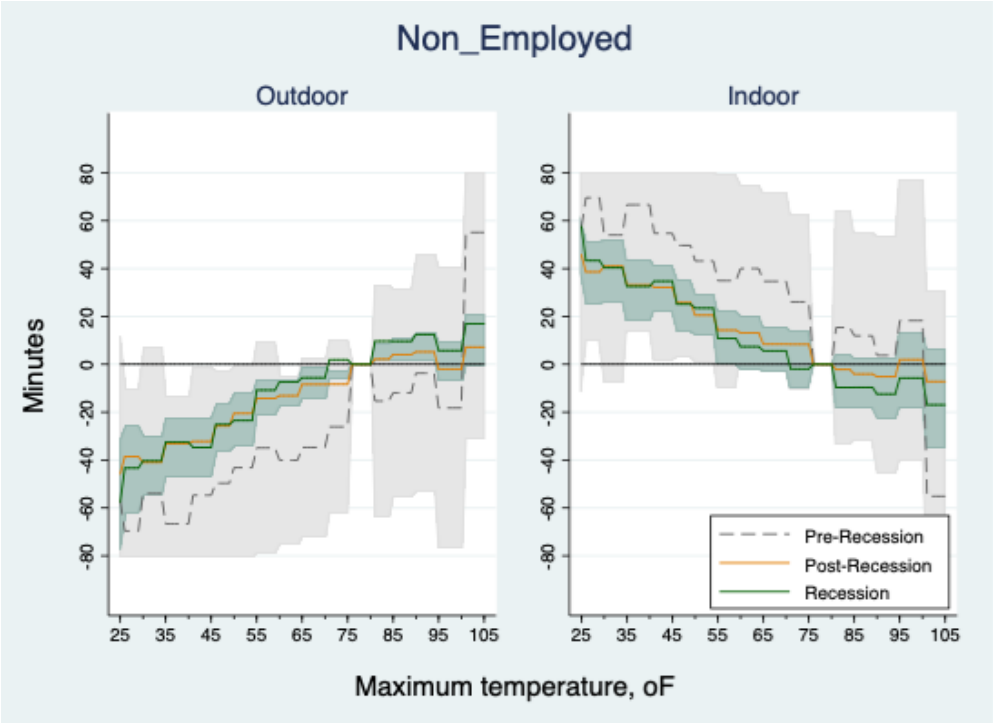
(B) Outdoor Leisure



Notes: The 95% confidence interval for regressions is shaded in gray. Each figure displays the estimated impact of temperature on time allocation based on equations (1) – (3) in the text. Covariates include age, gender, number of children, earnings, employment status, race, education, marital status, family income, day-of-week dummies, minimum temperature, precipitation, and county fixed effects.

The above results are true for the non-employed group as well. Although the responsiveness of time allocation to changes in temperature becomes more statistically significant during and after the great recession, the pattern of the responsiveness remains the same.

Figure 4-11. Variations of Relationship between temperature and time allocation over recession periods for Non-employed group



Notes: The 95% confidence interval for regressions in Pre-recession and Recession periods is shaded in gray and green, respectively. Each figure displays the estimated impact of temperature on time allocation based on equations (4) – (6) in the text. Covariates include age, gender, number of children, annual earnings, employment status, race, education, marital status, family income, day-of-week dummies, minimum temperature, precipitation, and county fixed effects.

In conclusion, although the unemployment rates[5] changed dramatically in the Great Recession, in opposition to my expectations I find no evidence of recessional effects on the relationship between temperature and time allocation.

[5] I estimate a simple regression of time allocated to labor on unemployment rates and interaction between each temperature bin and unemployment rates, including all individual covariates. This estimate shows significant effect of unemployment rate on time allocated to working. However, most of the coefficients associated with interaction terms are not statistically significant. The results imply that unemployment directly affects time allocated to labor but may not affect the responsiveness of time use behavior to other factors such as temperature.

5. Conclusion

The aim of this paper is to check the robustness of GZN model by using a fine-resolution weather data, examine the change in the trend of time allocation to labor, outdoor and indoor activities from the higher temperature in the period 2007-2016 in comparison to the period of 2003-2006, and investigate effects of the Great Recession on the relationship between temperature and time allocation.

My findings for each labor group and non-employed group confirm that although the allocation of time in 2007-2016 tend to be less responsive to temperature changes than in 2003-2006 especially in the warm weather, the relationship between the time allocation and temperature is stable over time.

Regarding the period of 2007-2016, a day with a max temperature below 65°F leads to a decrease in the time allocated to outdoor leisure activities, relative to a day in 76-80°F bin. In general, comparing locations experiencing temperatures of 76-80°F with those experiencing temperatures of 25-35°F, all groups spent, on average, 30 minutes less per day doing outdoor leisure activities. In both low-risk and non-employed groups, the decreased time in outdoor leisure is substituted with indoor leisure time. While time allocated to outdoor and indoor activities changes following temperature changes in the cold weather, it is not significantly responsive to the higher temperature in the warm weather. The lack of significance in relationship between time allocation and daily maximum temperature at high temperatures (over 80oF) suggest that external factors, such as the development of cooling technology, may play an important role in individual responses. In terms of labor time, I find that time allocated to working is not impacted by temperature changes, neither in cold nor in warm weather.

The comparison between GZN's results and my analysis provides evidence of sensitivity in the estimation results due to temperature measurement. While GZN finds time allocated to labor and indoor leisure activities is responsive at the temperature over 100°F, my result is insignificant. The only different input between GZN and this paper is the weather data~~, in which I obtain less observations over 90°F and more observations in 60-80°F than that in GZN~~. Therefore, studies examining the trend of economic outcomes in response to temperature should use a consistent data source of temperatures over time to provide reliable results.

Besides the development of adaptive technology, other external factors could be an explanation for the lack of responsiveness of time allocation to temperature changes. One of those may be the business cycle, but when comparing the estimation results of changes in time allocation due to temperature variations over each of three periods – before, during, and after the Great Recession - the pattern of changes in time allocation is similar between groups. This stable pattern also remains across different industrial groups who experienced different level of recession severity. Thus, the Great Recession does not directly affect the relationship between temperature and time allocation.

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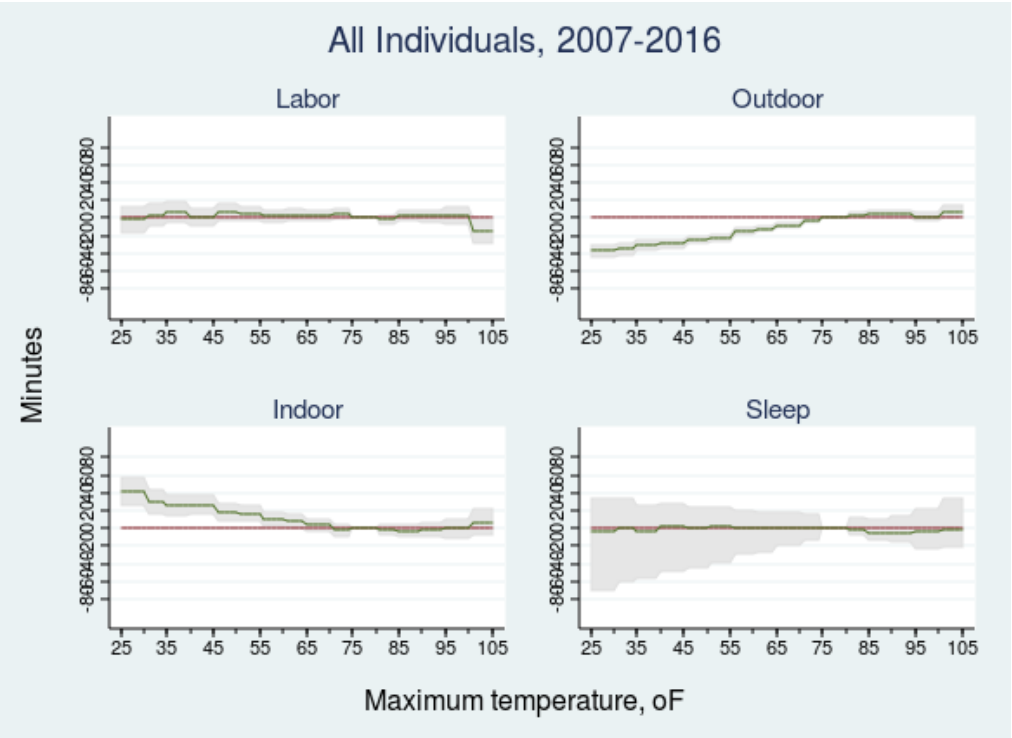
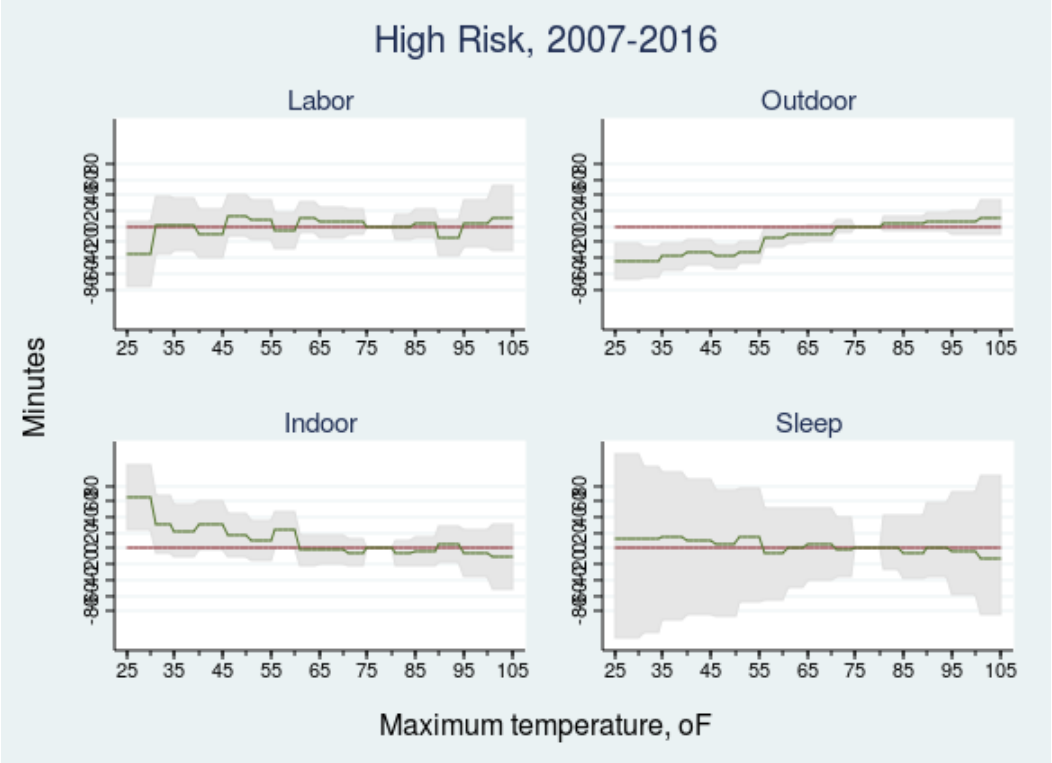
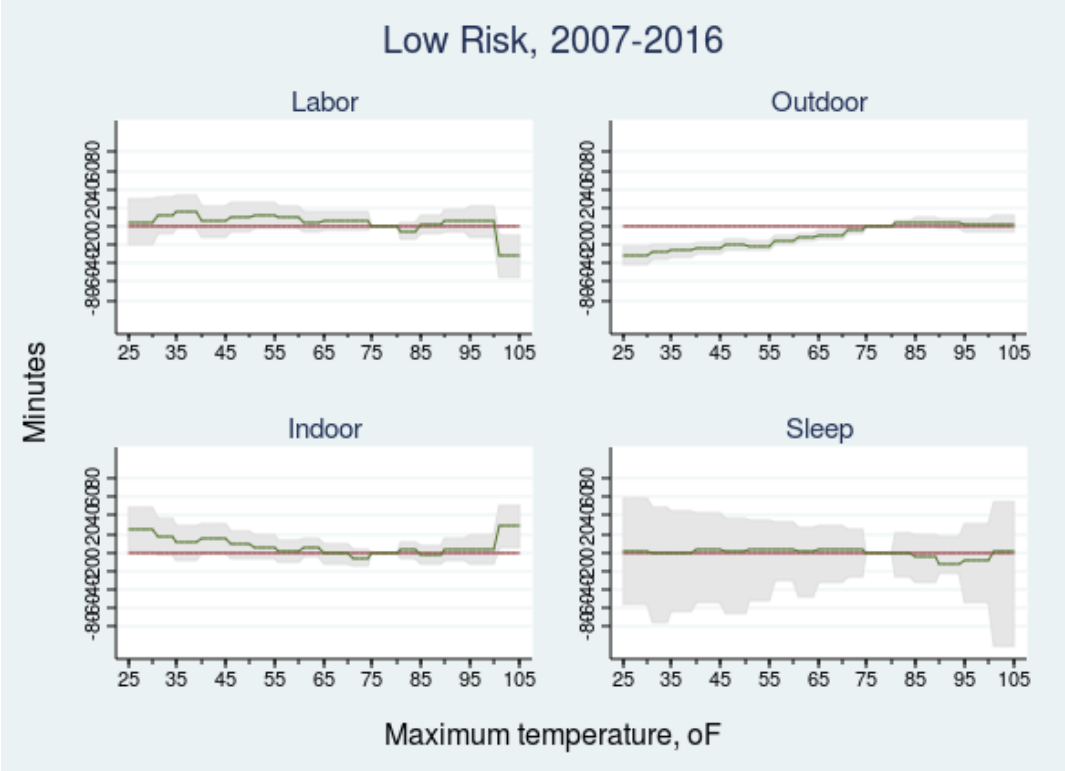
Appendix A1.

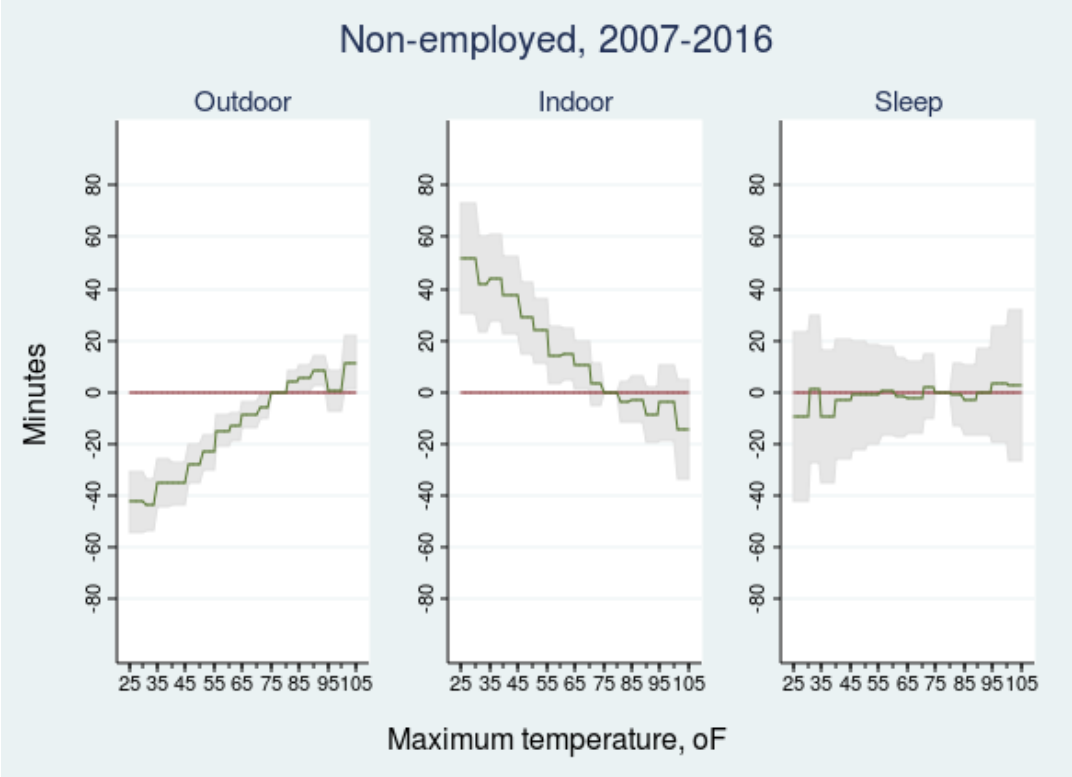
Relationship between Temperature and Time allocation, including Sleeping Time in the period of 2007 – 2016

In each bellowing figure, the 95% confidence interval for regressions is shaded in gray. Each figure displays the estimated impact of temperature on time allocation based on equations (1) – (3) in the text. Covariates include age, gender, number of children, earnings, employment status, race, education, marital status, family income, day-of-week dummies, minimum temperature, precipitation, year-month dummies, and county fixed effects.




High Risk, 2007-2016
Labor
Outdoor
Indoor
Sleep
Minutes
25 35 45 55 65 75 85 95 105
Maximum temperature, oF


Low Risk, 2007-2016
Labor
Outdoor
Indoor
Sleep
Minutes
25 35 45 55 65 75 85 95 105
Maximum temperature, oF

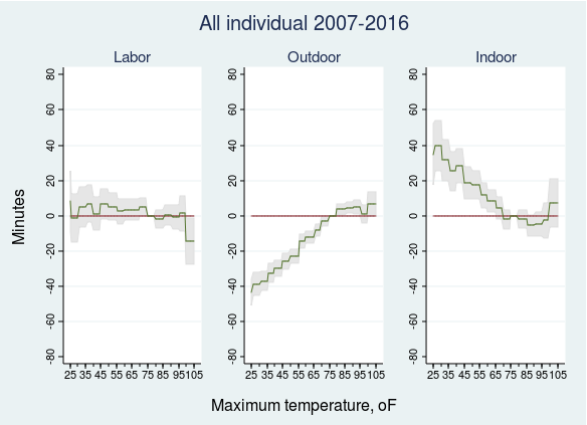


Appendix A2.

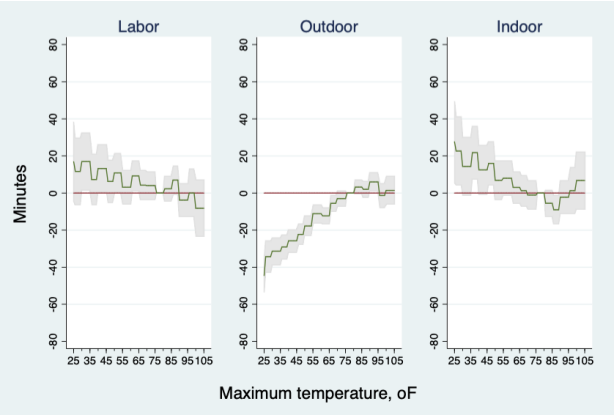
Relationship between Temperature and Time allocation in the period of 2007 – 2016

Figure 1 - All individual

Full sample (N=83,666)



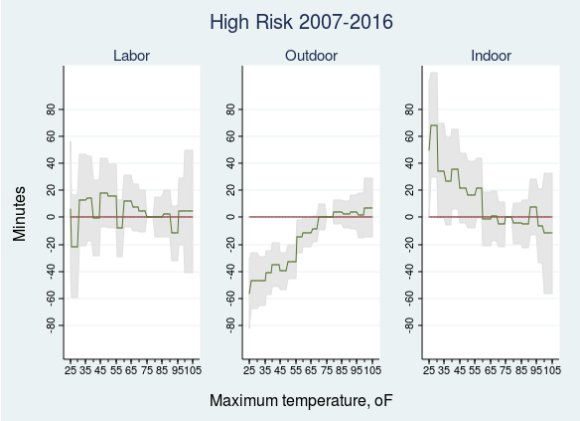
Restricted sample (N=51,582)



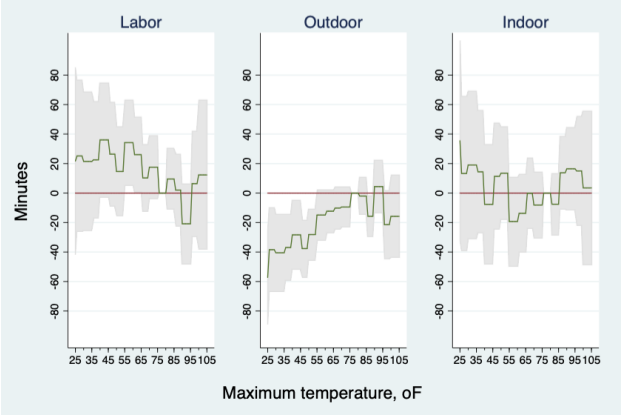
Notes: Full sample includes individuals with county identified by highest population county in the CBSA; Restricted sample includes individuals with county exactly identified.

Figure 2 – High-risk group

Full sample (N=11,418)



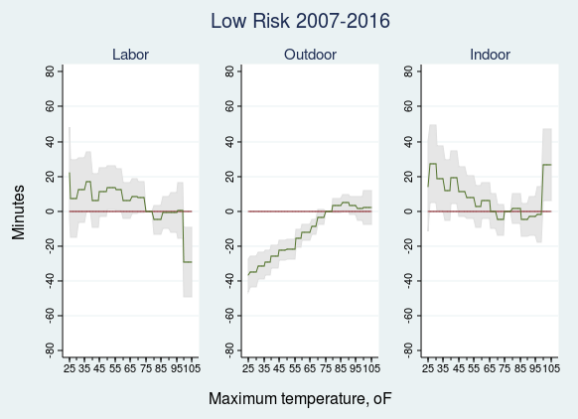
Restricted sample (N=6,628)



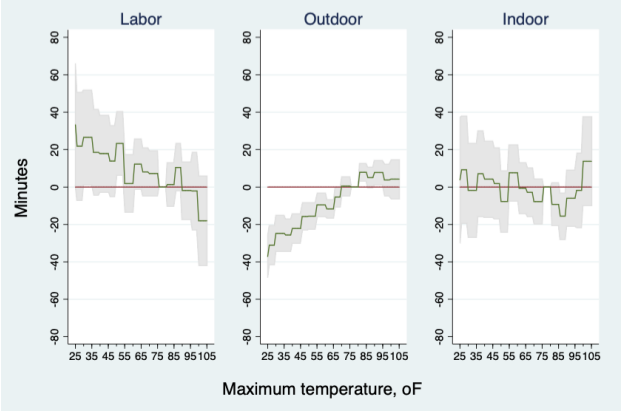
Notes: Full sample includes individuals with county identified by highest population county in the CBSA; Restricted sample includes individuals with county exactly identified.

Figure 3 – Low-risk group

Full sample (N=40,741)



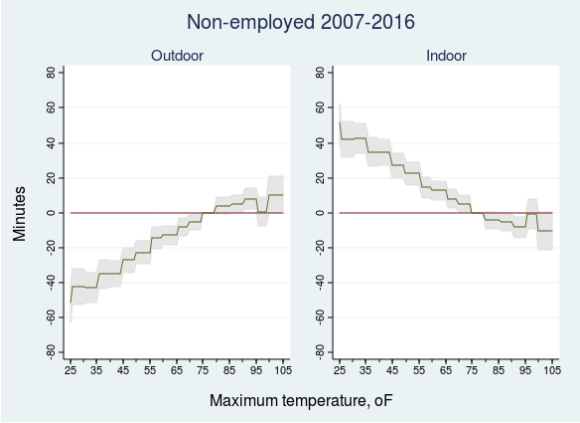
Restricted sample (N=24,867)



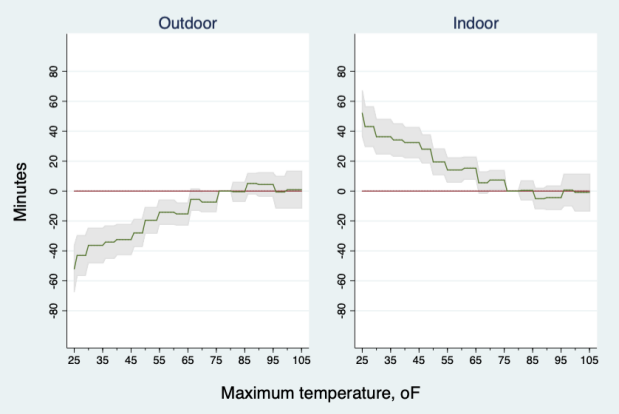
Notes: Full sample includes individuals with county identified by highest population county in the CBSA; Restricted sample includes individuals with county exactly identified.

Figure 4 – Non-employed group

Full sample (N=31,507)



Restricted sample (N=20,087)



Notes: Full sample includes individuals with county identified by highest population county in the CBSA; Restricted sample includes individuals with county exactly identified.

Appendix A3.

Relationship between Temperature and Time allocation in different phases of the business cycle

In each bellowing figure, the 95% confidence interval for regressions is shaded in gray. Each figure displays the estimated impact of temperature on time allocation based on equations (1) – (3) in the text. Covariates include age, gender, number of children, earnings, employment status, race, education, marital status, family income, day-of-week dummies, minimum temperature, precipitation, year-month dummies, and county fixed effects.

Figure 1 – All individuals

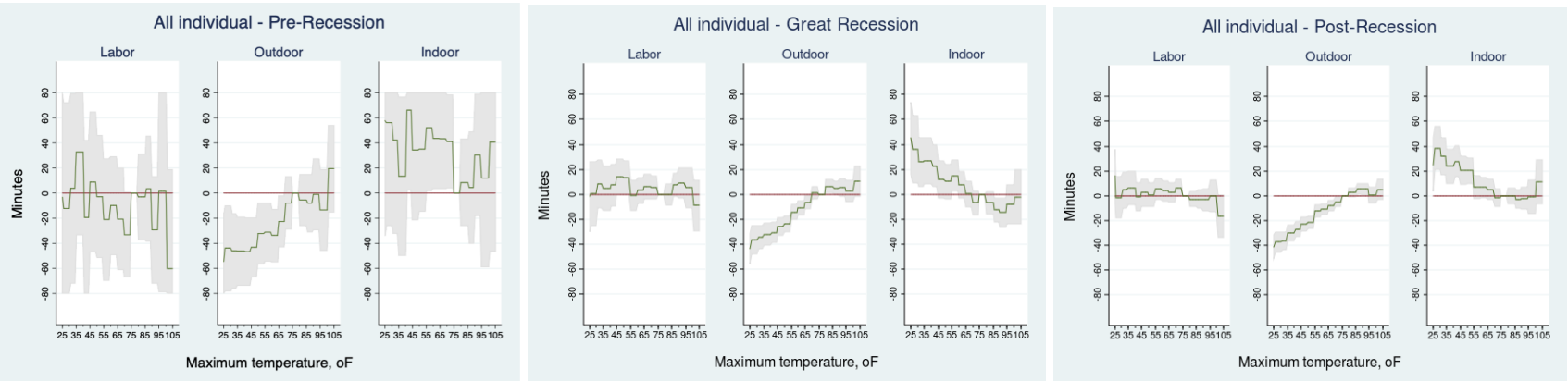


Figure 2 – Employed group

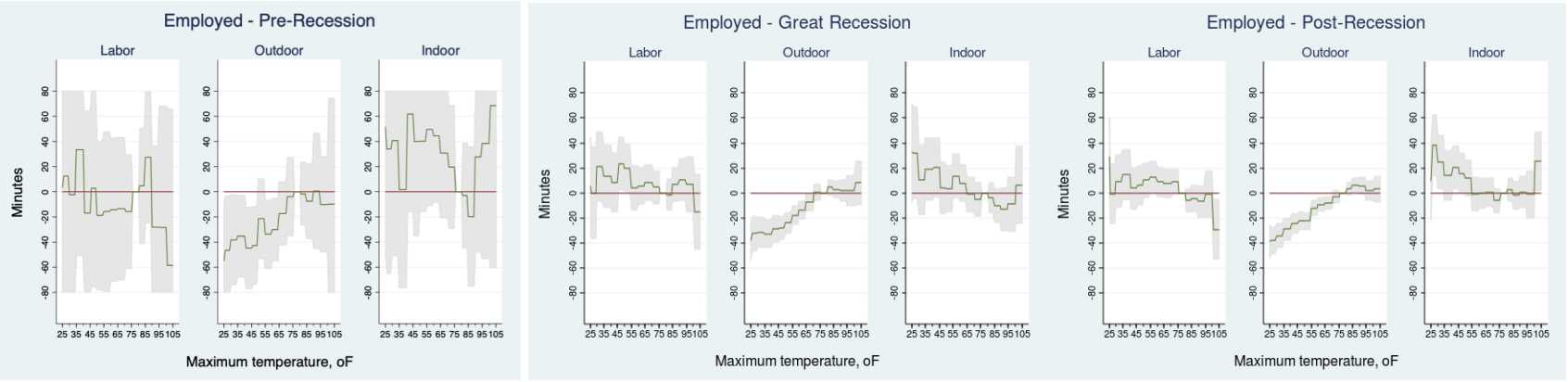


Figure 3 – Non-Employed group