Extreme Temperatures and Non-work at Work

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Abstract

Understanding the determinants of worker effort is central to Economics, as even small changes in productivity can have significant implications for economic growth and labor market performance. This study examines the relationship between extreme temperatures and work effort—proxied by non-work time while at the workplace—using data from the American Time Use Survey (ATUS) for the period 2003–2019. Results indicate that extremely hot days (≥ 100ºF) are related to increased time spent at work not working, particularly among women in non-supervised occupations. On these days, women in non-supervised occupations spend 6.79 more minutes at work not working compared to comfortable temperature days. Men, by contrast, do not exhibit significant changes in non-work time at work. Furthermore, the results align with increased worker bargaining power during economic expansions, which facilitates labor supply adjustments on extremely hot days, and with hypotheses regarding adaptation and acclimation to high temperatures in warmer counties. These findings underscore the relevance of temperature as a determinant of worker effort, reveal a previously overlooked margin of labor adjustment, and highlight the moderating role of occupational supervision in shaping behavioral responses to environmental stressors.

Keywords: Climate change, temperature, non-work time at work, supervision, ATUS
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1. Introduction

How workers allocate effort is a foundational concern in Economics, with direct implications for firm productivity, labor market dynamics, and long-run economic growth. Even marginal disruptions to workplace effort, especially when persistent or systematic, can scale into substantial economic losses (Syverson, 2011). This issue is particularly salient in the context of global warming, which introduces a pervasive and increasingly frequent source of environmental stress that can affect worker behavior and cognitive performance (Dell et al., 2014). The economic consequences are substantial, hard to insure against, and likely to grow over time (Burke et al., 2015; Hsiang et al., 2017). While economists have long studied labor supply responses to heat, especially in climate-exposed industries (Graff Zivin and Neidell, 2014; Dillender, 2021; Heyes and Saberian, 2022; Drescher and Janzen, 2025), less attention has been paid to within-workplace behavioral adjustments such as effort allocation. Yet, these responses matter: if rising temperatures reduce attention, motivation, or task adherence (Chang et al., 2019; Cassar and Meier, 2021), they may distort labor productivity even when attendance or hours worked remain constant. By focusing on time spent at work but not working as a proxy for individual-level work effort, this study offers novel evidence on a behavioral response that complements and deepens our understanding of climate-related productivity losses.

The interest in the relationship between extreme temperatures and worker productivity is not new, and is driven by a substantial body of prior research showing that extreme temperatures are linked to considerable economic losses (for reviews, see Heal and Park, 2016; Lai et al., 2023). Previous research documents how extreme heat reduces labor supply in climate-exposed industries (Graff Zivin and Neidell, 2014; Garg et al., 2020; Neidell et al., 2021; Ireland et al., 2024), diminishes worker productivity (Somanathan et al., 2021; Heyes and Saberian, 2022; LoPalo, 2023; Ireland et al., 2024; Picchio and van Ours, 2024), and increases workplace accidents (Dillender, 2021; Ireland et al., 2023; Filomena and Picchio, 2024; Drescher and Janzen, 2025).

Within this context, this paper examines the relationship between daily temperatures and what respondents do while at the workplace, focusing on time spent in non-work-related activities while at work. This represents an important but often overlooked labor margin in labor economic studies. Unlike absenteeism, which reflects a proxy for worker effort at the extensive margin that captures workers' decisions to forgo work entirely, this proxy of workplace effort reflects within-day worker effort allocation and may have significant implications for workplace efficiency and employer monitoring strategies. In particular, we analyze whether extreme temperatures increase the time workers spend on non-work activities at their workplace, shedding light on a novel behavioral mechanism through which weather conditions affect labor market outcomes.

To investigate this question, we utilize nationally representative time diary data from the American Time Use Survey (ATUS) for the period 2003-2019. The ATUS allows for a detailed measure of time spent at various locations, including workplaces, and is widely regarded as one of the most accurate tools, in terms of reduced aggregation bias, recall bias, and social desirability bias, for recording time allocation (Bonke, 2005; Kan, 2008). Unlike traditional household surveys based on stylized questions, time diaries minimize measurement errors and can offer insights into workplace behavior (Hamermesh, 1990; Burda et al., 2020; Gimenez-Nadal and Sevilla, 2024). These data are merged with high-frequency weather data at the county level from the National Climatic Data Center (NCDC), enabling a robust analysis of daily temperatures and workplace behavior.

We exploit daily variations in local temperature within counties and find a non-linear relationship between daily temperatures and time spent non-working at the workplace, where extreme hot temperatures are associated with reduced effort at work. Specifically, our findings indicate that a day with a maximum temperature of 100 ºF or above is associated with 4.34 additional daily minutes spent non-working at work among women, compared to a day with a temperature in the comfortable range of [75, 80) ºF. However, no significant relationship is observed among men. Moreover, these relationships are particularly pronounced among women in non-supervised occupations, who increase their time spent in non-work-related activities at work by 6.79 minutes on days with maximum temperatures above 100 ºF. Additionally, we find that these relationships are stronger during periods of economic expansion, suggesting that increased worker bargaining power and better outside job opportunities (Boone and van Ours, 2006; Boone et al., 2011; Lazear et al., 2016; Senney and Dunn, 2019; Burda et al., 2020; Neidell et al., 2021) may amplify these behavioral responses. Finally, women in colder regions exhibit stronger responses, consistent with hypotheses regarding long-term adaptation. All in all, our results suggest that extreme hot temperatures influence labor productivity not only through absenteeism or reduced working hours, as extensively analyzed in previous research, but also by altering effort levels and workplace behavior.

This paper contributes to a growing body of literature examining the relationship between temperature and worker productivity by exploring a novel labor response. Existing research has shed light on the adverse effects of extreme temperatures on labor markets, emphasizing the detrimental impacts of heat on worker productivity, working hours, and workplace accidents (Graff Zivin and Neidell, 2014; Dillender, 2021; Somanathan et al., 2021). While this literature has advanced our understanding of the temperature–labor relationship, it has largely focused on primary labor market adjustments without addressing the question of how temperature influences within-workplace behavior. This gap in the literature is important because understanding the behavioral responses of workers at the workplace, beyond absenteeism and working hours, can provide a more comprehensive view of the economic costs of heat.

To fill this gap, our paper investigates the relationship between daily temperatures and labor supply behavior, exploring a novel margin of labor market adjustment: task avoidance during work hours. This is particularly relevant because the time spent in non-work-related activities while at the workplace directly impacts workplace efficiency and may reveal additional costs associated with heat exposure (Syverson, 2011). Using nationally representative time use data from the ATUS and merging it with high-frequency weather data, we provide insights into how extreme temperatures relate to work effort. Our approach allows us to move beyond previous studies that have mostly focused on absenteeism or labor supply reductions, particularly in sectors with higher outdoor exposure (e.g., construction, agriculture). As a result, we uncover a novel channel through which temperature may affect labor productivity, contributing a new dimension to the existing understanding of climate's economic impacts.

Furthermore, our paper highlights the role of occupational supervision in shaping the temperature–productivity relationship. While prior research has shown heterogeneity in responses to temperature based on exposure level, gender, and business cycle stage (Graff Zivin and Neidell, 2014; Garg et al., 2020; Neidell et al., 2021), our study reveals that the extent of supervision may play a critical role in moderating the effects of heat on worker behavior. Specifically, women in non-supervised occupations show a significant increase in time spent non-working at the workplace on extremely hot days, while those in supervised positions do not exhibit such a response. This finding adds a new channel to the existing literature, emphasizing that employer monitoring and workplace design can mitigate the productivity losses associated with extreme heat.

The rest of this paper is organized as follows. Section 2 reviews the related literature and provides the empirical context for the research. Section 3 describes the data sources, sample selection criteria, and descriptive statistics. Section 4 outlines the econometric methodology. Section 5 presents the results, and Section 6 concludes.

2. Literature review

This paper contributes to the growing climate economics literature investigating the adverse consequences of climate change on labor markets. Over the past decade, this research area has expanded significantly, delving into many domains such as working hours, absenteeism, workers' productivity, and the incidence of workplace accidents, among others.

A seminal contribution in this domain is that of Graff Zivin and Neidell (2014), which established a significant relationship between extreme hot temperatures and labor supply.[1] Using data from the ATUS for the years 2003 to 2006, they identified a substantial reduction of 59 minutes in working hours for employees in outdoor occupations—including agriculture, forestry, fishing and hunting, construction, mining, manufacturing, and transportation and utilities—when daily maximum temperatures surpass 100ºF, compared to the [75, 80) ºF range. Neidell et al. (2021) extended this analysis by incorporating an additional 12 years of ATUS data (2003-2018). Their findings underscored the persistence of these estimates during periods of economic growth, lending support to the hypothesis that favorable economic conditions—characterized by ample labor market opportunities and greater worker bargaining power—ease labor supply adjustments during extremely hot days among workers.

Gender disparities in labor supply responses have also garnered attention. Jiao et al. (2021), analyzing ATUS data from 2003 to 2017, highlighted pronounced gender differences in the temperature-hours worked relationship. They found that women reduce

[1] We concentrate on studies examining the relationship between extreme temperatures and hours worked. Other studies have shown that weather conditions affect time allocation. For example, Connolly (2008) conducted the first investigation into the relationship between daily weather conditions and time use, analyzing responses to rainy days using data from the ATUS 2003-2004. Similarly, Liu and Hirsch (2021) paid attention to snowfall utilizing the Current Population Survey for the period 2004-2014. In contrast, Alberto et al. (2021) and Nguyen et al. (2021) concentrated on children's time allocation under varying weather conditions. More recently, Bigler and Janzen (2024) and Hajdu (2024) examined the association between temperature and sleeping time. Finally, Belloc et al. (2025) concentrated on the relationship between daily weather conditions and commuting mode choices using the ATUS 2003-2023.

their working hours by an additional 58 minutes compared to men on extremely hot days. In a complementary context, Garg et al. (2020) examined similar dynamics in China, reporting that high temperatures significantly reduce working hours, particularly for women in climate-sensitive sectors like agriculture.

Apart from the hours worked, another critical strand of research focuses on workplace accidents. Dillender (2021), for instance, explored the relationship between temperature and worker health in Texas and the US, demonstrating that high temperatures elevate claim rates in Texas. Moreover, his broader analysis of the US mining sector revealed limited adaptation to high temperatures, with high temperatures showing a more severe impact on injury rates among those in historically warmer climates than those in colder regions. This highlights the constrained adaptive capacity to extreme temperatures of outdoor workers across different climatic contexts, due to their unavoidable exposure to environmental conditions. As a result, firm-level interventions, like climate-control systems or remote work practices, offer limited protective benefits for this occupation group.

Expanding beyond the US, Ireland et al. (2023) and Filomena and Picchio (2024) documented rising injury rates in the Australian state of Victoria and Italy, respectively, due to high temperatures. The findings of Ireland et al. (2023) particularly emphasize the increasing vulnerability of workers to heat exposure in recent years, which have also been the hottest, echoing Dillender's conclusions. Otherwise, Drescher and Janzen (2025) focused on Switzerland and reveal that both high and low temperatures increase workplace accidents.

Another strand of this literature examines labor productivity, often evaluated through external metrics regarding absenteeism and work performance (Cai et al., 2018; Heyes and Saberian, 2019, 2022; Fesselmeyer, 2021; Somanathan et al., 2021; LoPalo, 2023; Ireland et al., 2024; Picchio and van Ours, 2024).

For instance, Cai et al. (2018) found that days with maximum temperatures exceeding 95 ºF decrease workers' productivity by approximately 8.5% in a Chinese manufacturing firm. Similarly, Somanathan et al. (2021) showed that hot days reduce worker output while they increase absenteeism across manufacturing firms in India. Consistent with these findings, Heyes and Saberian (2022) reported that experiencing an additional extremely hot day within a 30-day period, defined as a day with maximum temperatures higher than 100 ºF, led to a 7.3% increase in the inability to work in India, and that the effect is largest for females and in colder areas. Similarly, Ireland et al. (2024) found that a day with a maximum temperature above 100 ºF increases workers' absenteeism by 5.1% in Australia.

Additionally, other studies, mostly based on sports data, provide further evidence of the detrimental effects of extreme temperatures on work performance. For instance, Heyes and Saberian (2019) observed that a 10 ºF rise in temperature decreases the probability of favorable immigration decisions by 1.075 percentage points among US immigration judges, which is equivalent to an average decline in the grant rate of 6.55%. Similarly, Fesselmeyer (2021), analyzing Major League Baseball data, noted that extreme hot temperatures of 95 ºF and above reduce umpire accuracy in calling no-batted pitches by 0.726 percentage points. LoPalo (2023) extended this line of research by demonstrating that female interviewers conducted 13.6% fewer interviews *per hour* for the Demographic and Health Surveys on the hottest and most humid days. Nevertheless, the total number of interviews completed per day did not decline on these days, suggesting that interviewers may have compensated by working longer hours. Finally, Picchio and van Ours (2024) demonstrated that ambient temperature significantly affected performance in tennis matches, with both first serve and second serve success rates declining with higher temperatures, particularly on the first serve where there is less at stake.[2]

In addition to advancing the literature on the labor impacts of climate change, our study contributes to the relatively limited body of research on the determinants of effort at work (Gimenez-Nadal et al., 2018; Burda et al., 2020; Hamermesh et al., 2021; Darity Jr et al., 2022; Gimenez-Nadal and Sevilla, 2024) by integrating environmental factors into this framework, an aspect that has not been previously analyzed. For example, Gimenez-Nadal et al. (2018) test the efficiency wage hypothesis in the US (2003–2014) and find that leisure and time spent at work not working are substitutes, while commuting time is positively correlated with that proxy of workers' effort. These findings support the assumptions of the urban efficiency wage theory and align with the model proposed by Ross and Zenou (2008). In contrast, Burda et al. (2020) analyze the impact of business

[2] At the aggregate level, research has shown that high temperatures negatively affect various economic outcomes, including employment (Jessoe et al., 2018; Colmer, 2021; Liu et al., 2023; Lyu et al., 2024), and output (Miller et al., 2021; Dell et al., 2012; Burke and Emerick, 2016; Berg et al., 2024; Meierrieks and Stadelmann, 2024). Additionally, other studies examine the broader economic consequences of extreme weather events and natural disasters (Karbownik and Wray, 2019; Groen et al., 2020; Afridi et al., 2022; Johar et al., 2022).

cycle fluctuations in the labor market by examining the relationship between unemployment and workplace effort using data from the ATUS for the period 2003-2012, showing that the fraction of time spent at work not working is positively associated with unemployment among those who remained employed. On the other hand, unemployment is negatively correlated to the probability of engaging in non-work-related activities at work.[3] Finally, Hamermesh et al. (2021), Darity Jr et al. (2022) and Gimenez-Nadal and Sevilla (2024) focus on specific socio-demographic and job characteristics. For example, Hamermesh et al. (2021) and Darity Jr et al. (2022) analyze racial and ethnic differences in time spent not working at the workplace in the US between 2003 and 2015, whereas Gimenez-Nadal and Sevilla (2024) find that workers in routine task-intensive occupations in the UK increase their effort at work.[4]

3. Data description

3.1. The American Time Use Survey

We employ time use data from the ATUS. The ATUS, conducted as part of the Current Population Survey (CPS) by the US Census Bureau and sponsored by the Bureau of Labor Statistics (BLS), is a large cross-sectional survey that serves as the official time use survey of the United States. It has been conducted annually on a continuous basis since 2003 (publicly available up to 2023 at the time of writing this article), except for March-May 2020 when data collection was temporarily disrupted due to the COVID-19 pandemic, which also impacted data quality that year (Flood et al., 2022). As a result, the ATUS represents the state of the art in time use surveys, with few comparable surveys offering such an extensive temporal horizon (Hamermesh et al., 2005; Aguiar et al., 2012). For our analysis, we use individual-level data from the ATUS for the years 2003 to 2019.

The ATUS is a unique national survey that collects detailed information on individuals' daily activities for a representative sample of Americans over a 24-hour period, referred to as the "diary day", which spans from 4:00 a.m. on the day before the interview to 4:00 a.m. on the interview day. The survey sample is randomly selected from households that previously participated in the CPS, with one individual aged 15 or older

[3] Biddle (2014) reviews the literature on the cyclical behavior of productivity.

[4] Although the definition of effort at work by Gimenez-Nadal and Sevilla (2024) aligns with our approach, they define two additional measures: the frequency of time spent in non-working activities while at the workplace and the time spent before engaging in a non-working activity at work.

selected from each household for the ATUS interview. These interviews are conducted two to five months after the completion of the final month interviews for the CPS, using computer-assisted telephone interviews (CATI). Participants complete a time diary, only once, in which they provide a minute-by-minute account of their time use *episodes* for the preceding day in sequential order. A time use *episode* is defined as a continuous period during which there is no change in any activity domain, including primary activity, co-presence of others, location, or mode of travel. Hence, since the ATUS determines the exact start and end times of each time use *episode*, we can calculate the duration of time spent in different activities and locations per day (see below for further details).

3.2. Weather data

We combine individual-level data from the ATUS with detailed weather data provided by the NCDC, a division of the National Oceanic and Atmospheric Administration (NOAA). The NCDC provides daily weather summaries, including variables such as maximum and minimum temperatures, precipitation, and snowfall, from all weather stations spread over the United States.[5] We aggregate this station-level weather data from 23,339 weather stations spread across the US to the county-level by taking the simple average of the observed measures, and subsequently match it with our individual-level ATUS sample. The linkage between ATUS and weather data is facilitated by the detailed regional and temporal information provided in the ATUS. Specifically, the ATUS includes the county of residence and the exact date of each diary day for all respondents. These crucial data points make it possible to merge the ATUS data for each individual with weather information. For individuals whose county of residence is not observed but whose metropolitan statistical area (MSA) is known, we assign them to the most populous county within their respective MSA.[6]

[5] Most weather stations report only daily summaries of precipitation and snowfall, as well as minimum and maximum temperatures. The absence of humidity data in our source prevents the calculation of the heat index.

[6] Following standard practice in the literature (Connolly, 2008; Graff Zivin and Neidell, 2014; Jiao et al., 2021; Cosaert et al., 2025a), we exclude individuals for whom only the state of residence is observed. This group represents over 40% of the respondents targeted by the survey.

3.3. Sample selection

For this study, we focus on employees between the ages of 21 and 65 (Mazzocco, 2007; Gimenez-Nadal and Sevilla, 2012), inclusive, restricting the analysis to workdays and deleting self-employed workers from the sample (Gimenez-Nadal et al., 2018; Burda et al., 2020; Hamermesh et al., 2021). By focusing on the age band between 21 and 65 years we avoid cofounding effects related to retirement and weak labor market attachment. A workday is defined as any day on which an individual reports working *at the workplace* for at least 60 minutes, excluding commuting (Gimenez-Nadal et al., 2018).[7] Consequently, we exclude people who are working entirely from their homes and only include respondents who report at least 60 minutes of work while at work, as done in previous research focusing on time spent on activities while the respondent was at the workplace (Gimenez-Nadal et al., 2018; Burda et al., 2020; Hamermesh et al., 2021; Darity Jr et al., 2022; Gimenez-Nadal and Sevilla, 2024). Besides, we exclude atypical diary days. In doing so, we remove holidays from the final sample, as they do not reflect the usual behavior of workers and could introduce bias in the time use estimates. Finally, using the "BACON" (blocked adaptive computationally efficient outlier nominators) method proposed by Billor et al. (2000), we exclude two observations identified as multivariate outliers at the 5% significance level. After applying these criteria, the analysis includes a total 26,751 observations/individuals, of whom 13,543 are men and 13,208 are women, from 402 counties observed during 5,758 unique diary days.

3.4. Non-work at work

From the time diary structure of the ATUS, we define the time devoted to non-work-related activities at work per day. Specifically, a critical variable derived from the time diary of the survey, apart from the main activity reported by respondents, is the place where activities are taking place. These locations encompass a range of places, with one of the possible locations being the "respondent's workplace", which allows us to analyze what exactly workers do when they are at work. In doing so, we calculate the total amount of time that workers report not working while at the workplace. This precise source of information on workplace behaviors, very rarely available in other datasets such as

[7] The definition of the "market work time" variable resembles that of Gimenez-Nadal et al. (2018) and Burda et al. (2020).

household surveys based on stylized questionnaires over normal or recalled hours *worked* per week, month or year (Barrett and Hamermesh, 2019; Burda et al., 2020), serves as the main dependent variable in our study.

Following other works which have also constructed this variable, such as those of Hamermesh (1990), Gimenez-Nadal et al. (2018), Burda et al. (2020), Hamermesh et al. (2021), Darity Jr et al. (2022), or Gimenez-Nadal and Sevilla (2024), we categorize this measure into total time spent at work not working, and time spent at the workplace not working excluding eating.[8] These variables represent the main dependent variables in the analysis and are measured in minutes per day. For further details on the activity codes included in our time use variables, we refer to Appendix Table A1.

Table 1 provides the summary statistics of the time use variables included in the analysis. On average, individuals spend 31.05 minutes per day not working at the workplace in our sample, with a standard deviation of 36.04 minutes. This figure includes workers who did not engage in non-work at the workplace on the diary day, representing approximately 31.1% of workers. Conditional on any non-work time, time allocated to non-work-related activities at work is 45.08 minutes per day. Excluding eating at work, the average time spent on other non-work-related activities at work is equal to 10.88 minutes per day, whereas those who spend any time average about 31.27 minutes. These figures align closely with previous research utilizing the same dataset, such as Gimenez-Nadal et al. (2018) and Burda et al. (2020), albeit in different time periods. Specifically, Burda et al. (2020) show that eating at work represents the most important activity of the time spent at work not working, amounting to about 54.07% of non-work time, whereas Gimenez-Nadal et al. (2018), who abstract from that specific activity code in their analysis, report an average of about 30 minutes spent on other non-work-related activities at the workplace. By comparison, market work time averages 484.81 minutes per day (approximately 8 hours).

[8] We omit activities related to socializing and eating as part of the job in the definition of time spent at work not working (Gimenez-Nadal et al., 2018, 2021; Burda et al., 2020), which can be considered as meal breaks and scheduled interruptions. Hamermesh (1990) shows that the time spent at work eating is as productive as normal work time, and that time spent on other breaks is relatively unproductive.

3.5. Socio-demographic characteristics

In addition to the core time diary survey, the ATUS also provides extensive set of information on respondents' demographic, socioeconomic, and household characteristics, some of which we incorporate as control variables into our analysis. Hence, we define a set of characteristics to control for the *observed* heterogeneity of workers in the econometric analysis. These variables encompass the following: respondents' gender, age (measured as a continuous variable in years old), maximum educational level achieved, recoded into three categories identifying individuals who have achieved primary education (the reference category in the regression analyses), secondary education, and university education, respectively, an indicator for full-time workers, another for those who live with a (married or unmarried) partner, the total number of individuals in the household, and the number of children under 18 in the household. Appendix Table A2 displays the summary statistics of these variables in our sample, whereas Tables A3 and A4 outlines the occupations classified as supervised and climate-exposed, respectively, in line with the early works of Gimenez-Nadal et al. (2018) and Graff Zivin and Neidell (2014).

4. Econometric strategy

To study the relationship between daily temperatures and time spent at work not working, we follow the standard methodology in the climate econometrics literature (Dell et al., 2014; Hsiang, 2016; Lai et al., 2023), either at the individual or aggregate level, and estimate the following equation using Ordinary Least Squares (OLS):

$$Y_i = \alpha + \sum_{\substack{k=1 \\ k\neq 11}}^{16} \beta^k \times temp_{ct}^k + \boldsymbol{weather}'_{ct}\theta + \boldsymbol{X}'_i\gamma + \tau + \xi_c + \varepsilon_{ic}, \qquad (1)$$

where the subindex $i = 1, \ldots, 26{,}751$ stands for each individual "i", $c = 1, \ldots, 402$ denotes the county "c" where the individual "i" resides, and $t = 1, \ldots, 5758$ is the diary day "t" (the day preceding the interview, which is the day to which the outcome measure of time effectively refers). The dependent variable, Y_i, is the time spent in non-work-related activities at work by individual i residing in county c on diary day t, measured in minutes per day. The variable $temp_{ct}^k$, the main explanatory variable, denotes the maximum temperature in county c on diary day t. The term $\boldsymbol{weather}_{ct}$ is a vector of other weather controls which are correlated with temperature and may also impact hours worked

(Connolly, 2008; Dell et al., 2014; Liu and Hirsch, 2021), including daily *amount* of precipitation and snowfall, as well as the average maximum temperature over the past week. This latter weather control accounts for potential local seasonal trends in maximum temperatures at the week level. $\boldsymbol{X}_i$ contains individual-level variables, including gender, age, the squared term of age, educational attainment, full-time work status, marital status, household size, number of children, and occupation and industry dummies.

Moreover, to account for temporal variations and regional idiosyncrasies, the terms τ and ξ_c represent fixed effects for day of the week, month, year, and county, respectively. The inclusion of time fixed effects τ aims to account for within-week variations (i.e., across days of the week), seasonal patterns in both time use and temperature, and broader cyclical trends in the data, as demonstrated by Burda et al. (2020), over the analysis period. To do so, we incorporate vectors of fixed effects for days of the week, months, and years, respectively. Additionally, county fixed effects ξ_c control for time-invariant regional characteristics of a respondent's location, including historical climate conditions and geography (i.e., static differences across counties). Finally, ε_{ic} represents the stochastic error term. To account for within-county correlations over time in the error term, standard errors are clustered at the county level, which is the level at which we measure temperature. Additionally, we apply survey-provided sample weights to address design features such as nonresponse rates and oversampling of specific demographic groups or days of the week. The weights ensure that each group and day of the week are correctly represented.

Our central temperature measure corresponds to the maximum temperature on the diary day, ensuring an accurate representation of temperature exposure in the daytime, which better captures the actual temperature faced by workers at the workplace, since most work is done during the day which is closer to the daily maximum temperature, and likely exerts the greatest influence on daily work patterns according to a large body of literature (Graff Zivin and Neidell, 2014; Cai et al., 2018; Dillender, 2021; Somanathan et al., 2021; Heyes and Saberian, 2022; Drescher and Janzen, 2025). Following empirical strategies in other studies examining the relationship between temperature and the labor market domain (see e.g., Graff Zivin and Neidell, 2014; Cai et al., 2018; Garg et al., 2020; Dillender, 2021; Somanathan et al., 2021; Heyes and Saberian, 2019, 2022; Ireland et al., 2023; LoPalo, 2023; Filomena and Picchio, 2024; Drescher and Janzen, 2025; among others), we allow for potentially non-linear relationships between daily maximum temperature and time spent in non-work-related activities at work through the use of "temperature bins", a semi-parametric specification defined by dummy variables at which the maximum temperature falls. This methodology stands as the workhorse for empirical studies in the climate econometrics literature (Dell et al., 2014; Hsiang, 2016; Lai et al., 2023). In total, we define sixteen bins ($k = 16$) with each bin being 5ºF wide.

Consequently, we include a flexible specification for maximum temperature that allows estimation of non-linear effects associated with different daily maximum temperatures, using sixteen five-degree temperature bins covering the full range of the daily maximum temperature distribution, with the highest (lowest) bin for days with maximum temperatures equal to or over 100ºF (below 30ºF).[9] The [75, 80) ºF bin ($k = 11$) is set as the reference bin, and is thus not included in the estimation to avoid perfect multicollinearity. Previous studies in the US (Connolly, 2013; Gaff Zivin and Neidell, 2014; Jiao et al., 2021; Belloc et al., 2025) have recognized this range as the most comfortable. Consequently, our coefficient of interest β^k associated with the temperature bin k gauges the relationship between a day on which the daily maximum temperature is in the k-th bin and time spent at the workplace but not working, relative to a day on which the maximum temperature is in the reference range [75, 80) ºF, and is identified from daily variations in temperature within a county.

5. Results

5.1. Main results

Table 2 displays the results of estimating Eq. (1). (Estimates for the remaining covariates in this specification are in Appendix Table A5.) Column (1) presents estimates for the total time spent at work not working, whereas Column (2) excludes time spent eating at the workplace. The estimates in Column (1) indicate that extreme temperatures, whether at the lower or upper ends of the distribution, are not significantly associated with the

[9] In our sample, 1.05% of individuals are exposed to extremely hot temperature days, while 3.40% experience extremely cold temperature days. Meanwhile, the modal bin [80, 85) ºF accounts for about 12.21% of the daily maximum temperatures. (These summary statistics are computed using survey demographic weights provided by the ATUS, as in Table 1.) Appendix Figure A1 presents the distribution of our temperature measure across these sixteen five-degree temperature bins in the final sample with time use information, alongside a comparison to the distribution for the same counties over the entire 2003-2019 period, mimicking Graff Zivin and Neidell (2014). Notably, these distributions closely align with those recently reported in Neidell et al. (2021) and Belloc et al. (2025) and alleviate any concern regarding the representativeness of the sample and temperature-driven selection bias.

total time spent at work not working per day. However, after removing the time spent eating at work per day, we find that extreme hot temperatures are significantly related to the amount of time spent on non-work-related activities at the workplace. Specifically, a day with a maximum temperature of 100 ºF or above, relative to a day in the comfortable range of [75, 80) ºF, is associated with 3.35 additional minutes spent in other non-work-related activities at the workplace, with this coefficient being statistically significant at the 5% level (p = 0.026). As a result, extremely hot temperature days are related to a higher amount of time spent at work not working. In addition, in terms of magnitude, our estimate suggests a quite substantial increase in time spent on non-work-related activities at the workplace, with this figure rising by an average of 30.76% of the sample mean on such extreme hot temperature days.

Table 3 provides estimates disaggregated by gender for the total time spent in non-work-related activities at the workplace, excluding time spent eating at work, to account for potential gender differences in time allocation decisions (Aguiar and Hurst, 2007; Gimenez-Nadal and Sevilla, 2012). The gender-specific estimates reveal notable gender differences in the previous estimated relationships and align with prior research documenting distinct weather-labor supply relationships by gender (Connolly, 2008; Garg et al., 2020; Jiao et al., 2021; Heyes and Saberian, 2022), with evidence suggesting that women's labor supply outcomes, rather than men's, are more sensitive to extreme heat (Garg et al., 2020; Jiao et al., 2021; Heyes and Saberian, 2022).

Specifically, we find a positive and statistically significant association between extremely hot days, defined as those with maximum temperatures of 100 ºF or above, and non-work time at work among female workers. This relationship is statistically significant at the 5% level (p = 0.032). In contrast, no significant relationship is observed for male workers (p = 0.400). Quantitatively, a day with a maximum temperature of 100 ºF or above corresponds to an additional 4.34 minutes spent at work not working among women, compared to a day within the comfortable temperature range of [75, 80) ºF.

Since much of the existing literature focuses on work hours and productivity, we can compare our results with established estimates. This comparison helps contextualize the magnitude of our findings. Our results suggest potential productivity losses linked to global warming, particularly among women workers. This finding is qualitatively consistent with prior research indicating that, compared to men's labor supply, women's labor supply is more responsive to high temperatures across different geographic settings

(Garg et al., 2020; Jiao et al., 2021; Heyes and Saberian, 2022). However, in terms of magnitude, our estimate suggests a quite substantial increase in daily time spent in non-work-related activities at the workplace in response to extreme hot temperatures, with this figure rising by an average of 30.76% of the sample mean on such days. This effect size is larger than previous estimates for other labor supply adjustments, such as labor supply reductions (Graff Zivin and Neidell, 2014; Garg et al., 2020), which report average declines, in absolute terms, ranging from 3% (Garg et al., 2020) to 12.83% (Graff Zivin and Neidell, 2014) in occupations with climate exposure, or absenteeism (Heyes and Saberian, 2022; Ireland et al., 2024), which increases by an average ranging from 5.1% (Ireland et al., 2024) to 7.3% (Heyes and Saberian, 2022) in distinct geographical settings.

5.1.1. Robustness checks

We perform a set of sensitivity checks to test the robustness of our main estimates concerning time spent at work not working, excluding eating at work, for the pooled sample and gender sub-sample. First, the literature employs various temperature bins as reference categories. In Tables 2 and 3, we use the [75, 80) ºF as the reference bin. Alternatively, to test the sensitivity of our main estimates to this choice, we also use the [65, 70) ºF or [70, 75) ºF maximum temperature ranges as reference bins, both recognized as optimal for human thermal comfort (Fesselmeyer, 2021; Heyes and Saberian, 2022; Picchio and van Ours, 2024). The results, presented in Appendix Table A6, yield similar outcomes. As part of our sample selection criteria, we excluded a large proportion of respondents residing outside metropolitan areas or for whom county-level data were unavailable. Nevertheless, assigning weather data based on the most populous county in each state for respondents whose state of residence is known but not their specific MSA or county does not substantially affect our estimates, as shown in Appendix Table A7.

Given that our dependent variable contains many zero values, we alternatively estimate Eq. (1) using a Poisson estimator (Silva and Tenreyro, 2006; Correia et al., 2020; Garg et al., 2020; Heyes and Saberian, 2022), an alternative, non-linear, econometric model recommended by Chen and Roth (2024) and Mullahy and Norton (2024) for non-negative outcomes with a substantial proportion of zero values. For instance, an average of 31.13-65.21% of respondents in our sample report no time spent at work not working on the diary day. Coefficient estimates for the daily temperature dummy variables, reported in Appendix Table A8, indicate that a day with a maximum temperature exceeding 100 ºF is associated with a 34.312% increase in time spent in non-work-related activities at work, compared to a day with a maximum temperature in the [75, 80) ºF range. This elasticity is derived from the transformation exp(0.295) = 1.343. Therefore, the results are qualitatively robust and these estimates offer additional validity to our main results, which rely on linear regression models.

The ATUS provides information on 22 occupation and 51 industry intermediate codes based on the four-digit Census classifications. Following Burda et al. (2020), we re-estimate Eq. (1) using the most detailed occupation and industry categories available in the ATUS (i.e., 535 occupation and 271 industry categories) and obtain robust results. These results are available in Appendix Table A9. We additionally exclude the approximately one-sixth of the respondents who are public workers, and find that our results are primarily driven by female private-sector workers in Appendix Table A10. This finding is consistent with Burda et al. (2020), who document that the non-work time at work among private-sector workers is more elastic. Alternatively, deleting those part-time workers who have a weaker attachment to the labor market translate into larger coefficient estimates in Appendix Table A11.

We also exclude respondents' characteristics from the estimates, to avoid the over-controlling problem (Dell et al., 2014), and find largely similar results in Appendix Table A12. These findings indicate that the main model results accurately capture the true effects of temperature on our proxy of worker effort, and that our estimates are not compromised by issues of bad control that could otherwise bias the results. Besides, we run our main specification including local macroeconomic variables, such as the monthly unemployment rate by state (seasonally adjusted) from the BLS Local Area Unemployment Statistics (Burda et al., 2020), and the results in Appendix Table A13 are quantitatively similar. By definition, time spent at work not working depends on the total time spent working. Although we control for the full-time status of workers in our main estimates, we go beyond this and also include a control for the usual hours worked per week. The results, reported in Appendix Table A14, are robust.

The main results include continuous measures in inches per day for precipitation and snowfall. However, the findings remain similar when controlling non-linearly for these factors in Appendix Table A15 and incorporating specific categories aligning with previous research in the US (Connolly, 2013; Dillender, 2021; Liu and Hirsch, 2021; Belloc et al., 2025). This suggests that precipitation and snowfall do not capture any influence of daily temperature on our time use measures. Incorporating the daily-county level air quality index (AQI) data from the Environmental Protection Agency does not materially alter our estimates, as shown in Appendix Table A16. In this context, air pollution has been found to correlate with daily temperature and adversely affect workers' productivity (Lichter et al., 2017; Chang et al., 2019; Hoffmann and Rud, 2024).

Finally, we employ a continuous linear spline function to model maximum temperature, employing either two knots at 70 and 90 ºF, as suggested by Neidell et al. (2021), or five knots selected at the 20th (49 ºF), 40th (64 ºF), 60th (76 ºF), and 80th (85 ºF) percentiles of maximum temperature, following Fesselmeyer (2021). The results, dividing our temperature measure into either three or five bins, corroborate the earlier finding of a non-linear relationship between temperature and workers' effort. Moreover, extremely hot days are consistently associated with increased non-work time at the workplace, irrespective of the specific temperature threshold used to define such days. For additional details, we refer to Appendix Tables A17 and A18.[10]

5.2. Level of supervision

We now estimate Eq. (1), focusing exclusively on the sample of women,[11] and stratify the analysis by the level of supervision of the occupation. This approach allows us to examine whether the observed relationship between extremely hot days and increased time spent at work not working among women varies depending on the level of supervision in their occupations. Following previous research (Ross and Zenou, 2008; Gimenez-Nadal et al., 2018), we estimate Eq. (1) for women workers employed in supervised and non-supervised occupations.

The results, presented in Table 4, reveal that the relationship between daily temperatures and non-work time differs significantly according to the level of supervision of workers. Specifically, the earlier findings appear to be driven by women in non-

[10] We also investigate additional outcomes, including total time spent on market work activities, regardless of whether it is performed at the workplace or elsewhere, and find no significant effects of extreme heat days. These results align with previous evidence (Connolly, 2008; Graff Zivin and Neidell, 2014; Dillender, 2021; Cosaert et al., 2025b), which suggests that time allocated to labor is largely unresponsive to temperature variation. Likewise, we identify no statistically significant effects on the proportion of time spent not working while present at the workplace, nor on the probability of engaging in time spent at work not working (Burda et al., 2020; Hamermesh et al., 2021).

[11] All heterogeneity analyses presented hereafter show no significant effects among men workers (see Appendix Figures A2-A5). Additionally, we find no heterogeneity effects by educational attainment or age. These results are available upon request.

supervised occupations. For this subgroup, we find that a day with a maximum temperature equal to or above 100 ºF is associated with an increase of 6.79 minutes in the daily time spent in non-work-related activities at work, compared to a day with temperatures in the [75, 80) ºF range. In contrast, no significant relationship is observed for women in supervised occupations. In summary, the relationship between extreme hot temperatures and time spent at work in non-work-related activities depends on the level of supervision of workers, with the overall estimates being concentrated among women in non-supervised occupations.

5.3. Economic conditions

Table 5 presents estimates of Eq. (1) for women, disaggregating the analysis by business cycle periods. Our sample covers a seventeen-year period from 2003 through 2019, a time period which combines both macroeconomic expansions and recessions. To the extent that labor supply adjustments are affected by such macroeconomic circumstances (Boone and van Ours, 2006; Boone et al., 2011; Lazear et al., 2016; Senney and Dunn, 2019; Burda et al., 2020; Neidell et al., 2021), we examine whether the relationship between temperature and our measure of work effort varies across economic periods. The rationale is that during periods of economic growth, workers are likely to have more and better outside job opportunities, which can enhance their bargaining power and potentially influence their work effort under less comfortable environmental conditions, such as extremely hot days. In contrast, workers may have worse outside options in economic recessions, meaning that they are less likely to reduce their effort at work due to reduced chances of finding a new job elsewhere if fired. As a result, in times of economic downturn workers do not adjust their effort at work.

To investigate this, we divide the ATUS 2003-2019 sample into two periods: economic expansions (2003-2007, 2015-2019) and recessions (2008-2014). This classification aligns with prior studies employing similar timelines (Neidell et al., 2021). The results, shown in Table 5, support the proposed hypothesis. Specifically, during periods of economic expansion, women spend an additional 7.025 minutes engaged in non-working activities while at the workplace on extremely hot days, compared to days with milder temperature days. Conversely, no significant relationship is observed on such temperature days during periods of economic recession.

As an alternative approach to dating US business cycles, we utilize the Business Cycle Dating developed by the National Bureau of Economic Research (NBER) (https://www.nber.org/research/business-cycle-dating, accessed January 2025), following a methodology similar to Lazear et al. (2016) and Burda et al. (2020). This approach allows us to identify the most severe months of the Great Recession, specifically defined by the NBER as spanning from December 2007 to June 2009 (inclusive). The results for this alternative classification, presented in Appendix Table A19, are consistent with our main findings. Specifically, women increase their time spent at the workplace in non-work-related activities by 4.63 minutes on days with maximum temperatures of 100 ºF or above, compared to days with maximum temperatures in the [75, 80) ºF range.

5.4. Parental status

The presence of children in the household may influence women's work effort by imposing additional time constraints. To explore potential heterogeneity, we alternatively estimate Eq. (1) separately for women with and without children, focusing on time spent at work but not working, and excluding time spent eating at work. The results, presented in Table 6, suggest that extremely hot days are associated with a significant increase in non-work-related time at work among women without children. Specifically, these women spend an additional 9.306 minutes on non-work-related activities at work during extremely hot days, compared to days with comfortable temperatures in the [75, 80) ºF range.

The finding that extremely high temperatures increase time spent not working at work among women without children can be interpreted in light of the tighter time constraints and higher opportunity costs likely faced by women with children. Specifically, their caregiving and financial responsibilities may limit their flexibility to adjust work effort in response to adverse environmental conditions. As a result, mothers may be more likely to maintain productivity at work despite extreme heat. Additionally, workplace norms and expectations may differ by parental status. Mothers could be subject to closer supervision or feel greater pressure to demonstrate commitment to work and counteract statistical discrimination.

5.5. Long-run and short-run adaptation to high temperatures

We examine the role of adaptative behavior by analyzing whether the estimates reported in Table 3 vary across historical climate regions. To examine regional variation, we classify the sample of counties into colder and warmer areas based on the historical distribution of maximum summer temperatures (July-August) from 2003 to 2019. We define warmer counties as those with an average maximum temperature during July-August exceeding the sample-wide average of 86.18 ºF. Conversely, counties with average maximum temperatures at or below this threshold are classified as colder counties (Belloc et al., 2025; Cosaert et al., 2025a, 2025b).[12]

The motivation for this analysis is that workers in warmer counties are more likely to have been historically exposed to high temperatures and, as a result, may be better equipped to cope with such common weather events. This adaptation may occur through psychological mechanisms or investments in technologies such as air conditioning to mitigate heat exposure. We divide the sample into warm and cold counties and present the results for women workers in Table 7.

The findings suggest that extreme hot temperatures significantly increase time spent at work not working among workers residing in cold counties ($p < 0.10$). Specifically, days with maximum temperatures at the upper end of the distribution are associated with an additional 25.928 minutes spent in non-work-related activities at work per day among women in cold counties ($p = 0.080$), a substantial effect relative to a day within the comfortable temperature range. These results support the adaptation and acclimation hypotheses, indicating that non-work time responds to extreme heat primarily among women workers in colder regions, who may lack the same level of preparedness to such conditions compared to their counterparts in warmer areas.

The results remain robust when applying alternative cut-off points, such as the median of maximum temperature among the included counties during July-August (Alberto et

[12] Colder and warmer areas are defined based on the full set of counties included in the final sample during the observation period from 2003 to 2019 (i.e., the distribution of daily maximum temperatures for the counties included in the analysis over the entire observation period). Colder places predominantly consist of counties in the Northeast and Midwest, and warmer places of counties in the South and West, consistent with Graff Zivin and Neidell (2014) and Jiao et al. (2021). We focus on the summer months, as extreme hot temperature days are predominantly concentrated within this period. Similar results hold when defining summer as the period from June to September.

al., 2021; Dillender, 2021; Bigler and Janzen, 2024; Drescher and Janzen, 2025), which corresponds to 85.55 ºF, and are displayed in Appendix Table A20.

6. Conclusions

This paper analyzes the relationship between daily temperatures and effort at work. To do so, we analyze the time spent at work not working using time diary data from the ATUS over 2003-2019, combined with weather information from over 23,000 weather stations spread across the United States. Our findings reveal that extreme hot temperature days, defined as those with maximum temperatures equal to or above 100 ºF, are associated with a significant increase in time spent at work in non-work-related activities, particularly among women in non-supervised occupations. Specifically, women in non-supervised occupations spend an additional 6.79 minutes at work not working on extremely hot days compared to days with comfortable temperatures.

One potential explanation for the observed gendered response is that non-supervised jobs afford greater flexibility, enabling women to reallocate their effort in response to thermal discomfort. Another possibility is that social norms around workplace behavior differ by gender, affecting how men and women adapt to heat stress. Future research could investigate whether managerial expectations, peer monitoring, or occupational norms mediate these effects. Additionally, further analysis of job flexibility is needed to ascertain whether women in such roles have greater autonomy to regulate work intensity under extreme temperatures.

While these results provide valuable insights into the climate-economy-welfare connection, they should be interpreted within the context of certain limitations. The ATUS collects a single time use diary per respondent, as each individual participates in the survey only once. Consequently, the data are drawn from repeated cross-sectional surveys and we cannot implement more sophisticated econometric strategies that would allow to rule out any unobserved individual heterogeneity that may impact our estimates. Future research would benefit from the availability of longitudinal data; however, such datasets containing information comparable to the ATUS are currently *unavailable*. Additionally, the growing prevalence of flexible work arrangements, such as remote and hybrid work, has affected people's time allocation and may alter our findings. An elevated number of respondents may consider their home as their workplace from 2020 onwards, warranting further investigation in a different context. Finally, we note that non-work time at the workplace does not necessarily imply lower output.

Despite these limitations, our study addresses a critical question. While our dataset does not allow us to directly analyze individual productivity, the literature on worker productivity has shown that interruptions and multitasking are important for explaining performance and output at work (Coviello et al., 2015; Adams et al., 2025). As climate change accelerates, the frequency of extreme heat is expected to increase, thereby amplifying the potential for heat-induced productivity losses. Unlike previous research, which has primarily focused on the relationship between temperature and primary labor market adjustments such as working hours or absenteeism, our findings shed light on a distinct productivity channel related to effort at work or task avoidance during work hours, providing important implications.

Given that weather patterns are largely beyond human control, both employers and policymakers should adopt targeted adaptive strategies to mitigate potential performance losses associated with extreme heat and to better protect workers in the face of heat. Employers aiming to enhance productivity could implement flexible work schedules that allow shifting work hours to cooler periods of the day, or offer remote work options to minimize workers' exposure to high temperatures and avoid task avoidance at work. Moreover, investing in workplace climate control systems, such as air conditioning technologies that improve ventilation, can help create more resilient work environments and sustain productivity during periods of extreme heat, particularly in colder regions that may lack sufficient heat management infrastructure. Finally, enhanced supervision mechanisms, including real-time monitoring or performance-based incentives, could help minimize output losses.

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Table 1. Summary statistics

	Mean	SD
Time use variables		
Total time spent at work not working	31.051	36.040
- % equal to 0	31.128	46.303
- Conditional on any time	45.085	35.401
Time spent at work not working, excluding eating at work	10.879	25.153
- % equal to 0	65.209	47.632
- Conditional on any time	31.270	34.364
Market work time	484.811	134.836
Observations	**26,751**	

Notes: This table reports the summary statistics. Data come from the ATUS 2003-2019. Sample is restricted to employees aged 21-65 on working days. Time use variables are measured in minutes per day. Summary statistics are weighted using ATUS weights.

Table 2. Relationship between daily temperature and time spent at work not working

	(1)	(2)
	Total	Non-work not eating
< 30 ºF	-1.852	-0.503
	(2.247)	(1.499)
[30, 35) ºF	-0.882	-0.034
	(2.353)	(1.677)
[35, 40) ºF	-2.592	-1.140
	(2.257)	(1.328)
[40, 45) ºF	-0.992	0.299
	(2.084)	(1.244)
[45, 50) ºF	-1.192	1.285
	(1.763)	(1.200)
[50, 55) ºF	1.643	2.656*
	(1.987)	(1.404)
[55, 60) ºF	-1.254	0.176
	(1.433)	(0.831)
[60, 65) ºF	0.598	1.154
	(1.369)	(0.833)
[65, 70) ºF	-0.631	-0.100
	(1.332)	(0.851)
[70, 75) ºF	-0.343	0.368
	(1.624)	(1.161)
[80, 85) ºF	-1.219	-0.068
	(1.063)	(0.733)
[85, 90) ºF	-0.623	0.461
	(1.401)	(0.876)
[90, 95) ºF	2.369	1.606
	(1.658)	(1.004)
[95, 100) ºF	1.574	4.017
	(3.107)	(2.484)
≥ 100 ºF	-0.178	3.347**
	(2.146)	(1.495)
Individual controls	✓	✓
Other weather variables	✓	✓
Occupation F.E.	✓	✓
Industry F.E.	✓	✓
Day of the week F.E.	✓	✓
Month F.E.	✓	✓
Year F.E.	✓	✓
County F.E.	✓	✓
Observations	26,751	26,751
R-squared	0.086	0.059

Notes: This table reports the OLS estimates. Data come from the ATUS 2003-2019. Sample is restricted to employees aged 21-65 on working days. All estimates include a constant. Dependent variables are measured in minutes per day. The reference temperature bin is [75, 80) ºF, which is omitted to avoid perfect multicollinearity issues in the regressions. Individual controls include gender (in Column (1)), age (and its square), educational attainment (secondary and university education), full-time status, living in couple, household size and number of children, whereas weather variables denote daily amount of precipitation, snowfall and weekly average maximum temperature. Estimates are weighted using ATUS weights. Standard errors, clustered at the county level, are reported in parentheses. ***Significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

Table 3. Relationship between daily temperature and time spent at work not working (excluding eating), by gender

	(1)	(2)
	Men	Women
< 30 ºF	1.299	-2.469
	(2.314)	(2.318)
[30, 35) ºF	2.312	-2.285
	(2.810)	(2.081)
[35, 40) ºF	0.136	-2.624
	(2.427)	(1.817)
[40, 45) ºF	3.785*	-3.939**
	(2.030)	(1.814)
[45, 50) ºF	2.932*	-0.515
	(1.599)	(2.328)
[50, 55) ºF	5.025**	-0.012
	(2.232)	(1.751)
[55, 60) ºF	1.765	-1.680
	(1.250)	(1.677)
[60, 65) ºF	3.442**	-0.961
	(1.433)	(1.667)
[65, 70) ºF	1.101	-1.503
	(1.289)	(1.622)
[70, 75) ºF	1.196	-0.628
	(1.231)	(1.644)
[80, 85) ºF	1.687*	-1.794
	(0.963)	(1.327)
[85, 90) ºF	1.051	-0.427
	(1.079)	(1.525)
[90, 95) ºF	3.025**	0.343
	(1.523)	(1.480)
[95, 100) ºF	2.215	6.699
	(2.230)	(4.975)
≥ 100 ºF	1.760	4.342**
	(2.089)	(2.020)
Individual controls	✓	✓
Other weather variables	✓	✓
Occupation F.E.	✓	✓
Industry F.E.	✓	✓
Day of the week F.E.	✓	✓
Month F.E.	✓	✓
Year F.E.	✓	✓
County F.E.	✓	✓
Observations	13,543	13,208
R-squared	0.098	0.076
Mean of Y	11.421	10.238

Notes: This table reports the OLS estimates. Data come from the ATUS 2003-2019. Sample is restricted to employees aged 21-65 on working days. All estimates include a constant. Dependent variables are measured in minutes per day. The reference temperature bin is [75, 80) ºF, which is omitted to avoid perfect multicollinearity issues in the regressions. Individual controls include age (and its square), educational attainment (secondary and university education), full-time status, living in couple, household size and number of children, whereas weather variables denote daily amount of precipitation, snowfall and weekly average maximum temperature. Estimates are weighted using ATUS weights. Standard errors, clustered at the county level, are reported in parentheses. ***Significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

Table 4. Relationship between daily temperatures and time spent at work not working, by level of supervision (women)

	(1)	(2)
	Supervised	Non-supervised
< 30 ºF	4.274	-3.489
	(3.988)	(2.844)
[30, 35) ºF	2.130	-1.861
	(3.911)	(2.561)
[35, 40) ºF	2.401	-2.949
	(3.948)	(2.331)
[40, 45) ºF	-1.441	-3.905*
	(3.675)	(2.000)
[45, 50) ºF	8.109	-2.511
	(6.829)	(1.924)
[50, 55) ºF	4.020	-0.771
	(3.311)	(1.954)
[55, 60) ºF	2.380	-2.558
	(2.592)	(1.911)
[60, 65) ºF	-2.870	0.282
	(2.404)	(1.887)
[65, 70) ºF	0.518	-1.458
	(2.416)	(1.709)
[70, 75) ºF	0.762	-0.928
	(3.890)	(1.378)
[80, 85) ºF	-3.802	-0.747
	(2.357)	(1.570)
[85, 90) ºF	-2.983	0.662
	(2.641)	(1.950)
[90, 95) ºF	-1.591	0.960
	(3.537)	(1.751)
[95, 100) ºF	-3.409	10.832
	(3.587)	(7.500)
≥ 100 ºF	-2.923	6.791**
	(5.317)	(2.754)
Individual controls	✓	✓
Other weather variables	✓	✓
Occupation F.E.	✓	✓
Industry F.E.	✓	✓
Day of the week F.E.	✓	✓
Month F.E.	✓	✓
Year F.E.	✓	✓
County F.E.	✓	✓
Observations	3,561	9,647
R-squared	0.212	0.086
Mean of Y	12.812	9.242

Notes: This table reports the OLS estimates. Data come from the ATUS 2003-2019. Sample is restricted to *women* employees aged 21-65 on working days. All estimates include a constant. Dependent variables are measured in minutes per day. The reference temperature bin is [75, 80) ºF, which is omitted to avoid perfect multicollinearity issues in the regressions. Individual controls include age (and its square), educational attainment (secondary and university education), full-time status, living in couple, household size and number of children, whereas weather variables denote daily amount of precipitation, snowfall and weekly average maximum temperature. Estimates are weighted using ATUS weights. Standard errors, clustered at the county level, are reported in parentheses. ***Significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

Table 5. Relationship between daily temperatures and time spent at work not working, by business economic cycle (women)

	(1)	(2)
	Expansion	Recession
< 30 ºF	-3.485	-1.484
	(3.194)	(3.318)
[30, 35) ºF	-1.483	-1.862
	(2.871)	(3.478)
[35, 40) ºF	-1.600	-3.878
	(2.487)	(2.726)
[40, 45) ºF	-3.937	-3.121
	(2.932)	(2.555)
[45, 50) ºF	1.378	-3.428
	(3.418)	(2.465)
[50, 55) ºF	2.442	-2.976
	(2.642)	(2.547)
[55, 60) ºF	-0.169	-3.148*
	(2.397)	(1.875)
[60, 65) ºF	1.358	-4.077**
	(2.538)	(1.788)
[65, 70) ºF	-0.242	-3.047
	(2.309)	(2.063)
[70, 75) ºF	0.032	-1.538
	(1.724)	(2.553)
[80, 85) ºF	-0.135	-3.569**
	(1.829)	(1.693)
[85, 90) ºF	2.147	-3.843*
	(2.009)	(2.035)
[90, 95) ºF	2.387	-2.264
	(2.014)	(2.125)
[95, 100) ºF	5.708*	8.421
	(3.092)	(11.469)
≥ 100 ºF	7.025**	2.309
	(3.400)	(4.061)
Individual controls	✓	✓
Other weather variables	✓	✓
Occupation F.E.	✓	✓
Industry F.E.	✓	✓
Day of the week F.E.	✓	✓
Month F.E.	✓	✓
Year F.E.	✓	✓
County F.E.	✓	✓
Observations	7,634	5,574
R-squared	0.118	0.133
Mean of Y	10.290	10.165

Notes: This table reports the OLS estimates. Data come from the ATUS 2003-2019. Sample is restricted to *women* employees aged 21-65 on working days. All estimates include a constant. Dependent variables are measured in minutes per day. The reference temperature bin is [75, 80) ºF, which is omitted to avoid perfect multicollinearity issues in the regressions. Individual controls include age (and its square), educational attainment (secondary and university education), full-time status, living in couple, household size and number of children, whereas weather variables denote daily amount of precipitation, snowfall and weekly average maximum temperature. Estimates are weighted using ATUS weights. Standard errors, clustered at the county level, are reported in parentheses. ***Significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

Table 6. Relationship between daily temperatures and time spent at work not working, by parental status (women)

	(1)	(2)
	Women with children	Women without children
< 30 ºF	1.828	-5.126
	(2.114)	(3.836)
[30, 35) ºF	1.509	-4.887
	(2.380)	(3.242)
[35, 40) ºF	2.769	-5.722*
	(1.744)	(3.177)
[40, 45) ºF	-0.140	-5.460*
	(1.872)	(2.895)
[45, 50) ºF	3.677	-3.282
	(2.230)	(3.373)
[50, 55) ºF	3.302**	-3.050
	(1.630)	(2.717)
[55, 60) ºF	-0.093	-3.147
	(1.355)	(2.735)
[60, 65) ºF	2.172	-3.390
	(1.383)	(2.667)
[65, 70) ºF	1.011	-2.835
	(1.653)	(2.383)
[70, 75) ºF	1.026	-2.600
	(1.770)	(2.088)
[80, 85) ºF	-0.075	-3.018
	(1.440)	(2.037)
[85, 90) ºF	-0.446	-0.734
	(1.422)	(2.291)
[90, 95) ºF	1.568	-1.296
	(1.899)	(2.314)
[95, 100) ºF	3.440	9.556
	(2.378)	(9.080)
≥ 100 ºF	-2.359	9.306***
	(2.374)	(2.815)
Individual controls	✓	✓
Other weather variables	✓	✓
Occupation F.E.	✓	✓
Industry F.E.	✓	✓
Day of the week F.E.	✓	✓
Month F.E.	✓	✓
Year F.E.	✓	✓
County F.E.	✓	✓
Observations	6,769	6,439
R-squared	0.123	0.126
Mean of Y	9.711	10.614

Notes: This table reports the OLS estimates. Data come from the ATUS 2003-2019. Sample is restricted to *women* employees aged 21-65 on working days. Dependent variables are measured in minutes per day. The reference temperature bin is [75, 80) ºF, which is omitted to avoid perfect multicollinearity issues in the regressions. Individual controls include age (and its square), educational attainment (secondary and university education), full-time status, living in couple, household size and number of children, whereas weather variables denote daily amount of precipitation, snowfall and weekly average maximum temperature. Estimates are weighted using ATUS weights. Standard errors, clustered at the county level, are reported in parentheses. ***Significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

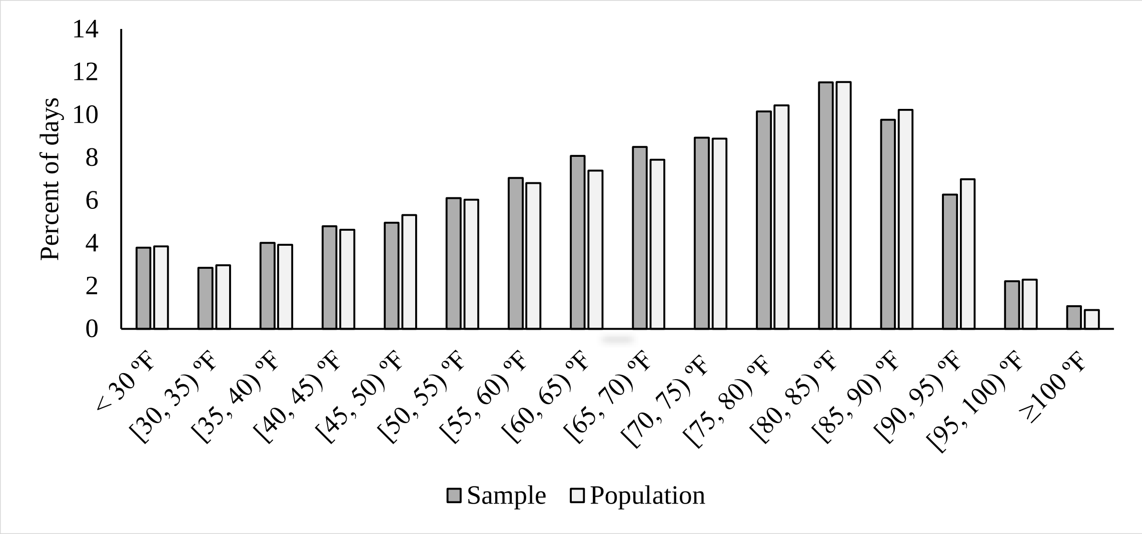
Table 7. Relationship between daily temperatures and time spent at work not working, by historical climatic regions (women)

	(1)	(2)
	Cold counties	Warm counties
< 30 ºF	-2.659	-1.032
	(3.206)	(5.136)
[30, 35) ºF	-2.543	1.864
	(2.883)	(5.429)
[35, 40) ºF	-2.764	-0.624
	(2.531)	(3.823)
[40, 45) ºF	-3.588	-5.183*
	(2.516)	(2.966)
[45, 50) ºF	-1.099	0.930
	(3.215)	(3.749)
[50, 55) ºF	-0.347	0.572
	(2.483)	(2.962)
[55, 60) ºF	-1.114	-2.691
	(2.684)	(1.856)
[60, 65) ºF	-1.511	0.269
	(2.684)	(2.215)
[65, 70) ºF	-2.348	0.203
	(2.637)	(2.052)
[70, 75) ºF	-3.632*	3.354
	(2.004)	(2.292)
[80, 85) ºF	-2.196	-0.525
	(2.091)	(1.583)
[85, 90) ºF	0.928	-0.395
	(2.935)	(1.786)
[90, 95) ºF	1.111	0.529
	(2.084)	(2.200)
[95, 100) ºF	4.806	6.766
	(5.042)	(5.786)
≥ 100 ºF	25.928*	3.714
	(14.737)	(2.793)
Individual controls	✓	✓
Other weather variables	✓	✓
Occupation F.E.	✓	✓
Industry F.E.	✓	✓
Day of the week F.E.	✓	✓
Month F.E.	✓	✓
Year F.E.	✓	✓
County F.E.	✓	✓
Observations	7,318	5,890
R-squared	0.100	0.079
Mean of Y	9.813	10.784

Notes: This table reports the OLS estimates. Data come from the ATUS 2003-2019. Sample is restricted to *women* employees aged 21-65 on working days. Dependent variables are measured in minutes per day. The reference temperature bin is [75, 80) ºF, which is omitted to avoid perfect multicollinearity issues in the regressions. Individual controls include age (and its square), educational attainment (secondary and university education), full-time status, living in couple, household size and number of children, whereas weather variables denote daily amount of precipitation, snowfall and weekly average maximum temperature. Estimates are weighted using ATUS weights. Standard errors, clustered at the county level, are reported in parentheses. ***Significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

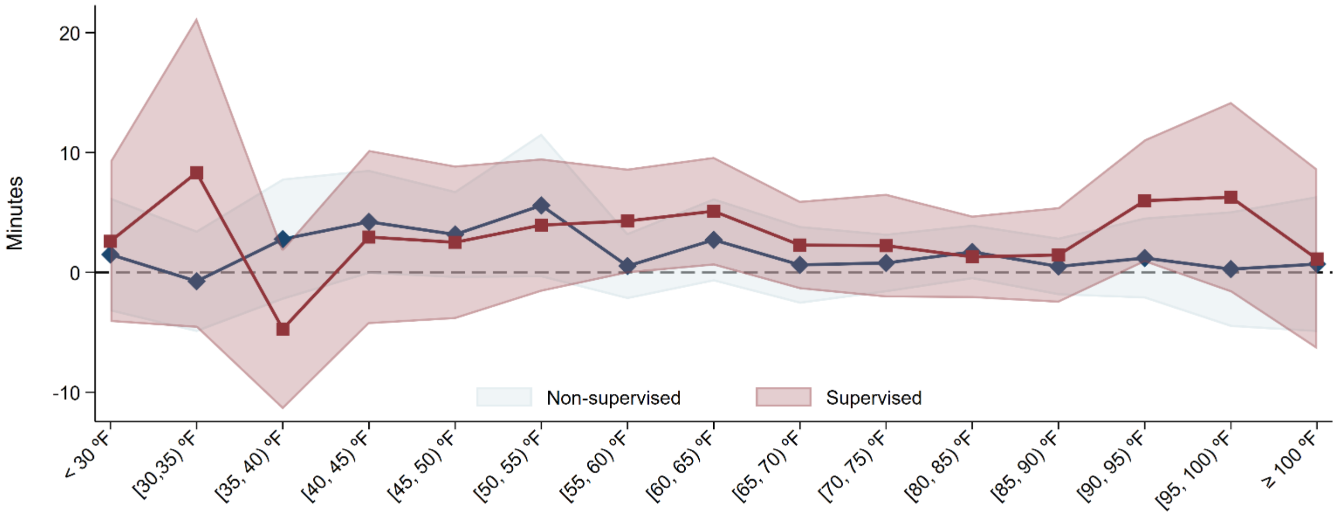
APPENDIX

Figure A.1. Distribution of daily maximum temperature, 2003-2019



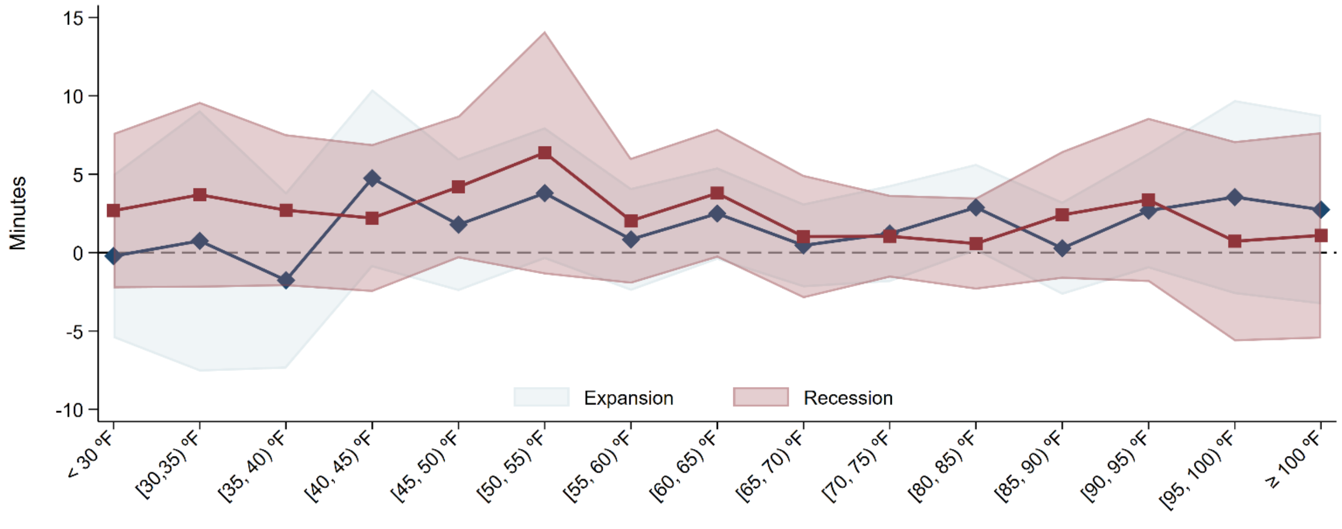
Notes: Authors' own elaboration. This figure presents the average percent of days into sixteen five-degree maximum temperature bins in the 2003-2019 period. 'Sample' denotes the distribution of maximum temperatures in the subset of counties for which diary days are available, while 'Population' represents the distribution of maximum temperatures for the same counties included in the sample, regardless of the availability of time use data. Data source for temperature: National Climatic Data Center (NCDC) of the National Oceanic and Atmospheric Administration (NOAA).

Figure A2. Relationship between daily temperature and time spent at work not working by level of supervision, males



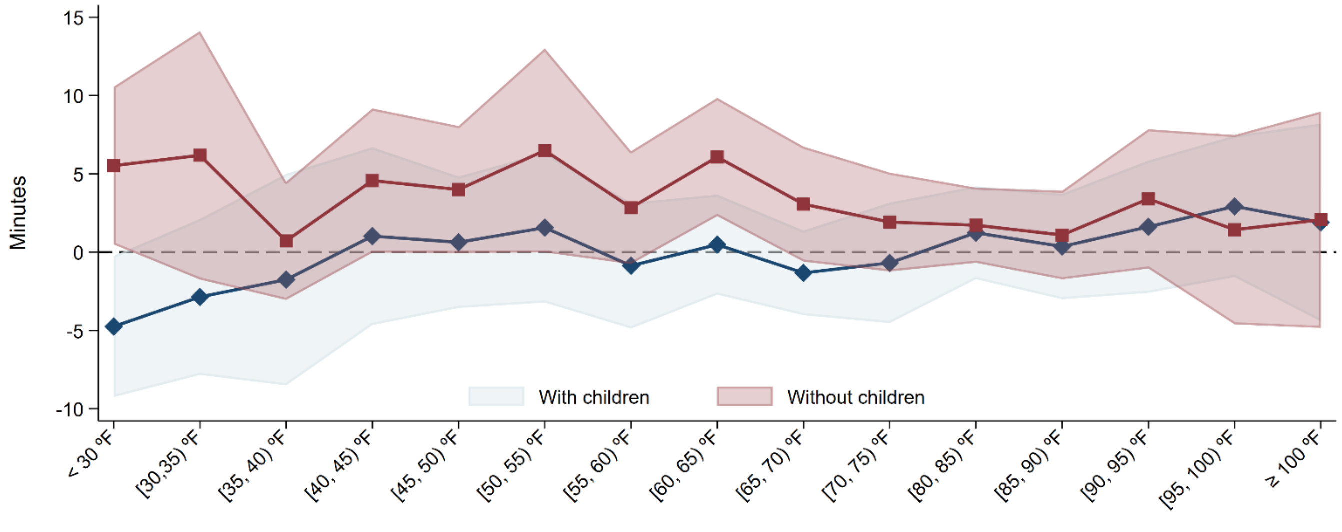
Notes: Authors' own elaboration. This figure reports the OLS estimates on fifteen five-degree maximum temperature bins on time spent at work not working per day, among males. All regressions include the same set of controls and fixed effects as the baseline regression. Data come from the ATUS 2003-2019. Sample is restricted to employees aged 21-65 on working days. Estimates are weighted using ATUS weights. The reference temperature bin is [75, 80) ºF. The shaded areas represent pairwise 95% confidence intervals based on standard errors clustered at the state-month level. Standard errors and point estimates are available upon request.

Figure A3. Relationship between daily temperature and time spent at work not working by business economic cycle, males



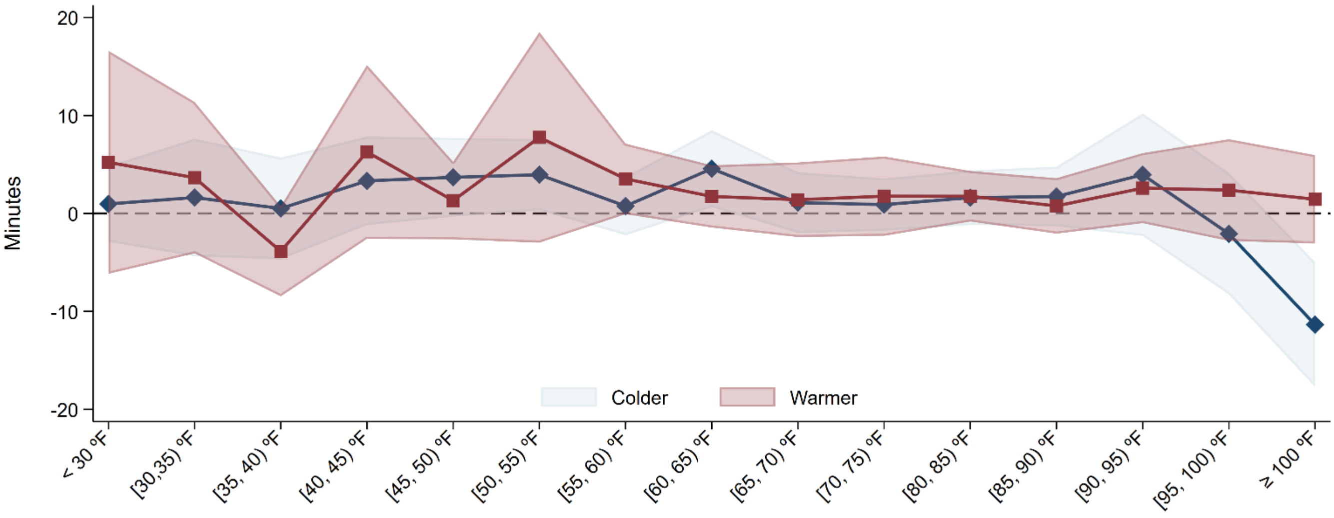
Notes: Authors' own elaboration. This figure reports the OLS estimates on fifteen five-degree maximum temperature bins on time spent at work not working per day, among males. All regressions include the same set of controls and fixed effects as the baseline regression. Data come from the ATUS 2003-2019. Sample is restricted to employees aged 21-65 on working days. Estimates are weighted using ATUS weights. The reference temperature bin is [75, 80) ºF. The shaded areas represent pairwise 95% confidence intervals based on standard errors clustered at the state-month level. Standard errors and point estimates are available upon request.

Figure A4. Relationship between daily temperature and time spent at work not working by parental status, males



Notes: Authors' own elaboration. This figure reports the OLS estimates on fifteen five-degree maximum temperature bins on time spent at work not working per day, among males. All regressions include the same set of controls and fixed effects as the baseline regression. Data come from the ATUS 2003-2019. Sample is restricted to employees aged 21-65 on working days. Estimates are weighted using ATUS weights. The reference temperature bin is [75, 80) ºF. The shaded areas represent pairwise 95% confidence intervals based on standard errors clustered at the state-month level. Standard errors and point estimates are available upon request.

Figure A5. Relationship between daily temperature and time spent at work not working by historical climatic regions, males



Notes: Authors' own elaboration. This figure reports the OLS estimates on fifteen five-degree maximum temperature bins on time spent at work not working per day, among males. All regressions include the same set of controls and fixed effects as the baseline regression. Data come from the ATUS 2003-2019. Sample is restricted to employees aged 21-65 on working days. Estimates are weighted using ATUS weights. The reference temperature bin is [75, 80) ºF. The shaded areas represent pairwise 95% confidence intervals based on standard errors clustered at the state-month level. Standard errors and point estimates are available upon request.

Table A.1. List of activity codes included

Time use variables	Activity codes
Non-work	Health-related self care (103XX), Personal emergencies (10501), Personal care, n.e.c. (19999), Interior cleaning (20101), Laundry (20102), Sewing, repairing, and maintaining textiles (20103), Storing interior household items, including food (20104), Food and drink preparation (20201), Food presentation (20202), Kitchen and food clean-up (20203), Interior arrangement, decoration, and repairs (20301), Building and repairing furniture (20302), Heating and cooling (20303), Exterior maintenance, repair, and decoration (204XX), Lawn, garden, and houseplant care (20501), Care for animals and pets (not veterinary care) (2003-2007) (20601), Care for animals and pets (not veterinary care) (2008+) (20602), Walking, exercising, playing with animals (2008+) (20603), Vehicles (207XX), Appliances, tools, and toys (208XX), Household management (209XX), Household activities, n.e.c. (299XX), Physical care for household children (30101), Reading to or with household children (30102), Playing with household children, not sports (30103), Talking with or listening to household children (30106), Organization and planning for household children (30108), Looking after household children (as a primary activity) (30109), Waiting for or with household children (30111), Picking up or dropping off household children (30112), Housework (household children) (30201), Meetings and school conferences (household children) (30202), Obtaining medical care for household children (30302), Helping household adults (305XX), Physical care for non-household children (40101), Reading to or with non-household children (40102), Playing with non-household children, not sports (40103), Arts and crafts with non-household children (40104), Talking with or listening to non-household children (40106), Looking after non-household children (as primary activity) (40109), Attending non-household children's events (40110), Waiting for or with non-household children (40111), Dropping off or picking-up non household children (40112), Caring for and helping non-household children, n.e.c. (40199), Housework (non-household children) (40201), Home schooling of non-household children (40203), Physical care for non-household adults (40401), Providing medical care to non-household adult (40403), Obtaining medical and care services for non-household adult (40404), Waiting associated with caring for non-household adults (40405), Housework, cooking, and shopping assistance for non-household adults (40501), House and lawn maintenance and repair assistance for non-household adults (40502), Animal and pet care assistance for non-household adults (40503), Vehicle and appliance maintenance or repair assistance for non-household adults (40504), Household management and paperwork assistance for non-household adults (40506), Picking up or dropping off non-household adult (40507), Waiting associated with helping non-household adults (40508), Helping non-household adults, n.e.c. (40599), Caring for and helping non-household members, n.e.c. (499XX), Security procedures related to work (50103), Sports and exercise as part of job (50203), Security procedures as part of job (50204), Income-generating hobbies, crafts, and food (50301), Income-generating services (50303), Income-generating rental property activities (50304), Waiting associated with other income generating activities (2004+) (50305), Other income-generating activities, n.e.c. (50399), Job search activities (50401), Job interviewing (50403), Waiting associated with job search or interview (50404), Job search and interviewing, n.e.c. (50499), Taking class for degree, certification, or licensure (60101), Taking class for personal interest (60102), Research or homework for class (for degree, certification, or licensure) (60301), Research or homework for class (for personal interest) (60302), Research or homework (60399), Administrative activities: class for degree, certification, or licensure (60401), Education, n.e.c. (699XX), Grocery shopping (70101), Purchasing gas (70102), Purchasing food (not groceries) (70103), Shopping, except groceries, food, and gas (70104), Waiting associated with shopping (70105), Comparison shopping (70201), Using paid childcare services (80101), Banking (80201), Using other financial services (80202), Using health and care services outside the home (80401), Waiting associated with medical services (80403), Using personal care services (80501), Activities related to purchasing or selling real estate (80601), Using veterinary services (80701), Professional and personal services, n.e.c. (899XX), Using home maintenance, repair, decoration, or construction services (90201), Using vehicle maintenance or repair services (90501), Waiting associated with vehicle maintenance or repair services (90502), Using police and fire services (100101), Using social services (100102), Obtaining licenses and paying fines, fees, or taxes (100103), Civic obligations and participation (100201), Eating and drinking (110101), Waiting associated with eating and drinking (110201), Socializing and communicating with others (120101), Attending or hosting social events (1202XX), Relaxing, thinking (120301), Tobacco and drug use (120302), Television and movies (not religious) (120303), Listening to the radio (120305), Listening to or playing music (not radio) (120306), Plating games (120307), Computer use for leisure (120308), Arts and crafts as a hobby (120309), Hobbies, except arts and crafts and collecting (120311), Reading for personal interest (120312), Writing for personal interest (120313), Relaxing and leisure, n.e.c. (120399), Attending performing arts (120401), Attending movies or film (120403), Attending gambling establishments (120404), Arts and entertainment, n.e.c. (120499), Waiting associated with socializing and communicating (120501), Doing aerobics (130101), Playing basketball (130103), Biking (130104), Playing billiards (130105), Participating in equestrian sports (130110), Fishing (130112), Playing football (130113), Golfing (130114), Hunting (130118), Participating in martial arts (130119), Playing racquet sports (130120), Rollerblading (130122), Running (130124), Playing soccer (130126), Using cardiovascular equipment (130128), Vehicle touring or racing (130129), Playing volleyball (130130), Walking (130131), Participating in water sports (130132), Weightlifting or strength training (130133), Working out, unspecified (130134), Wrestling (130135), Doing yoga (130136), Playing sports, n.e.c. (130199), Watching baseball (130202), Watching basketball (130203), Watching billiards (130205), Watching football (130213), Watching wrestling (130232), Waiting related to playing sports or exercising (130301), Attending religious services (140101), Participating in religious services (140102), Waiting associated with religious and spiritual activities (140103), Religious education activities (2007+) (140105), Administrative and support activities (1501XX), Social service and care activities (except medical) (1502XX), Building houses, wildlife sites, and other structures (150301), Indoor and outdoor maintenance, repair, and clean-up (150302), Performing (150401), Serving at volunteer events and cultural activities (150402), Attending meetings, conferences, and training (150501), Public health and safety activities (1506XX), Waiting associated with volunteer activities (2004+) (150701), Volunteer activities, n.e.c. (159999), Telephone calls (1601XX), Waiting associated with telephone calls (2004+) (160201), Telephone calls, n.e.c. (169999), Travel related to personal care (180101), Travel related to housework (180201), Travel related to food and drink preparation, clean-up, and presentation (2004+) (180202), Travel related to interior maintenance, repair, and decoration (2004+) (180203), Travel related to exterior maintenance, repair, and decoration (2004+) (180204), Travel related to care for animals and pets (not veterinary care) (2004+) (180206), Travel related to vehicle care and maintenance (by self) (2004+) (180207), Travel related to household management (180209), Travel related to household activities (180299), Travel related to caring for and helping household children, inclusive (2003, 2004) (180301), Travel related to caring for and helping household children (2005+) (180302), Travel related to helping household adults (2005+) (180306), Travel related to caring for and helping household adultts (2003, 2004) (180307), Travel related to caring for and helping non-household (2005+) (180402), Travel related to caring for non-household adults (2005+) (180405), Travel relatedto helping non-household adults (2005+) (180406), Travel related to caring for and helping non-household adults (2003, 2004) (180407), Travel related to working (180501), Travel related to work-related activities (180502), Travel related to income-generating activities (2004+) (180503), Travel related to taking class (180601), Travel related to research or homework (2005+) (180603), Travel related to grocery shopping (180701), Travel related to other shopping, inclusive (2003, 2004) (180702), Travel related to purchasing food (not groceries) (2005+) (180703), Travel related to sjopping, ex groceries, food, and gas (2005+) (180704), Travel related to purchasing gas (2004+) (180705), Travel related to using financial services and banking (180802), Travel related to using medical services (180804), Travel related to using personal care services (180805), Travel related to using real estate services (180806), Travel related to using professional and personal care services, n.e.c. (180899), Travel related to using household services (180901), Travel related to using vehicle maintenance and repair services (180905), Travel related to using government services (181001), Travel related to civic obligations and participation (181002), Travel related to ating and drinking (181101), Travel related to socializing and communicating (181201), Travel related to attending or hosting social events (181202), Travel related to relaxing and leisure (181203), Travel related to arts and entertainment (181204), Travel related to entertainment (2005+) (181205), Travel related to relaxing and leisure (2005+) (181206), Travel related to participating in sports, exercise and recreation (181301), Travel related to attending sporting or recreational events (181302), Travel related to religious or spiritual activities (181401), Travel related to volunteering (1815XX), Travel related to phone calls (181601), Security procedures related to traveling (181801), Traveling, n.e.c. (189999)

Market work	Work, main job (50101), Work, other jobs (50102), Waiting associated with working (50104), Working, n.e.c. (50199), Waiting associated with work-related activities (50205), Work-related activities, n.e.c. (50299), Work and work-related activities, n.e.c. (59999)

Notes: This table lists the activity codes included in each time use variable. 'n.e.c.' stands for "not elsewhere classified".

Table A.2. Summary statistics, additional results

	Mean	SD
Weather variables		
Maximum temperature	67.633	18.895
Precipitation	10.483	27.293
Snowfall	0.611	4.508
Socio-demographic variables		
Male	0.542	0.498
Age	40.681	12.014
Primary education	0.079	0.270
Secondary education	0.252	0.434
University education	0.668	0.471
Full-time worker	0.876	0.330
Living in couple	0.566	0.496
Household size	3.092	1.538
Number of children	0.788	1.106
Supervised occupation	0.337	0.473
Climate-exposed occupation	0.167	0.373

Notes: This table reports the summary statistics of the weather and socio-demographic variables. Data come from the ATUS 2003-2019. Sample is restricted to employees aged 21-65 on working days. Summary statistics are weighted using ATUS weights.

Table A.3. Classification of supervised and non-supervised occupations

Category	Occupations
Supervised occupations	Office and administrative support occupations; Farming, fishing, and forestry occupations; Construction and extraction occupations; Installation, maintenance, and repair occupations; Production occupations; Transportation and material moving occupations
Non-supervised occupations	Management occupations; Business and financial operations occupations; Computer and mathematical science occupations; Architecture and engineering occupations; Life, physical, and social science occupations; Community and social service occupations; Legal occupations; Education, training, and library occupations; Arts, design, entertainment, sports, and media occupations; Healthcare practitioner and technical occupations; Healthcare support occupations; Protective service occupations; Food preparation and serving related occupations; Building and grounds cleaning and maintenance occupations; Personal care and service occupations; Sales and related occupations

Notes: This table reports the classification of supervised and non-supervised occupations. Classification based on the broader 22 occupations provided by the ATUS for the respondent's primary occupation, coded as 'occ2'.

Table A.4. Classification of climate-exposed and climate-unexposed industries

Category	Occupations
Climate-exposed	Farming, fishing, and forestry occupations; Construction and extraction occupations; Production occupations; Transportation and material moving occupations
Climate-unexposed	Management occupations; Business and financial operations occupations; Computer and mathematical science occupations; Architecture and engineering occupations; Life, physical, and social science occupations; Community and social service occupations; Legal occupations; Education, training, and library occupations; Arts, design, entertainment, sports, and media occupations Healthcare practitioner and technical occupations; Healthcare support occupations; Protective service occupations; Food preparation and serving related occupations; Building and grounds cleaning and maintenance occupations; Personal care and service occupations; Sales and related occupations; Office and administrative support occupations; Installation, maintenance, and repair occupations

Notes: This table reports the classification of climate-exposed and climate-unexposed industries. Classification based on the broader 22 occupations provided by the ATUS for the respondent's primary occupation, coded as 'occ2'.

Table A.5. Main results, remaining coefficient estimates

	(1)	(2)
	Total	Non-work not eating
Precipitation	0.013	0.000
	(0.012)	(0.006)
Snowfall	-0.051	0.004
	(0.059)	(0.035)
Weekly average maximum temperature	-0.045	-0.016
	(0.046)	(0.033)
Male	0.227	0.357
	(0.713)	(0.427)
Age	-0.419**	-0.193
	(0.208)	(0.162)
$Age^2/100$	0.481**	0.231
	(0.238)	(0.186)
Secondary education	-1.368	0.313
	(1.399)	(1.015)
University education	-5.809***	-1.438
	(1.458)	(1.056)
Full-time worker	8.720***	0.814
	(1.020)	(0.747)
Living in couple	-2.105***	-2.509***
	(0.709)	(0.447)
Household size	0.835**	0.523**
	(0.332)	(0.259)
Number of children	-1.163**	-0.481
	(0.464)	(0.355)
Constant	85.596*	71.300
	(48.965)	(51.980)
Occupation F.E.	✓	✓
Industry F.E.	✓	✓
Day of the week F.E.	✓	✓
Month F.E.	✓	✓
Year F.E.	✓	✓
County F.E.	✓	✓
Observations	26,751	26,751
R-squared	0.086	0.059

Notes: This table reports the OLS estimates. Data come from the ATUS 2003-2019. Sample is restricted to employees aged 21-65 on working days. Dependent variables are measured in minutes per day. Estimates are weighted using ATUS weights. Standard errors, clustered at the county level, are reported in parentheses. ***Significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

Table A.6. Relationship between daily temperature and time spent at work not working, alternative reference bins

	(1)	(2)	(3)
	Non-work not eating	Men	Women
Panel A. Reference bin = [65, 70) ºF			
≥ 100 ºF	3.448**	0.659	5.845***
	(1.688)	(2.364)	(2.242)
Individual controls	✓	✓	✓
Other weather variables	✓	✓	✓
Occupation F.E.	✓	✓	✓
Industry F.E.	✓	✓	✓
Day of the week F.E.	✓	✓	✓
Month F.E.	✓	✓	✓
Year F.E.	✓	✓	✓
County F.E.	✓	✓	✓
Observations	26,751	13,543	13,208
R-squared	0.059	0.098	0.076
Panel B. Reference bin = [70, 75) ºF			
≥ 100 ºF	2.979*	0.564	4.969**
	(1.798)	(2.347)	(2.400)
Individual controls	✓	✓	✓
Other weather variables	✓	✓	✓
Occupation F.E.	✓	✓	✓
Industry F.E.	✓	✓	✓
Day of the week F.E.	✓	✓	✓
Month F.E.	✓	✓	✓
Year F.E.	✓	✓	✓
County F.E.	✓	✓	✓
Observations	26,751	13,543	13,208
R-squared	0.059	0.098	0.076

Notes: This table reports the OLS estimates of Eq. (1), considering different reference temperature bins. Data come from the ATUS 2003-2019. Sample is restricted to employees aged 21-65 on working days. All estimates include a constant. Dependent variables are measured in minutes per day. Individual controls include gender (in Column (1)), age (and its square), educational attainment (secondary and university education), full-time status, living in couple, household size and number of children, whereas weather variables denote daily amount of precipitation, snowfall and weekly average maximum temperature. Estimates are weighted using ATUS weights. Standard errors, clustered at the county level, are reported in parentheses. ***Significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

Table A.7. Relationship between daily temperature and time spent at work not working, including workers outside metro areas

	(1)	(2)	(3)
	Non-work not eating	Men	Women
< 30 ºF	-0.563	0.249	-1.174
	(1.232)	(1.812)	(1.549)
[30, 35) ºF	0.120	0.342	0.390
	(1.298)	(1.941)	(1.568)
[35, 40) ºF	-1.378	-0.157	-2.611*
	(1.085)	(1.861)	(1.473)
[40, 45) ºF	-0.167	1.948	-2.445*
	(0.980)	(1.624)	(1.452)
[45, 50) ºF	0.527	1.549	-0.381
	(0.930)	(1.371)	(1.494)
[50, 55) ºF	1.101	2.123	-0.063
	(1.019)	(1.553)	(1.237)
[55, 60) ºF	-0.043	0.936	-1.059
	(0.830)	(1.273)	(1.137)
[60, 65) ºF	0.580	1.415	-0.097
	(0.683)	(1.142)	(1.116)
[65, 70) ºF	-0.092	0.793	-0.999
	(0.891)	(1.388)	(1.136)
[70, 75) ºF	-0.227	-0.115	-0.610
	(0.881)	(1.275)	(1.047)
[80, 85) ºF	-0.891	-0.454	-1.446
	(0.648)	(0.979)	(0.965)
[85, 90) ºF	-0.168	-0.248	-0.227
	(0.721)	(1.113)	(1.068)
[90, 95) ºF	0.611	0.745	0.424
	(0.781)	(1.139)	(1.062)
[95, 100) ºF	2.552	1.173	4.724
	(1.581)	(1.701)	(3.314)
≥ 100 ºF	1.971	-0.212	3.898**
	(1.422)	(1.863)	(1.830)
Individual controls	✓	✓	✓
Other weather variables	✓	✓	✓
Occupation F.E.	✓	✓	✓
Industry F.E.	✓	✓	✓
Day of the week F.E.	✓	✓	✓
Month F.E.	✓	✓	✓
Year F.E.	✓	✓	✓
County F.E.	✓	✓	✓
Observations	47,086	23,864	23,222
R-squared	0.047	0.068	0.059
Mean of Y	11.062	11.703	10.294

Notes: This table reports the OLS estimates. Data come from the ATUS 2003-2019. Sample is restricted to employees aged 21-65 on working days. All estimates include a constant. Dependent variables are measured in minutes per day. The reference temperature bin is [75, 80) ºF, which is omitted to avoid perfect multicollinearity issues in the regressions. Individual controls include gender (in Column (1)), age (and its square), educational attainment (secondary and university education), full-time status, living in couple, household size and number of children, whereas weather variables denote daily amount of precipitation, snowfall and weekly average maximum temperature. Estimates are weighted using ATUS weights. Standard errors, clustered at the county level, are reported in parentheses. ***Significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

Table A.8. Relationship between daily temperature and time spent at work not working, Poisson estimates

	(1)	(2)	(3)
	Non-work not eating	Men	Women
< 30 ºF	-0.057	0.111	-0.250
	(0.139)	(0.194)	(0.219)
[30, 35) ºF	-0.017	0.194	-0.214
	(0.147)	(0.210)	(0.202)
[35, 40) ºF	-0.129	-0.026	-0.273
	(0.130)	(0.222)	(0.184)
[40, 45) ºF	0.022	0.314**	-0.424**
	(0.112)	(0.152)	(0.181)
[45, 50) ºF	0.101	0.250*	-0.072
	(0.102)	(0.131)	(0.196)
[50, 55) ºF	0.226*	0.420***	-0.008
	(0.116)	(0.159)	(0.157)
[55, 60) ºF	0.003	0.142	-0.194
	(0.078)	(0.108)	(0.158)
[60, 65) ºF	0.088	0.273**	-0.105
	(0.076)	(0.111)	(0.155)
[65, 70) ºF	-0.015	0.103	-0.135
	(0.081)	(0.117)	(0.149)
[70, 75) ºF	0.027	0.114	-0.061
	(0.107)	(0.109)	(0.145)
[80, 85) ºF	-0.020	0.152*	-0.185
	(0.072)	(0.091)	(0.127)
[85, 90) ºF	0.031	0.085	-0.046
	(0.083)	(0.100)	(0.137)
[90, 95) ºF	0.128	0.241*	0.038
	(0.087)	(0.125)	(0.129)
[95, 100) ºF	0.324*	0.213	0.537*
	(0.180)	(0.184)	(0.282)
≥ 100 ºF	0.295**	0.129	0.411**
	(0.136)	(0.193)	(0.175)
Individual controls	✓	✓	✓
Other weather variables	✓	✓	✓
Occupation F.E.	✓	✓	✓
Industry F.E.	✓	✓	✓
Day of the week F.E.	✓	✓	✓
Month F.E.	✓	✓	✓
Year F.E.	✓	✓	✓
County F.E.	✓	✓	✓
Observations	26,706	13,480	13,065
R-squared	0.044	0.073	0.057

Notes: This table reports the Poisson estimates, employing the Poisson Pseudo Maximum Likelihood (PPML) estimator. Data come from the ATUS 2003-2019. Sample is restricted to employees aged 21-65 on working days. All estimates include a constant. Dependent variables are measured in minutes per day. The reference temperature bin is [75, 80) ºF, which is omitted to avoid perfect multicollinearity issues in the regressions. Individual controls include gender (in Column (1)), age (and its square), educational attainment (secondary and university education), full-time status, living in couple, household size and number of children, whereas weather variables denote daily amount of precipitation, snowfall and weekly average maximum temperature. Estimates are weighted using ATUS weights. Standard errors, clustered at the county level, are reported in parentheses. ***Significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

Table A.9. Relationship between daily temperature and time spent at work not working, including the highest-level of occupation and industry categories

	(1)	(2)	(3)
	Non-work not eating	Men	Women
< 30 ºF	-0.299	0.580	-2.966
	(1.516)	(2.159)	(2.355)
[30, 35) ºF	-0.141	1.325	-2.828
	(1.719)	(3.046)	(2.227)
[35, 40) ºF	-0.586	0.743	-2.772
	(1.335)	(2.351)	(1.807)
[40, 45) ºF	0.256	2.993	-3.978**
	(1.300)	(1.943)	(1.927)
[45, 50) ºF	1.318	2.998*	-0.798
	(1.265)	(1.557)	(2.301)
[50, 55) ºF	2.582*	4.261*	0.138
	(1.481)	(2.372)	(1.812)
[55, 60) ºF	-0.080	1.420	-1.565
	(0.847)	(1.187)	(1.654)
[60, 65) ºF	0.778	2.521**	-0.936
	(0.871)	(1.220)	(1.609)
[65, 70) ºF	-0.251	0.790	-1.323
	(0.910)	(1.395)	(1.528)
[70, 75) ºF	0.243	0.885	-0.761
	(1.266)	(1.287)	(1.500)
[80, 85) ºF	0.096	1.988**	-1.571
	(0.681)	(0.994)	(1.262)
[85, 90) ºF	0.371	1.113	-0.261
	(0.834)	(1.064)	(1.422)
[90, 95) ºF	1.520	3.100**	0.041
	(0.971)	(1.479)	(1.273)
[95, 100) ºF	4.116*	2.519	7.713
	(2.476)	(2.091)	(4.905)
≥ 100 ºF	2.664*	2.293	3.442**
	(1.430)	(2.238)	(1.748)
Individual controls	✓	✓	✓
Other weather variables	✓	✓	✓
Occupation F.E.	✓	✓	✓
Industry F.E.	✓	✓	✓
Day of the week F.E.	✓	✓	✓
Month F.E.	✓	✓	✓
Year F.E.	✓	✓	✓
County F.E.	✓	✓	✓
Observations	26,751	13,543	13,208
R-squared	0.120	0.204	0.165

Notes: This table reports the OLS estimates. Data come from the ATUS 2003-2019. Sample is restricted to employees aged 21-65 on working days. Dependent variable are measured in minutes per day. The reference temperature bin is [75, 80) ºF, which is omitted to avoid perfect multicollinearity issues in the regressions. Individual controls include gender (in Column (1)), age (and its square), educational attainment (secondary and university education), full-time status, living in couple, household size and number of children, whereas weather variables denote daily amount of precipitation, snowfall and weekly average maximum temperature. Estimates are weighted using ATUS weights. Standard errors, clustered at the county level, are reported in parentheses. ***Significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

Table A.10. Relationship between daily temperature and time spent at work not working, excluding public-sector workers

	(1)	(2)	(3)
	Non-work not eating	Men	Women
< 30 ºF	-0.345	0.936	-2.038
	(1.543)	(2.310)	(2.696)
[30, 35) ºF	0.590	2.451	-1.788
	(1.920)	(3.188)	(2.408)
[35, 40) ºF	-0.952	-0.351	-1.892
	(1.458)	(2.710)	(2.146)
[40, 45) ºF	0.703	3.735*	-3.734*
	(1.417)	(2.142)	(2.139)
[45, 50) ºF	1.149	1.658	0.256
	(1.355)	(1.707)	(2.783)
[50, 55) ºF	3.057*	4.851**	0.567
	(1.569)	(2.401)	(1.929)
[55, 60) ºF	0.261	1.975	-2.046
	(0.896)	(1.388)	(1.800)
[60, 65) ºF	1.366	3.087**	-0.486
	(0.913)	(1.525)	(2.022)
[65, 70) ºF	0.569	1.510	-0.895
	(0.970)	(1.473)	(1.825)
[70, 75) ºF	0.291	0.817	-0.697
	(1.312)	(1.343)	(1.908)
[80, 85) ºF	0.076	1.714	-1.957
	(0.833)	(1.123)	(1.441)
[85, 90) ºF	0.353	0.720	-0.685
	(0.867)	(1.143)	(1.505)
[90, 95) ºF	1.973*	3.796**	0.208
	(1.043)	(1.695)	(1.483)
[95, 100) ºF	4.322	2.688	6.881
	(2.989)	(2.604)	(6.399)
≥ 100 ºF	3.696**	0.906	5.656**
	(1.673)	(2.317)	(2.471)
Individual controls	✓	✓	✓
Other weather variables	✓	✓	✓
Occupation F.E.	✓	✓	✓
Industry F.E.	✓	✓	✓
Day of the week F.E.	✓	✓	✓
Month F.E.	✓	✓	✓
Year F.E.	✓	✓	✓
County F.E.	✓	✓	✓
Observations	22,105	11,518	10,587
R-squared	0.068	0.113	0.092
Mean of Y	10.805	11.178	10.334

Notes: This table reports the OLS estimates. Data come from the ATUS 2003-2019. Sample is restricted to employees aged 21-65 on working days. Public-sector workers are excluded. All estimates include a constant. Dependent variables are measured in minutes per day. The reference temperature bin is [75, 80) ºF, which is omitted to avoid perfect multicollinearity issues in the regressions. Individual controls include gender (in Column (1)), age (and its square), educational attainment (secondary and university education), full-time status, living in couple, household size and number of children, whereas weather variables denote daily amount of precipitation, snowfall and weekly average maximum temperature. Estimates are weighted using ATUS weights. Standard errors, clustered at the county level, are reported in parentheses. ***Significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

Table A.11. Relationship between daily temperature and time spent at work not working, excluding part-time workers

	(1)	(2)	(3)

	Non-work not eating	Men	Women
< 30 ºF	-0.323	1.171	-2.337
	(1.603)	(2.285)	(2.477)
[30, 35) ºF	0.992	2.694	-0.997
	(1.863)	(2.956)	(2.428)
[35, 40) ºF	-0.889	-0.361	-1.688
	(1.409)	(2.422)	(1.997)
[40, 45) ºF	0.054	2.765	-4.069**
	(1.182)	(1.901)	(1.900)
[45, 50) ºF	1.766	2.689*	0.655
	(1.309)	(1.624)	(2.674)
[50, 55) ºF	2.930*	4.975**	0.223
	(1.505)	(2.364)	(1.923)
[55, 60) ºF	0.050	0.636	-1.166
	(0.851)	(1.193)	(1.775)
[60, 65) ºF	1.490*	3.299**	-0.291
	(0.888)	(1.419)	(1.779)
[65, 70) ºF	0.390	0.770	0.108
	(0.898)	(1.288)	(1.896)
[70, 75) ºF	0.749	1.352	-0.174
	(1.087)	(1.274)	(1.450)
[80, 85) ºF	0.142	0.913	-0.550
	(0.711)	(0.950)	(1.409)
[85, 90) ºF	0.856	0.587	0.882
	(0.874)	(1.055)	(1.637)
[90, 95) ºF	2.618**	3.073*	2.548
	(1.093)	(1.627)	(1.616)
[95, 100) ºF	2.105	1.441	3.388
	(1.418)	(2.180)	(2.346)
≥ 100 ºF	3.606**	2.019	4.827**
	(1.632)	(2.179)	(2.310)
Individual controls	✓	✓	✓
Other weather variables	✓	✓	✓
Occupation F.E.	✓	✓	✓
Industry F.E.	✓	✓	✓
Day of the week F.E.	✓	✓	✓
Month F.E.	✓	✓	✓
Year F.E.	✓	✓	✓
County F.E.	✓	✓	✓
Observations	23,399	12,719	10,680
R-squared	0.067	0.102	0.091
Mean of Y	10.916	11.317	10.374

Notes: This table reports the OLS estimates. Data come from the ATUS 2003-2019. Sample is restricted to employees aged 21-65 on working days. Part-time workers are excluded. All estimates include a constant. Dependent variables are measured in minutes per day. The reference temperature bin is [75, 80) ºF, which is omitted to avoid perfect multicollinearity issues in the regressions. Individual controls include gender (in Column (1)), age (and its square), educational attainment (secondary and university education), living in couple, household size and number of children, whereas weather variables denote daily amount of precipitation, snowfall and weekly average maximum temperature. Estimates are weighted using ATUS weights. Standard errors, clustered at the county level, are reported in parentheses. ***Significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

Table A.12. Relationship between daily temperature and time spent at work not working, excluding individual controls

	(1)	(2)	(3)
	Non-work not eating	Men	Women
< 30 ºF	-1.075	0.431	-3.050
	(1.524)	(2.385)	(2.302)
[30, 35) ºF	-0.420	1.301	-2.234
	(1.683)	(2.877)	(2.023)
[35, 40) ºF	-1.989	-0.946	-3.172*
	(1.365)	(2.601)	(1.782)
[40, 45) ºF	-0.258	3.095	-4.473**
	(1.206)	(2.048)	(1.871)
[45, 50) ºF	1.005	2.577	-0.671
	(1.199)	(1.671)	(2.327)
[50, 55) ºF	2.079	3.944*	-0.154
	(1.385)	(2.284)	(1.737)
[55, 60) ºF	-0.223	0.966	-1.555
	(0.811)	(1.354)	(1.678)
[60, 65) ºF	1.115	3.188*	-0.935
	(0.835)	(1.650)	(1.607)
[65, 70) ºF	-0.334	0.577	-1.463
	(0.837)	(1.259)	(1.592)
[70, 75) ºF	0.159	0.574	-0.585
	(1.162)	(1.250)	(1.683)
[80, 85) ºF	-0.090	1.274	-1.739
	(0.726)	(0.952)	(1.281)
[85, 90) ºF	0.498	0.672	-0.008
	(0.888)	(1.089)	(1.465)
[90, 95) ºF	1.648	2.887*	0.089
	(1.043)	(1.560)	(1.441)
[95, 100) ºF	4.070*	1.855	7.148
	(2.444)	(2.260)	(4.924)
≥ 100 ºF	3.193**	1.691	4.468**
	(1.501)	(2.095)	(2.095)
Individual controls	✗	✗	✗
Other weather variables	✓	✓	✓
Occupation F.E.	✗	✗	✗
Industry F.E.	✗	✗	✗
Day of the week F.E.	✓	✓	✓
Month F.E.	✓	✓	✓
Year F.E.	✓	✓	✓
County F.E.	✓	✓	✓
Observations	26,751	13,543	13,208
R-squared	0.032	0.058	0.051

Notes: This table reports the OLS estimates. Data come from the ATUS 2003-2019. Sample is restricted to employees aged 21-65 on working days, defined as days workers spend at least 60 minutes working at the workplace. All estimates include a constant. Dependent variables are measured in minutes per day. The reference temperature bin is [75, 80) ºF, which is omitted to avoid perfect multicollinearity issues in the regressions. Weather variables denote daily amount of precipitation, snowfall and weekly average of maximum temperature. Estimates are weighted using ATUS weights. Standard errors, clustered at the county level, are reported in parentheses. ***Significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

Table A.13. Relationship between daily temperature and time spent at work not working, including monthly unemployment rate by state

	(1)	(2)	(3)
	Non-work not eating	Men	Women
< 30 ºF	-0.484	1.297	-2.440
	(1.500)	(2.317)	(2.320)
[30, 35) ºF	-0.026	2.296	-2.267
	(1.678)	(2.810)	(2.081)
[35, 40) ºF	-1.143	0.132	-2.624
	(1.332)	(2.429)	(1.816)
[40, 45) ºF	0.313	3.764*	-3.906**
	(1.245)	(2.029)	(1.816)
[45, 50) ºF	1.297	2.950*	-0.508
	(1.200)	(1.599)	(2.326)
[50, 55) ºF	2.662*	5.025**	-0.006
	(1.404)	(2.234)	(1.750)
[55, 60) ºF	0.193	1.776	-1.664
	(0.832)	(1.248)	(1.677)
[60, 65) ºF	1.171	3.443**	-0.938
	(0.834)	(1.435)	(1.664)
[65, 70) ºF	-0.085	1.122	-1.496
	(0.854)	(1.294)	(1.621)
[70, 75) ºF	0.367	1.183	-0.622
	(1.162)	(1.234)	(1.641)
[80, 85) ºF	-0.065	1.693*	-1.795
	(0.732)	(0.964)	(1.327)
[85, 90) ºF	0.464	1.063	-0.433
	(0.875)	(1.081)	(1.526)
[90, 95) ºF	1.615	3.042**	0.345
	(1.002)	(1.521)	(1.477)
[95, 100) ºF	4.012	2.223	6.682
	(2.488)	(2.230)	(4.993)
≥ 100 ºF	3.284**	1.657	4.308**
	(1.502)	(2.081)	(2.035)
Monthly unemployment rate by state	-0.395	-0.517	-0.242
	(0.250)	(0.415)	(0.346)
Individual controls	✓	✓	✓
Other weather variables	✓	✓	✓
Occupation F.E.	✓	✓	✓
Industry F.E.	✓	✓	✓
Day of the week F.E.	✓	✓	✓
Month F.E.	✓	✓	✓
Year F.E.	✓	✓	✓
County F.E.	✓	✓	✓
Observations	26,751	13,543	13,208
R-squared	0.060	0.098	0.076

Notes: This table reports the OLS estimates. Data come from the ATUS 2003-2019. Sample is restricted to employees aged 21-65 on working days. Dependent variables are measured in minutes per day. The reference temperature bin is [75, 80) ºF, which is omitted to avoid perfect multicollinearity issues in the regressions. Individual controls include gender (in Column (1)), age (and its square), educational attainment (secondary and university education), full-time status, living in couple, household size and number of children, whereas weather variables denote daily amount of precipitation, snowfall and weekly average of maximum temperature. Estimates are weighted using ATUS weights. Standard errors, clustered at the county level, are reported in parentheses. ***Significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

Table A.14. Relationship between daily temperature and time spent at work not working, including hours usually worked per week

	(1)	(2)	(3)
	Non-work not eating	Men	Women
< 30 ºF	-0.786	0.621	-1.997
	(1.607)	(2.338)	(2.384)
[30, 35) ºF	-0.155	1.978	-1.962
	(1.818)	(2.971)	(2.155)
[35, 40) ºF	-1.608	-0.516	-2.671
	(1.250)	(2.196)	(1.810)
[40, 45) ºF	0.052	3.203	-3.686*
	(1.369)	(2.061)	(1.901)
[45, 50) ºF	0.980	2.164	-0.243
	(1.256)	(1.535)	(2.374)
[50, 55) ºF	2.432	4.631*	0.144
	(1.521)	(2.359)	(1.801)
[55, 60) ºF	-0.091	1.268	-1.523
	(0.888)	(1.256)	(1.717)
[60, 65) ºF	0.477	2.309*	-1.006
	(0.942)	(1.230)	(1.742)
[65, 70) ºF	-0.396	0.497	-1.306
	(0.855)	(1.183)	(1.670)
[70, 75) ºF	-0.020	0.615	-0.756
	(1.179)	(1.288)	(1.621)
[80, 85) ºF	-0.075	1.746*	-1.811
	(0.742)	(1.002)	(1.350)
[85, 90) ºF	0.686	1.279	-0.168
	(0.900)	(1.119)	(1.584)
[90, 95) ºF	1.307	2.401	0.449
	(0.991)	(1.466)	(1.546)
[95, 100) ºF	4.307	2.310	7.231
	(2.612)	(2.321)	(5.219)
≥ 100 ºF	3.272**	1.947	3.755*
	(1.561)	(2.166)	(2.136)
Usual weekly hours	-0.011	-0.015	-0.020
	(0.025)	(0.033)	(0.041)
Individual controls	✓	✓	✓
Other weather variables	✓	✓	✓
Occupation F.E.	✓	✓	✓
Industry F.E.	✓	✓	✓
Day of the week F.E.	✓	✓	✓
Month F.E.	✓	✓	✓
Year F.E.	✓	✓	✓
County F.E.	✓	✓	✓
Observations	25,697	13,002	12,695
R-squared	0.056	0.094	0.078
Mean of Y	10.908	11.396	10.332

Notes: This table reports the OLS estimates. Data come from the ATUS 2003-2019. Sample is restricted to employees aged 21-65 on working days. Dependent variables are measured in minutes per day. The reference temperature bin is [75, 80) ºF, which is omitted to avoid perfect multicollinearity issues in the regressions. Individual controls include gender (in Column (1)), age (and its square), educational attainment (secondary and university education), full-time status, living in couple, household size and number of children, whereas weather variables denote daily amount of precipitation, snowfall and weekly average of maximum temperature. Estimates are weighted using ATUS weights. Standard errors, clustered at the county level, are reported in parentheses. ***Significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

Table A.15. Relationship between daily temperature and time spent at work not working, accounting for non-linear effects of precipitation and snowfall

	(1)	(2)	(3)
	Non-work not eating	Men	Women
≥ 100 ºF	3.471**	2.106	4.342**
	(1.488)	(2.075)	(2.026)
PRECIPITATION = (0, 0.1) inches	1.023	1.464	-0.466
	(1.222)	(1.697)	(1.707)
PRECIPITATION = [0.1, 0.5) inches	-0.712	0.026	-1.513
	(0.708)	(1.053)	(0.974)
PRECIPITATION = [0.5, 1) inches	-0.815	-1.154	-0.790
	(1.027)	(1.529)	(1.452)
PRECIPITATION = [1, 2) inches	0.009	-0.439	0.098
	(0.953)	(1.311)	(1.327)
PRECIPITATION = [2, ∞) inches	0.437	0.409	0.327
	(0.477)	(0.620)	(0.674)
SNOWFALL = (0, 0.1) inches	-3.682	-6.471**	-0.780
	(2.404)	(3.174)	(2.948)
SNOWFALL = [0.1, 0.5) inches	2.687	1.352	3.309*
	(2.203)	(3.190)	(1.951)
SNOWFALL = [0.5, 1) inches	-1.219	-4.625*	1.143
	(1.429)	(2.647)	(2.832)
SNOWFALL = [1, 2) inches	2.303	3.026	2.274
	(2.733)	(4.260)	(2.501)
SNOWFALL = [2, ∞) inches	0.131	0.996	-1.081
	(1.225)	(1.797)	(1.394)
Individual controls	✓	✓	✓
Other weather variables	✓	✓	✓
Occupation F.E.	✓	✓	✓
Industry F.E.	✓	✓	✓
Day of the week F.E.	✓	✓	✓
Month F.E.	✓	✓	✓
Year F.E.	✓	✓	✓
County F.E.	✓	✓	✓
Observations	26,751	13,543	13,208
R-squared	0.060	0.098	0.077

Notes: This table reports the OLS estimates. Data come from the ATUS 2003-2019. Sample is restricted to employees aged 21-65 on working days. Dependent variables are measured in minutes per day. The reference temperature bin is [75, 80) ºF, which is omitted to avoid perfect multicollinearity issues in the regressions. Individual controls include gender (in Column (1)), age (and its square), educational attainment (secondary and university education), full-time status, living in couple, household size and number of children, whereas weather variables denote dummy variables for the intensity of precipitation, snowfall during the diary day and weekly average maximum temperature. Estimates are weighted using ATUS weights. Standard errors, clustered at the county level, are reported in parentheses. ***Significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

Table A.16. Relationship between daily temperature and time spent at work not working, including AQI

	(1)	(2)	(3)
	Non-work not eating	Men	Women
< 30 ºF	-0.900	0.902	-2.564
	(1.644)	(2.466)	(2.523)
[30, 35) ºF	-1.959	0.173	-3.745*
	(1.411)	(2.208)	(2.132)
[35, 40) ºF	-2.090	-0.535	-2.955
	(1.446)	(2.567)	(1.913)
[40, 45) ºF	-0.353	3.460	-4.489**
	(1.356)	(2.147)	(1.899)
[45, 50) ºF	0.971	2.786	-0.681
	(1.259)	(1.706)	(2.483)
[50, 55) ºF	2.261	4.920**	-0.408
	(1.474)	(2.371)	(1.877)
[55, 60) ºF	-0.044	2.105	-2.409
	(0.884)	(1.311)	(1.784)
[60, 65) ºF	0.972	3.446**	-1.151
	(0.884)	(1.505)	(1.770)
[65, 70) ºF	-0.299	1.045	-1.828
	(0.892)	(1.374)	(1.714)
[70, 75) ºF	0.295	1.296	-0.741
	(1.202)	(1.280)	(1.703)
[80, 85) ºF	-0.241	1.428	-1.930
	(0.762)	(0.974)	(1.403)
[85, 90) ºF	0.363	0.791	-0.622
	(0.925)	(1.102)	(1.593)
[90, 95) ºF	1.198	2.012	0.349
	(1.054)	(1.561)	(1.583)
[95, 100) ºF	3.463	1.571	5.956
	(2.445)	(2.223)	(4.821)
≥ 100 ºF	3.419**	1.754	4.448**
	(1.542)	(2.079)	(2.074)
AQI	-0.001	0.011	-0.012
	(0.007)	(0.011)	(0.011)
Individual controls	✓	✓	✓
Other weather variables	✓	✓	✓
Occupation F.E.	✓	✓	✓
Industry F.E.	✓	✓	✓
Day of the week F.E.	✓	✓	✓
Month F.E.	✓	✓	✓
Year F.E.	✓	✓	✓
County F.E.	✓	✓	✓
Observations	24,984	12,647	12,337
R-squared	0.057	0.095	0.073
Mean of Y	10.831	11.306	10.272

Notes: This table reports the OLS estimates. Data come from the ATUS 2003-2019. Sample is restricted to employees aged 21-65 on working days. Dependent variables are measured in minutes per day. The reference temperature bin is [75, 80) ºF, which is omitted to avoid perfect multicollinearity issues in the regressions. Individual controls include gender (in Column (1)), age (and its square), educational attainment (secondary and university education), full-time status, living in couple, household size and number of children, whereas weather variables denote daily amount of precipitation, snowfall and weekly average maximum temperature. Estimates are weighted using ATUS weights. Standard errors, clustered at the county level, are reported in parentheses. ***Significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

Table A.17. Relationship between daily temperature and time spent at work not working, linear spline specification with two knots for daily maximum temperature

	(1)	(2)	(3)
	Non-work not eating	Men	Women
≤ 70 ºF	0.009	-0.016	0.041
	(0.028)	(0.040)	(0.039)
[70, 90] ºF	0.015	0.004	0.035
	(0.051)	(0.071)	(0.078)
≥ 90 ºF	0.354***	0.155	0.555***
	(0.126)	(0.176)	(0.177)
Individual controls	✓	✓	✓
Other weather variables	✓	✓	✓
Occupation F.E.	✓	✓	✓
Industry F.E.	✓	✓	✓
Day of the week F.E.	✓	✓	✓
Month F.E.	✓	✓	✓
Year F.E.	✓	✓	✓
County F.E.	✓	✓	✓
Observations	26,751	13,543	13,208
R-squared	0.059	0.095	0.074

Notes: This table reports the OLS estimates. Data come from the ATUS 2003-2019. Sample is restricted to employees aged 21-65 on working days. All estimates include a constant. Dependent variables are measured in minutes per day. The reference temperature bin is [75, 80) ºF, which is omitted to avoid perfect multicollinearity issues in the regressions. Individual controls include gender (in Column (1)), age (and its square), educational attainment (secondary and university education), full-time status, living in couple, household size and number of children, whereas weather variables denote daily amount of precipitation, snowfall and weekly average of maximum temperature. Estimates are weighted using ATUS weights. Standard errors, clustered at the county level, are reported in parentheses. ***Significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

Table A.18. Relationship between daily temperature and time spent at work not working, linear spline specification with knots at the 20th, 40th, 60th, and 80th percentiles of the daily maximum temperature

	(1)	(2)	(3)
	Non-work not eating	Men	Women
≤ 49 ºF	0.095**	0.109	0.075
	(0.047)	(0.072)	(0.053)
[49, 64] ºF	-0.047	-0.061	-0.009
	(0.060)	(0.095)	(0.099)
[64, 76] ºF	-0.059	-0.237**	0.119
	(0.068)	(0.106)	(0.144)
[76, 85] ºF	0.049	0.283**	-0.184
	(0.125)	(0.127)	(0.216)
≥ 85 ºF	0.233**	0.010	0.473***
	(0.094)	(0.120)	(0.144)
Individual controls	✓	✓	✓
Other weather variables	✓	✓	✓
Occupation F.E.	✓	✓	✓
Industry F.E.	✓	✓	✓
Day of the week F.E.	✓	✓	✓
Month F.E.	✓	✓	✓
Year F.E.	✓	✓	✓
County F.E.	✓	✓	✓
Observations	26,751	13,543	13,208
R-squared	0.059	0.097	0.075

Notes: This table reports the OLS estimates. Data come from the ATUS 2003-2019. Sample is restricted to employees aged 21-65 on working days. All estimates include a constant. Dependent variables are measured in minutes per day. The reference temperature bin is [75, 80) ºF, which is omitted to avoid perfect multicollinearity issues in the regressions. Individual controls include gender (in Column (1)), age (and its square), educational attainment (secondary and university education), full-time status, living in couple, household size and number of children, whereas weather variables denote daily amount of precipitation, snowfall and weekly average maximum temperature. Estimates are weighted using ATUS weights. Standard errors, clustered at the county level, are reported in parentheses. ***Significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

Table A.19. Robustness check: Relationship between daily temperatures and time spent at work not working, by business economic cycle according to the NBER dating (women)

	(1)	(2)
	Expansion	Recession
< 30 ºF	-2.541	-0.871
	(2.400)	(7.628)
[30, 35) ºF	-1.381	-6.882
	(2.133)	(8.543)
[35, 40) ºF	-2.272	-1.878
	(1.945)	(6.612)
[40, 45) ºF	-3.565*	-9.672
	(1.933)	(6.518)
[45, 50) ºF	0.091	-12.187*
	(2.520)	(6.512)
[50, 55) ºF	0.573	-5.190
	(1.849)	(5.516)
[55, 60) ºF	-1.739	-1.258
	(1.756)	(5.949)
[60, 65) ºF	-0.292	-5.509
	(1.765)	(5.078)
[65, 70) ºF	-1.270	-5.317
	(1.707)	(5.190)
[70, 75) ºF	-0.613	-2.501
	(1.405)	(5.070)
[80, 85) ºF	-1.336	-8.723*
	(1.432)	(4.698)
[85, 90) ºF	0.247	-10.575***
	(1.685)	(3.991)
[90, 95) ºF	0.331	1.830
	(1.573)	(7.546)
[95, 100) ºF	7.139	0.914
	(5.190)	(13.334)
≥ 100 ºF	4.632**	-1.669
	(2.165)	(6.813)
Individual controls	✓	✓
Other weather variables	✓	✓
Occupation F.E.	✓	✓
Industry F.E.	✓	✓
Day of the week F.E.	✓	✓
Month F.E.	✓	✓
Year F.E.	✓	✓
County F.E.	✓	✓
Observations	11,841	1,367
R-squared	0.081	0.426
Mean of Y	10.160	10.998

Notes: This table reports the OLS estimates. Data come from the ATUS 2003-2019. Sample is restricted to *women* employees aged 21-65 on working days. Dependent variables are measured in minutes per day. The reference temperature bin is [75, 80) ºF, which is omitted to avoid perfect multicollinearity issues in the regressions. Individual controls include age (and its square), educational attainment (secondary and university education), full-time status, living in couple, household size and number of children, whereas weather variables denote daily amount of precipitation, snowfall and weekly average of maximum temperature. Estimates are weighted using ATUS weights. Standard errors, clustered at the county level, are reported in parentheses. ***Significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.

Table A.20. Relationship between daily temperatures and time spent at work not working, by historical climatic regions based on the median (women)

	(1)	(2)
	Cold counties	Warm counties
< 30 ºF	-1.508	-4.086
	(3.341)	(4.319)
[30, 35) ºF	-1.570	-1.553
	(3.085)	(4.014)
[35, 40) ºF	-1.849	-2.845
	(2.668)	(2.950)
[40, 45) ºF	-2.642	-5.713**
	(2.722)	(2.383)
[45, 50) ºF	0.106	-1.127
	(3.428)	(3.581)
[50, 55) ºF	0.103	-0.065
	(2.760)	(2.517)
[55, 60) ºF	-0.668	-2.614
	(2.937)	(1.639)
[60, 65) ºF	-2.320	0.893
	(2.929)	(2.052)
[65, 70) ºF	-2.107	-0.110
	(2.943)	(1.866)
[70, 75) ºF	-3.677*	2.733
	(2.182)	(2.176)
[80, 85) ºF	-2.118	-0.554
	(2.315)	(1.463)
[85, 90) ºF	1.226	-0.149
	(3.297)	(1.593)
[90, 95) ºF	0.753	0.838
	(2.256)	(1.977)
[95, 100) ºF	3.215	7.296
	(5.033)	(5.596)
≥ 100 ºF	24.932*	4.448*
	(14.920)	(2.622)
Individual controls	✓	✓
Other weather variables	✓	✓
Occupation F.E.	✓	✓
Industry F.E.	✓	✓
Day of the week F.E.	✓	✓
Month F.E.	✓	✓
Year F.E.	✓	✓
County F.E.	✓	✓
Observations	6,623	6,585
R-squared	0.103	0.080
Mean of Y	10.105	10.377

Notes: This table reports the OLS estimates. Data come from the ATUS 2003-2019. Sample is restricted to *women* employees aged 21-65 on working days. All estimates include a constant. Dependent variables are measured in minutes per day. The reference temperature bin is [75, 80) ºF, which is omitted to avoid perfect multicollinearity issues in the regressions. Individual controls include age (and its square), educational attainment (secondary and university education), full-time status, living in couple, household size and number of children, whereas weather variables denote daily amount of precipitation, snowfall and weekly average of maximum temperature. Estimates are weighted using ATUS weights. Standard errors, clustered at the county level, are reported in parentheses. ***Significant at the 1% level, ** significant at the 5% level, * significant at the 10% level.