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Extreme temperatures: Gender differences in well-being

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ABSTRACT

This study examines how daily temperatures are related to individual well-being, using data from the American Time Use Survey. Results, derived from a flexible specification for daily temperatures that accounts for non-linear relationships between temperature and well-being and incorporates historical regional heterogeneity across counties, reveal gender-specific patterns at the upper tail of the temperature distribution. Men exhibit greater vulnerability to extreme hot days, experiencing fatigue and decreased meaningfulness on these days. These associations are particularly pronounced during market work episodes, suggesting a potential adverse relationship between extreme hot temperatures and productivity. The findings highlight the need for climate adaptation strategies that address these gender-specific vulnerabilities.

1. Introduction

Rising temperatures pose profound challenges to humankind, encompassing a spectrum of adverse impacts on various outcomes. Extreme temperatures cause loss of life (Barreca et al., 2016; Deschênes and Greenstone, 2011; Liao et al., 2023; Yu et al., 2019), violence (Nguyen, 2024; Otrachshenko et al., 2021), and economic losses (Burke et al., 2015; Dell et al., 2012; Kalkuhl and Wenz, 2020). Climate change also takes a toll on physical and mental health, causing reduced fitness levels, stress, anxiety, depression and suicides (Hailemariam et al., 2023; Hou and Zhang, 2024; Hou et al., 2023; Hua et al., 2023; Mullins and White 2019), leading to greater hospital admissions rates (Agarwal et al., 2021; Chen et al., 2023; Gibney et al., 2023). In the realm of labor supply, elevated temperatures yield repercussions on both labor supply and productivity, disminishing time use (Graff Zivin and Neidell, 2014; Neidell et al., 2021), affecting work performance across various occupations (Fesselmeyer, 2021; Heyes and Saberian, 2022; LoPalo, 2023; Picchio and van Ours, 2024; Somanathan et al., 2021) and elevating rates of work-related injuries (Dillender, 2021; Filomena and Picchio, 2024; Ireland et al., 2023). Overall, the increasing frequency and intensity of extreme weather events underscore the urgency of comprehending the relationship between weather conditions and individual well-being.

Within this context, this study analyzes the relationship between individuals' well-being and temperature, using data from the American Time Use Survey Well-Being Module (ATUS WB-Module) for the years 2010, 2012, 2013, and 2021, with a focus on gender differences. A growing body of literature on the gender well-being gap has highlighted a female well-being paradox, with women reporting higher levels of life satisfaction and happiness despite exhibiting worse mental health outcomes, such as depressive symptoms, restless sleep, and anxiety, among others (Becchetti and Conzo, 2022; Blanchflower and Bryson, 2024a, 2024b; Montgomery, 2022; Senik, 2017; Yang et al., 2024).[1] Furthermore, many studies indicate that the health-related effects of extreme heat differ by gender, with men's health outcomes being more susceptible to such conditions relative to those of women (Agarwal et al., 2021; Chen et al., 2023; Deschênes and Greenstone, 2011; Hailemariam et al., 2023; Hou and Zhang, 2024; Liao et al., 2023; Yu et al., 2019). However,

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[1] Recent discussion on this topic highlights the potential role of bad controls, which may lead to biased estimates of the gender well-being gap (Bartram, 2022), raising questions about the necessity of explicitly incorporating socio-demographic controls. On the other hand, Blanchflower and Bryson (2024b) note that this gender well-being gap had changed in recent years and suggest that there is no longer *any* female paradox.

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existing research has not explored whether the relationship between daily weather conditions and well-being varies by gender (Frijters et al., 2020; Noelke et al., 2016). This study aims to fill this gap.

A strand of literature has explored environmental factors as potential determinants of well-being, including daily weather conditions (Barrington-Leigh and Behzadnejad, 2017; Connolly, 2013; Frijters et al., 2020; Hailemariam et al., 2023; Noelke et al., 2016; von Möllendorff and Hirschfeld, 2016), natural disasters (Ahmadiani and Ferreira, 2021; Berlemann and Eurich, 2021; Frijters et al., 2023; Luechinger and Raschky, 2009), or air pollution levels (Behera et al., 2024; Dolan and Laffan, 2016; Ferreira et al., 2013; Han et al., 2023; Levinson, 2012; Luechinger, 2009; Sanduijav et al., 2021; Zhang et al., 2017a, 2017b). Building on these contributions, this study investigates the relationship between daily temperature fluctuations and subjective well-being, with a particular focus on affective measures.

Subjective well-being measures can be categorized into three distinct but related dimensions: cognitive, affective, and eudaimonic well-being (for comprehensive reviews on subjective well-being, see Frey and Stutzer, 2002; Diener and Seligman, 2004; Dolan et al., 2008; Helliwell and Barrington-Leigh, 2010; Benjamin et al., 2023). Despite initial skepticism among economists, there is now broad consensus that these measures offer valuable insights that would otherwise remain unavailable. Consequently, they are increasingly recognized as valuable *complements* to standard economic indicators and are widely adopted by researchers and policymakers (Deaton, 2018).

This study focuses on affective well-being measures—commonly referred to in the literature as emotional, experienced, hedonic, or momentary well-being—rather than evaluative or cognitive measures, which involve retrospective assessments of overall life satisfaction or satisfaction with specific life domains. The rationale for this focus stems from the nature of our variable of interest, which captures short-term, day-to-day fluctuations in temperature. Unlike cognitive measures, which are influenced by stable factors such as income and personal circumstances, experiential measures assess emotions over brief time frames (i.e., immediate experiences or feelings which change on a moment-to-moment basis), making them particularly well-suited for examining the relationship between daily environmental circumstances—such as weather conditions—and well-being.[2]

Momentary well-being measures offer valuable insights into individuals' lived experiences and have been shown to affect individual behaviors and objective outcomes (Bellet et al., 2024; Chandler and Kapelner, 2013; Grossman et al., 2018; Han and Kaiser, 2024; Kaiser and Oswald, 2022; Kosfeld et al., 2017; Lapalme et al., 2023; Lester et al., 2022; Nikolova and Cnossen, 2020; Oswald et al., 2015). The ATUS WB-Module further addresses concerns about context effects by randomizing the order of well-being questions, minimizing potential biases (Deaton, 2012, 2018; Deaton and Stone, 2016). By using these data, this study provides evidence on the relationship between daily temperatures and various affective emotions, complementing existing research focused on evaluative well-being.[3]

The findings indicate a link between daily temperatures and individual well-being, revealing a distinct gender-specific correlation between higher temperatures and well-being. In particular, extremely hot days are negatively associated with males' net affect and positively related to the U-index among males, due to reduced feelings of meaningfulness and increased feelings of tiredness on such days. In contrast, females' well-being shows no significant relationships with such conditions. Additionally, the findings suggest that extreme hot temperatures may be negatively related to workers' productivity. Men report higher levels of sadness, stress and fatigue at work on extremely hot days, while they declare lower levels of happiness and meaningfulness at work. All these insights provide valuable gender- and activity-specific evidence for informing the ongoing climate change debates, and highlight the need for tailored climate adaptation strategies.

This paper makes two key contributions. First, it uncovers novel gender differences in the relationship between daily temperatures and subjective well-being. Unlike previous studies that consider a limited set of well-being measures (Frijters et al., 2020; Noelke et al., 2016) or restrict their analysis to specific seasons (Connolly, 2013), our study provides a broader perspective. We utilize time diary data from four waves of the ATUS WB-Module, which captures detailed emotional well-being measures linked to specific activities shortly after they occur. This approach reduces recall bias and provides a more comprehensive framework to examine the relationship between daily temperatures and well-being.

Second, by linking daily temperatures to individuals' emotional well-being during specific activities, we contribute to research on the intersection of climate and labor economics. In particular, we examine workers' emotional states during paid work, shedding light on how temperature variations are related to affective well-being in the workplace—a dimension largely overlooked in the existing literature. To our knowledge, no previous study has explored daily temperatures as a determinant of workers' emotional experiences during working hours.

This analysis complements a growing body of research on the effects of temperature on labor market outcomes, including time spent working (Graff Zivin and Neidell, 2014; Neidell et al., 2021), absenteeism (Heyes and Saberian, 2022; Somanathan et al., 2021), and workplace accidents (Dillender, 2021; Drescher and Janzen, 2025; Filomena and Picchio, 2024; Ireland et al., 2023). Since workplace well-being has been linked to higher motivation and productivity (Bellet et al., 2024; Nikolova and Cnossen, 2020; Oswald et al., 2015), understanding how daily temperatures are related to workers' emotional states is crucial for assessing broader labor market dynamics. These insights have important implications for employers, firms, and policymakers, particularly in the context of climate change.

The remainder of the paper is organized as follows. Section 2 conducts a comprehensive literature review concerning the relationship between weather conditions and individuals' well-being. Section 3 describes the data used in this study. Section 4 presents the econometric strategy. Section 5 shows and discusses the principal findings. Finally, Section 6 concludes.

2. Literature review

Recent research has focused on the relationship between weather conditions and health outcomes. Despite these efforts, there are still gaps in the literature, particularly in the context of the United States where the existing evidence is mixed. Studies exploring the relationship between weather conditions and affective and cognitive measures of well-being include the work of Connolly (2013), Lucas and Lawless (2013), Noelke et al. (2016), and Frijters et al. (2020).[4]

[2] Subjective well-being is multifaceted and has different correlates depending on the measure used (Dolan and Laffan, 2016; Dolan et al., 2008, 2017; Kahneman and Deaton, 2010; Kahneman and Krueger, 2006; Krueger and Schkade, 2008; Luhmann et al., 2012).

[3] To date, most prior research on the relationship between daily weather conditions and well-being has focused on cognitive or global evaluative assessments, such as generalized life satisfaction measures (Barrington-Leigh and Behzadnejad, 2017; Feddersen et al., 2016; Hailemariam et al., 2023; Jones, 2023; Kämpfer and Mutz, 2013; Li et al., 2024; Lucas and Lawless, 2013; Schmiedeberg and Schröder, 2014; von Möllendorff and Hirschfeld, 2016), which are now widely included in surveys (Berlin and Connolly, 2019).

[4] In this literature review, we focus on studies located in the US. For studies in other geographical contexts, we can cite those of Kämpfer and Mutz (2013) and Schmiedeberg and Schröder (2014) in Germany, Feddersen et al. (2016) and Hailemariam et al. (2023) in Australia, Barrington-Leigh and Behzadnejad (2017) in Canada, Pailler and Tsaneva (2018) in India, and Li et al. (2024) in China.

Connolly (2013) uses data from the Princeton Affect and Time Survey (PATS) to examine the relationship between weather conditions and well-being, finding that women are more responsive than men to temperature and precipitation.[5] Rainier days and higher temperatures significantly decrease life satisfaction for women. Additionally, Connolly investigates emotional variables and a range of different affective measures and finds that low temperatures are positively associated with happiness and negatively related to tiredness, stress, sadness, and the U-index for women. Moreover, she shows that low temperatures are positively correlated to the net affect, while higher temperatures are negatively related, again only for women. On the other hand, no statistically significant estimates are reported for men. These results lead Connolly, *perhaps tentatively*, to conclude that women appear to be more responsive to environmental variables. However, a clear limitation of her study is that it only focuses on one season, Summer 2006, due to constraints of data availability, which restricts the analysis of other weather conditions, such as snowfall. In contrast, our study incorporates data from four distinct years where the ATUS gathers information on individual well-being, providing more comprehensive information for empirical analyses. In stark contrast to Connolly's findings, this study reveals that men appear to be more responsive to extreme hot temperatures.

Another study examining cognitive measures of individuals' well-being in the United States is conducted by Lucas and Lawless (2013), focusing on the association between daily weather conditions and life satisfaction. Using a representative cross-sectional sample of over one million Americans from the Behavioral Risk Factor Surveillance System (BRFSS) during 2005-2009, the authors find that weather does not impact life satisfaction. Even for the estimates that do show statistical significance, the effects are very small. This may be explained by the possibility that the effects of weather conditions are short-term, with individuals adapting over time and experiencing diminishing effects. This argument would suggest that the effects of weather conditions should manifest more strongly among affective emotions, relative to cognitive measures of well-being.

Other studies in the United States include Noelke et al. (2016) and Frijters et al. (2020). Noelke et al. (2016) analyze data from the Gallup G1K dataset from 2008 to 2013, and conclude that temperatures above 70°F, compared to temperatures in the 50-60°F range, decrease positive emotions (happiness, enjoyment, smiling) and increase negative feelings (stress, anger) and fatigue, while low temperatures reduce these negative emotions and fatigue. More recently, Frijters et al. (2020) use the Gallup Daily tracking survey from 2008 to 2015 to show that average temperatures have negative effects on an index which denotes positive emotions. From our perspective, the aggregation of different emotions conducted in Noelke et al. (2016) and Frijters et al. (2020) risks overlooking important variations in instant emotions. Our research takes advantage of the *multitude* of affective information on the *intensity* of various daily instant feelings collected in the ATUS WB-Module, and supports the (falsifiable) hypothesis that considering individual emotions can yield significant insights.

Although we acknowledge that the sample size of these two latter studies is impressive, a limitation of Noelke et al. (2016) and Frijters et al. (2020) is that their well-being measures are dichotomic, either yes or no, indicating the presence of certain feelings, but do not consider differences in *intensity* across emotions or variations by gender. While Noelke et al. (2016) and Frijters et al. (2020) use stylized questionnaires regarding feelings of the day prior to the interview, respondents in the ATUS WB-Module first complete a personal time diary and then they rate their emotions during three random activities performed during the same day on the survey waves 2010, 2012, 2013, and 2021. Consequently, the variables used by Noelke et al. (2016) and Frijters et al. (2020) are subject to greater recall biases that evaluate the prior day *as a whole*. Against this, we have up to three observations of six different emotions for the same respondent per day at the activity level, measured with episodic recall of yesterday, and the affective measures range from a minimum 0, indicating a low intensity of the feeling, to a maximum of 6, indicating a high intensity.

By combining detailed diary data on momentary emotional states with high-resolution weather information, our approach captures the relationship between daily temperatures and individual well-being while also revealing nuanced variations across specific activities. This comprehensive analysis contributes to the literature by addressing existing gaps and establishing the foundation for understanding the mechanisms that underlie the relationship between temperatures and individual labor market outcomes.

Table 1
Summary statistics.

	Mean	Std. Dev.
Instant feelings:		
Happy	4.381	1.578
Meaningful	4.353	1.834
Sad	0.598	1.307
Stress	1.479	1.801
Tired	2.299	1.920
Pain	0.861	1.560
Net affect	3.058	2.075
U-index	0.133	0.340
Episode characteristics:		
Episode duration (minutes)	166.794	151.101
Episode with other	0.689	0.463
Episode at home	0.577	0.494
Episode outdoors	0.064	0.244
Episode indoors	0.286	0.452
Episode travelling	0.074	0.261
Weekend day	0.321	0.467
Holiday	0.023	0.149
Weather conditions:		
Maximum temperature (TMAX)	69.505	18.148
TMAX $<$ 40°F	0.076	0.265
TMAX = 40°F – 50°F	0.089	0.284
TMAX = 50°F – 60°F	0.123	0.328
TMAX = 60°F – 70°F	0.162	0.368
TMAX = 70°F – 80°F	0.202	0.401
TMAX = 80°F – 90°F	0.239	0.426
TMAX $\geq$ 90°F	0.110	0.313
Socio-demographics:		
Male	0.481	0.500
Age	42.555	17.800
Native citizen	0.792	0.406
Primary education	0.166	0.372
Secondary education	0.253	0.435
University education	0.581	0.493
Employed	0.628	0.483
Married or cohabiting	0.529	0.499
Number of household members	3.334	1.745
Number of children	0.994	1.313
Family income	71,112.150	46,446.780
Number of episodes	**91,420**	
Number of individuals	**23,131**	

Notes: Data come from the 2010, 2012, 2013 and 2021 ATUS WB-Module. All observations are weighted using the activity weights provided by the ATUS.

3. Data and variables

Our data is sourced from two primary organizations, the Bureau of Labor Statistics and the National Climatic Data Center (NCDC) of the National Oceanic and Atmospheric Administration (NOAA). The ATUS is a collaborative effort between the Bureau of Labor Statistics and the US Census Bureau and has been conducted annually since January 2003.

[5] Like the ATUS WB-Module, the PATS collects contemporaneous subjective-wellbeing using the Day Reconstruction Method for only three of the many activities in which respondents had engaged the previous day, with the exception of sleep, grooming, and private activities. Both PATS and ATUS respondents show reported values of 0 to 6.

It is a publicly accessible time-diary study that provides nationally representative data on the activities of Americans who are at least 15 years old, throughout a 24-hour period on a designated day of the week, known as the "diary day". The data collection process involves randomly selecting respondents from the Current Population Survey (CPS) and conducting daily computer-assisted telephone interviews (CATI). The distribution of ATUS diary days throughout the year is designed to be evenly spread across different weeks, ensuring comprehensive coverage and a representative snapshot of daily life throughout the week.

The core purpose of the ATUS is to measure the time individuals allocate to various activities, with only one individual providing data per surveyed household, although some information about the entire household is also included. However, throughout the entire survey period, the regular time-use survey has been enhanced with specific modules comprising additional questions on topics of public interest, typically related to time use. Within this framework, during the survey years 2010, 2012, 2013, and 2021, the ATUS conducted a WB-Module, which collected affective data for three randomly chosen activities reported by each respondent on the diary day that lasted for at least 5 minutes.

This module focused on measuring feelings of happiness, sadness, fatigue, pain, and stress they experience during each activity, using a 7-point Likert scale ranging from 0 (indicating a low intensity or not experiencing the feeling at all) to 6 (indicating a high intensity or extremely strong feeling). Additionally, participants were asked about how meaningful they find each activity, on a range from 0 to 6.[6] Appendix A and Appendix Table A1 provides details of this module and lists the exact wording for the well-being questions taken from the ATUS WB-Module. We examine the relationship between temperature and individuals' well-being by using data from *all available waves* of the ATUS WB-Module.[7]

To aggregate these six instant feelings of the ATUS WB-Module, we construct two latent variables: net affect and the U-index. Net affect represents overall mood and is calculated by subtracting the mean of negative emotions (pain, sadness, fatigue, and stress) from the mean of positive emotions (happiness, meaningfulness) experienced during a particular activity. This yields a net affect score ranging from -6 to 6, where -6 represents the lowest possible negative mood and 6 represents the highest possible positive mood. This measure has been widely used in similar studies as a reliable predictor of overall self-ratings of happiness (Kahneman and Krueger, 2006; Kahneman et al., 2006).

The U-index, on the other hand, is a binary variable that classifies an activity as "unpleasant" if the maximum rating for any of the negative feelings (sadness, stress, fatigue, pain) is higher than the maximum rating for any of the positive feelings (happiness, meaningfulness) during that activity. If the maximum negative rating is not greater than the maximum positive rating, the U-index is set to 0. This indicates the predominance of negative emotions over positive ones during a given activity and measures the proportion of time an individual spends in an unpleasant state (Kahneman and Krueger, 2006).

We enrich the ATUS data set with weather information by incorporating details about the diary day and county of residence. This allows for a consistent assessment of weather conditions experienced by respondents within a particular county on the survey diary day, the preceding day of the ATUS interview, and the date when respondents reported their well-being. By utilizing the county as the primary unit of geographical analysis, we can effectively examine the connection between weather and well-being, as it provides the most appropriate geographic delineation for this purpose.

Unfortunately, county of residence is reported only for counties with more than 100,000 inhabitants. However, for some respondents, the reported geographic identifier is the Metropolitan Statistical Area (MSA) rather than the county of residence. In such cases, we assign weather data from the most populous county within the MSA (Graff Zivin and Neidell, 2014; Jiao et al., 2021; Neidell et al., 2021). Respondents lacking county- or MSA-level geocoding are excluded (Connolly, 2008, 2013; Graff Zivin and Neidell, 2014; Jiao et al., 2021; Neidell et al., 2021), representing 40% of those targeted by the ATUS WB-Module.[8]

Historical weather data for precipitation, snowfall, and temperature were sourced from the NCDC of the NOAA.[9] The NCDC offers a comprehensive collection of weather data from numerous weather stations throughout the United States. In this study, data for all variables were gathered at the county level, utilizing daily summaries from a total of 21,210 weather stations located across the US. We aggregate weather measurements from the station level to the county level by computing the simple average of the weather variables across all weather stations within a county on a given day (Connolly, 2008, 2013; Graff Zivin and Neidell, 2014; Jiao et al., 2021; Liu and Hirsch, 2021; Neidell et al., 2021). The precipitation and snowfall variables were initially recorded in inches, while the maximum temperature variable was measured in degrees Fahrenheit.[10] We focus the empirical analysis on maximum temperature, although we include precipitation and snowfall as control variables in a robustness check.

In addition to the 24-hour time diary and well-being questions, the ATUS dataset offers extensive information on the demographic and household characteristics of respondents. These variables serve as covariates in our models, considering prior research into determinants of individuals' well-being. The demographic and household variables included in our analysis are gender, categorized as a binary variable, where 1 indicates male and 0 represents female; age measured as a continuous variable, representing the respondent's age in years; native status, controlled by a dummy variable with a value of 1 for respondents born in the US and 0 for those who are foreign-born; maximum education level, transformed into three binary variables to capture different levels of education attainment (less than high school, some high school, and some college or more); labor force status, encoded as a dummy variable with a value of 1 for employed respondents and 0 for those who

[6] While meaningfulness is often viewed as a component of eudaimonic well-being (Dolan and Laffan, 2016), it can also capture momentary affective states when assessed at the episodic level. In the ATUS WB-Module, meaningfulness is reported for specific activities, reflecting the respondent's immediate perception at the time of occurrence. Prior research (Kahneman et al., 2004; White and Dolan, 2009) shows that perceived meaning fluctuates throughout the day, influenced by situational contexts. This study, therefore, considers meaningfulness as part of individuals' daily experiences and emotions, in line with previous research utilizing the same measure in the ATUS WB-Module (Bertrand, 2013; Connelly and Kimmel, 2015; Dolan et al., 2017; Kalil et al., 2025; Lee et al., 2016; Meier et al., 2016; Negraia and Augustine, 2020; Negraia et al., 2021; Qu, 2022; Stone and Schneider, 2016; Song and Gao, 2020, 2023). Thus, while meaningfulness has a broader interpretative scope, its episodic measurement allows us to analyze how external factors, such as extreme temperatures, affect variations in reported meaningfulness in daily activities.

[7] The 2021 ATUS WB-Module may not be comparable to the 2010, 2012, and 2013 ATUS WB-Module, due to the wide time gap between the surveys, COVID-related circumstances, and the non-complete coverage of the entire year (the 2021 data were collected from March through December 2021). However, we find robust results if we exclude data from 2021. This set of results is available upon request.

[8] While spatial variation in weather measurements within states is likely significant, the main results remain very similar when assigning weather data based on the most populous county in each state as the respondents' location. Although this approach is less precise due to the inclusion of large geographical areas, it remains consistent with the methodology of Gibson and Shrader (2018).

[9] The weather data were retrieved from https://www.ncdc.noaa.gov/cdo-web/datatools.

[10] Although a variety of weather-related variables are available, most stations only report total amount of precipitation, snowfall, minimum temperature, and maximum temperature for the day.

are not employed; marital status, measured through a dummy variable with a value of 1 indicating respondents who report having a partner (either married or cohabiting) and 0 otherwise. Other variables defined at the household level include the number of people in the household, the number of children under age 18 in the household, and the family income.[11]

Regarding episode characteristics, we take into account several factors in our analysis. These include episode duration, measured in minutes and transformed into logarithmic terms to accommodate the right-skewness typically observed in time use data; activity categories that capture the specific type of activity the respondent engaged in during the episode; the presence of others, indicating whether there were other individuals present while the respondent was involved in the episode; the location of activity, describing where the activity took place, including home, outdoors, indoors (excluding home), or while traveling (this information was obtained through a question asking,"Where were you?"); and diary day characteristics, since the diary day can fall on any date, so we control for whether it was a weekend and/or a holiday. Weekends and holidays may generally contribute to improved well-being, as individuals often have more leisure time and fewer time constraints to engage in enjoyable activities (Helliwell and Wang, 2015).[12] We incorporate these episode characteristics to gain a comprehensive understanding of the factors influencing individuals' well-being. For a more detailed explanation of each variable's definition, please refer to Appendix Table A2.

The ATUS has more than 470 activity codes and we reclassify those into fourteen activity categories: cooking, shopping, other housework, childcare, market work, outdoor leisure, indoor leisure, entertainment, socializing, religious, hobbies, reading, sports, and personal care. Our classification of leisure activities closely follows the framework proposed by Aguiar and Hurst (2007). Appendix Table A3 reports a comprehensive list of activities contained within each of these fourteen time-use categories.

Table 1 presents the descriptive statistics for all key variables, including instant feelings, episode characteristics, daily temperatures, and socio-demographic controls. The first eight rows of Table 1 display the average levels of feelings experienced during different activities, specifically for the three randomly selected activities with individuals' well-being information. On a scale ranging from 0 to 6, the average levels of happiness, meaningfulness, sadness, stress, tiredness, and pain are 4.381, 4.353, 0.598, 1.479, 2.299, and 0.861, respectively. The net affect, representing the difference between the average positive and negative feelings, has a sample average of 3.058, while the average U-index is 0.133.

Regarding episode characteristics, the average duration of each activity is 167 minutes. Approximately 68.9% of the activities are performed in the presence of another person. Furthermore, 57.7% of the activities take place at home, 6.4% outdoors, 28.6% indoors, and 7.4% while traveling. In terms of the sampled diary days, 32.1% correspond to weekends and 2.3% are holidays. These percentages reflect the proportion of diary days falling on weekends and holidays in our sample.

The average daily maximum temperature is 69.5 degrees Fahrenheit. The distribution of temperature across diary days is as follows: 7.6% have maximum temperatures below 40°F (i.e., exposure to extreme cold temperatures), 8.9% have temperatures between 40 and 50°F, 12.3% have temperatures between 50 and 60°F, 16.2% have temperatures between 60 and 70°F, 20.2% have temperatures between 70 and 80°F, 23.9% have temperatures between 80 and 90°F, and 11% have temperatures exceeding 90°F (i.e., exposure to high temperatures).

In terms of socio-demographics, men account for slightly less than half of the sample, around 48.1%. The average age of respondents in our sample is approximately 42 years old. Additionally, 79.2% of individuals are native citizens. Regarding education, 16.6% of individuals have a primary education level, 25.3% have obtained a secondary education level, and 58.1% have completed a tertiary education level. Moreover, 62.8% of respondents are part of the labor force. Regarding household characteristics, around half (52.9%) of the sample lives with a partner (married or unmarried). The average number of household members is 3.33, and the average number of children in the household is 1. Concerning household socio-economic status, the average family income is $71,112.15.

4. Econometric strategy

To examine the relationship between daily temperatures and affective well-being, we estimate linear regression models using the Ordinary Least Square (OLS) method of estimation while considering the sampling weights provided by the ATUS. Clustered standard errors by individual are adjusted to account for correlation within individuals, as the data contains multiple observations from each respondent at the activity level, compared to prior research examining this relationship (Frijters et al., 2020; Noelke et al., 2016).

To address the differences in the fraction of time spent on eligible activities and the probability of selecting an eligible activity in the module, we apply activity-level weights. These weights help account for various aspects of the ATUS sample design and data collection process, including the oversampling of certain demographic groups and weekends, nonresponse rates, and the requirement that activities should be at least 5 minutes in duration to be eligible. Using activity weights, we can appropriately adjust and compensate for these important aspects. It is worth noting that individuals' well-being questions are asked for three activities specifically, which is why activity weights are utilized in our analysis.[13]

The decision to use the OLS estimator in our analysis is based on its simplicity and ease of interpretation. Coefficients in the linear model can be directly interpreted as marginal effects, providing a quantitative understanding of the relationship between variables. In contrast, ordered models, such as ordered logit or probit models, do not allow for *direct* quantitative interpretation of coefficients. Prior research has demonstrated that the cardinal models (OLS regressions) and ordinal models (ordered latent response models) yield very similar results, at least qualitatively. Studies by Ferrer-i-Carbonell and Frijters (2004) and Rasciute et al. (2023) have supported this finding. Therefore, considering the similarity in results between cardinal and ordinal models, we choose to adopt a cardinal interpretation of individual responses as is common in the literature (De Rock and Périlleux, 2023; Flèche et al., 2020; Foliano et al., 2024), even though the survey provides ordinal measures of affective well-being.

Specifically, we estimate the following linear regression, separately by gender:

$$SWB_{ijk,t} = \alpha_0 + \sum_{1}^{l=6} \delta_l TMAXBin_{j,t} + X_{ij,t}\beta + E_{ijk,t}\gamma + \rho_j + \theta_m + \Phi_{j,mt} + \tau_t + \varepsilon_{ijk,t} \tag{1}$$

[11] The information regarding family income is initially reported in intervals by the survey, to minimize missing values. We recode this variable into a continuous variable, assigning the midpoint of each interval and the upper (lower) limit for the first (last) interval.

[12] All results reported remain identical if we control for day of week fixed effects, rather than weekend and holiday dummy variables.

[13] Note that our unit of analysis is activity, rather than individual. Thus, we cluster the standard errors on the person because the data contains multiple observations from each respondent (i.e., 3 episodes from the same respondent). Additionally, we test the results with regard to clustering at the regional level, utilizing either the state, state-month, county or county-month level, and the results remain robust across different clustering criteria. For the sake of simplicity, we estimate robust-cluster errors at the individual level, and those alternative results are available from the authors upon request.

In all models, subscript i denotes individuals, j denotes county of residence, k denotes episode, m denotes survey months and t denotes survey years. The dependent variable, $SWB_{ijk,t}$, is the feeling or measure of individual well-being (happiness, meaningfulness, sadness, fatigue, stress, pain, net affect, or U-index) reported by respondent i in county j at time t during episode k, where time is expressed in terms of the year, month and day of interview. For comparability, we standardize all of the *continuous* instant feeling measures (happiness, meaningfulness, sadness, fatigue, stress, pain, net affect) by subtracting their mean and dividing by their standard deviation to have a mean of 0 and a standard deviation of 1 for ease of interpretation (i.e., estimated coefficients can be interpreted as the change in terms of one standard deviation of each well-being measure). $X_{ij,t}$ represents a vector of socio-demographic characteristics of individual i. $TMAXBin_{j,t}$ is a vector of county-level maximum temperature bins, the main explanatory variables in our specifications, and $E_{ijk,t}$ is a vector of episode characteristics.

Regarding weather characteristics, we focus on the daily maximum temperature as a proxy for individual exposure to heat (Graff Zivin and Neidell, 2014; Jiao et al., 2021; Neidell et al., 2021). We include the maximum temperature on the diary day in the county, represented as dummy variables with widths of 10°F. That is, we divide the absolute value of maximum temperature into maximum temperature bins. This daily maximum temperature-binning approach allows us to capture non-linearities in the relationship between maximum temperature and well-being, and its main advantage is its flexibility (i.e., each maximum temperature bin has distinct–constant–effects on each well-being measure). The reference category is set as 70-80°F, which involves comfortable temperatures (Heyes and Saberian, 2022; Picchio and van Ours, 2024). Consequently, the parameters δ_l, for $l = 1, \ldots, 6$, represent the change in each instant feeling variable, expressed in terms of standard deviations, associated with a day falling within a specific maximum temperature range, compared to a day within the $70 - 80$°F range.

The individual control variables include age and its square (divided by 100), being a native citizen (ref.: immigrants), highest education completed (ref.: primary education), employment status (ref.: not in labor force), married or cohabiting (ref.: not cohabiting), family size, the number of children in the household, and the log of family income. Most of these variables have been demonstrated to have an impact on well-being by prior research (Della Giusta et al., 2011; Dolan et al., 2008; Kahneman and Deaton, 2010).

Since prior research has demonstrated that affective outcomes can vary based on activity characteristics (Kahneman et al., 2004), we control for episode features. Specifically, we control for the type of activity, with personal care serving as the reference category. We also consider the logarithm of activity duration in minutes (e.g., more minutes in unpleasant activities), whether the respondent interacted with someone else during the activity (e.g., spouse, parent, children, other family members, friends), whether the diary day falls on a weekend or a holiday, and the location where the activity took place (with travelling serving as the reference category).

While ambient temperatures recorded at weather stations may not fully reflect the actual thermal conditions faced by respondents, maximum temperature provides a reasonable approximation given that well-being measures are collected for daytime activities, excluding major activities such as sleeping. Since the actual temperature experienced depends on where activities take place, we explicitly account for location by incorporating activity-based classifications (outdoors, indoors, at home, or traveling). This variable provides important contextual information, as individuals can mitigate exposure by limiting outdoor activities or spending time in climate-controlled environments.

To account for time-specific fixed effects, we incorporate year dummies (τ_t) indicating the year in which the module was conducted. These dummies help control for unobserved factors specific to a particular year, such as time-varying shocks that occur nationwide, either macroeconomic fluctuations or COVID-19 related circumstances, and potential survey issues. The reference year is 2010. The variable θ_m represents month fixed effects that control for seasonal fluctuations in well-being, which have been shown to differ by gender (Blanchflower and Bryson, 2024c), as well as systematic variations in temperature across months. For instance, extreme temperatures in summer may have distinct effects compared to extreme temperatures in spring. To account for these seasonal patterns, we include month fixed effects in our specification, using December as the reference category. Additionally, we account for the local monthly average of maximum temperature in our estimates through the inclusion of $\Phi_{j,mt}$. Consequently, our coefficients of interest for maximum temperature bins abstract from the local mean temperature over the month when the survey was conducted, and account for the individual's adaptability to temperature.

To account for regional heterogeneity and address any unobserved, time-invariant characteristic at the county level, we include US county of residence fixed effects, denoted as ρ_j that capture, among other things, the greater frequency of hotter temperatures among counties and permanent adaptations for their climate. These fixed effects additionally control for permanent county characteristics that may simultaneously influence daily maximum temperature and individuals' well-being, such as their geography. Consequently, the parameters of interest regarding maximum temperature are identified from within-county variations over time. The final term $\varepsilon_{ijk,t}$ is the error term.

5. Results

5.1. Main results

Tables 2 and 3 present the OLS estimates that examine the relationship between daily maximum temperature and individual well-being, including happiness, meaningfulness, sadness, stress, tiredness, pain, net affect, and the U-index. The analysis takes into account demographic, household, episode, time, and county characteristics. The results are reported separately for men and women to explore any gender-specific differences and exposure to maximum temperatures.[14]

Our estimates reveal notable gender differences, indicating that men may be more sensitive to higher maximum temperatures. Specifically, we find that days with maximum temperatures above 80°F, compared to days with maximum temperatures in the $70 - 80$°F range, are negatively associated with positive instant feelings such as happiness and meaningfulness, and positively related to negative instant emotions like fatigue and pain among men. When calculating the standard deviation for each instant feeling, we observe that days with maximum temperatures around $80 - 90$°F, relative to days with maximum temperatures of $70 - 80$°F, are related to an increase of 0.154 and 0.084 standard deviations in fatigue and pain for men. Conversely, these same days are associated with a decrease of 0.129 standard deviations in happiness and a decrease of 0.170 standard deviations in meaningfulness for men. Consequently, days with maximum temperatures around $80 - 90$°F correspond to a decrease of 0.201 standard deviations in the net affect and an increase of 5.1 percentage points in the U-index for men.

Days with maximum temperatures of 90°F or above are associated with an increase of 0.169 standard deviations in fatigue for men, and with a decrease of 0.188 standard deviations in meaningfulness. Consequently, days with maximum temperatures above 90°F are related

[14] To account for the ordinal nature of the dependent variables, which range from -6 to 6, we also conduct additional analyses using ordered models, such as ordered logit or probit models. These provide a robustness check and allow for a more nuanced understanding of the relationship between the variables. The results from the ordered models are consistent with the findings from the OLS models in terms of the direction and statistical significance of the coefficients. It is important to note that the coefficients themselves are not *directly* comparable across the different models, unless marginal effects are calculated. These results are available on request.

Table 2
Relationship between maximum temperature and instant feelings, men.

	Happy (1)	Meaningful (2)	Sad (3)	Stress (4)	Tired (5)	Pain (6)	Net affect (7)	U-index (8)
TMAX < 40°F	0.042	0.039	0.082	-0.110	-0.072	-0.078	0.075	-0.027
	(0.084)	(0.080)	(0.104)	(0.088)	(0.082)	(0.091)	(0.087)	(0.027)
TMAX = 40°F – 50°F	0.021	-0.087	-0.023	0.032	-0.068	0.003	-0.021	-0.014
	(0.065)	(0.069)	(0.079)	(0.069)	(0.067)	(0.075)	(0.071)	(0.021)
TMAX = 50°F – 60°F	0.030	-0.115**	0.060	0.006	0.000	0.002	-0.053	0.005
	(0.056)	(0.055)	(0.066)	(0.060)	(0.059)	(0.062)	(0.059)	(0.019)
TMAX = 60°F – 70°F	-0.084*	-0.070	0.015	0.044	0.025	0.033	-0.088*	0.008
	(0.049)	(0.043)	(0.054)	(0.051)	(0.047)	(0.047)	(0.048)	(0.015)
TMAX = 80°F – 90°F	-0.129***	-0.170***	0.043	0.065	0.154***	0.084**	-0.201***	0.051***
	(0.047)	(0.042)	(0.048)	(0.049)	(0.044)	(0.043)	(0.046)	(0.014)
TMAX ≥ 90°F	-0.116*	-0.188***	0.065	0.123*	0.169***	-0.027	-0.202***	0.039**
	(0.060)	(0.059)	(0.067)	(0.063)	(0.058)	(0.058)	(0.062)	(0.018)
Monthly average TMAX	0.002	0.001	-0.004	-0.003	0.000	-0.004	0.003	-0.001
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.001)
(Log) Episode duration	0.021	0.058***	0.062***	0.086***	-0.018	0.028**	0.008	0.002
	(0.014)	(0.013)	(0.018)	(0.016)	(0.014)	(0.013)	(0.014)	(0.004)
Episode with other	0.223***	0.228***	-0.110***	-0.043	-0.030	-0.070***	0.239***	-0.031***
	(0.031)	(0.028)	(0.032)	(0.030)	(0.028)	(0.027)	(0.028)	(0.010)
Episode at home	-0.033	0.132***	-0.122**	-0.060	-0.065	-0.031	0.100***	-0.006
	(0.037)	(0.040)	(0.053)	(0.045)	(0.041)	(0.036)	(0.039)	(0.011)
Episode outdoors	0.064	0.151***	-0.073	0.002	-0.167***	-0.016	0.148***	-0.042***
	(0.049)	(0.050)	(0.068)	(0.062)	(0.057)	(0.050)	(0.052)	(0.015)
Episode indoors	-0.080**	0.072*	-0.061	-0.041	-0.100**	0.033	0.037	-0.004
	(0.040)	(0.041)	(0.052)	(0.044)	(0.043)	(0.039)	(0.041)	(0.013)
Age	-0.004	0.022***	0.032***	0.025***	-0.001	0.047***	-0.009*	0.002
	(0.005)	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.002)
Age squared/100	0.008*	-0.017***	-0.031***	-0.029***	-0.005	-0.042***	0.014***	-0.003*
	(0.005)	(0.005)	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)	(0.002)
Native citizen	-0.108***	-0.106***	-0.162***	-0.011	-0.009	0.058*	-0.074**	0.023**
	(0.036)	(0.035)	(0.042)	(0.038)	(0.037)	(0.035)	(0.037)	(0.011)
Secondary education	-0.109**	0.009	-0.201***	-0.054	-0.103*	-0.119**	0.047	0.005
	(0.048)	(0.050)	(0.066)	(0.051)	(0.053)	(0.057)	(0.054)	(0.017)
University education	-0.197***	-0.033	-0.141**	0.119**	-0.006	-0.177***	-0.062	0.023
	(0.045)	(0.048)	(0.065)	(0.048)	(0.049)	(0.051)	(0.051)	(0.016)
Employed	0.140***	0.014	-0.122***	-0.107***	0.099***	-0.234***	0.120***	-0.008
	(0.037)	(0.035)	(0.044)	(0.037)	(0.037)	(0.038)	(0.037)	(0.011)
Married or cohabiting	0.094***	0.059*	-0.038	-0.014	0.015	0.003	0.069**	-0.006
	(0.034)	(0.032)	(0.041)	(0.038)	(0.035)	(0.035)	(0.035)	(0.011)
Number of household members	0.016	0.029**	0.037**	-0.001	0.003	0.019	0.011	0.002
	(0.016)	(0.015)	(0.019)	(0.017)	(0.016)	(0.015)	(0.015)	(0.005)
Number of children	0.004	0.005	-0.081***	0.009	-0.018	-0.023	0.022	-0.011*
	(0.020)	(0.019)	(0.023)	(0.021)	(0.021)	(0.019)	(0.019)	(0.006)
(Log) Family income	0.007	-0.036*	-0.070***	-0.026	-0.014	-0.142***	0.030	-0.015**
	(0.021)	(0.020)	(0.022)	(0.019)	(0.020)	(0.022)	(0.021)	(0.007)
Weekend day	0.092***	-0.017	-0.088***	-0.139***	-0.156***	-0.033	0.110***	-0.011
	(0.027)	(0.026)	(0.032)	(0.028)	(0.028)	(0.027)	(0.027)	(0.008)
Holiday	-0.001	-0.211**	0.254	-0.064	0.208**	0.019	-0.177**	0.037
	(0.082)	(0.090)	(0.177)	(0.108)	(0.096)	(0.092)	(0.079)	(0.028)
Constant	-0.750**	-1.190***	0.334	-0.609**	0.468	0.319	-0.949***	0.218**
	(0.298)	(0.287)	(0.330)	(0.302)	(0.299)	(0.301)	(0.300)	(0.094)
F-test on temperature bins	1.98*	4.05***	0.60	1.25	2.67**	1.55	3.66***	2.43**
Activity categories	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of episodes	40,900	40,900	40,900	40,900	40,900	40,900	40,900	40,900
Number of individuals	10,439	10,439	10,439	10,439	10,439	10,439	10,439	10,439
R-squared	0.162	0.177	0.100	0.210	0.098	0.137	0.175	0.107

Notes: Clustered standard errors at the individual level in parentheses. Data come from the 2010, 2012, 2013 and 2021 ATUS WB-Module. Estimation method for models is OLS. Dependent variables in columns (1-7) are standardized. Omitted category is maximum temperature 70 – 80°F. Estimates are weighted using sampling demographic weights at the activity level. All models control for activity categories, month, year and county fixed effects, but not shown for brevity. The *F*-tests report the *F*-statistics for the joint significance of the six temperature bin coefficients.

* $p < 0.1$
** $p < 0.05$
*** $p < 0.01$.

Table 3
Relationship between maximum temperature and instant feelings, women.

	Happy (1)	Meaningful (2)	Sad (3)	Stress (4)	Tired (5)	Pain (6)	Net affect (7)	U-index (8)
TMAX < 40°F	-0.047	-0.108	0.054	0.095	-0.041	0.107	-0.106	0.036
	(0.080)	(0.074)	(0.076)	(0.081)	(0.085)	(0.089)	(0.081)	(0.028)
TMAX = 40°F – 50°F	0.009	-0.081	0.147**	0.116	0.029	0.122*	-0.112	0.021
	(0.068)	(0.063)	(0.072)	(0.071)	(0.069)	(0.073)	(0.069)	(0.024)
TMAX = 50°F – 60°F	-0.049	-0.041	0.068	0.040	0.061	0.106*	-0.091*	0.022
	(0.052)	(0.047)	(0.051)	(0.054)	(0.052)	(0.056)	(0.052)	(0.019)
TMAX = 60°F – 70°F	-0.002	0.032	0.012	0.043	0.002	-0.051	0.012	0.003
	(0.043)	(0.037)	(0.045)	(0.046)	(0.044)	(0.044)	(0.043)	(0.015)
TMAX = 80°F – 90°F	0.021	0.041	-0.032	-0.035	-0.017	-0.032	0.049	0.006
	(0.040)	(0.037)	(0.040)	(0.041)	(0.040)	(0.043)	(0.040)	(0.014)
TMAX ≥ 90°F	0.045	0.068	-0.060	-0.053	-0.007	-0.072	0.084	0.005
	(0.057)	(0.049)	(0.057)	(0.060)	(0.056)	(0.062)	(0.057)	(0.019)
Monthly average TMAX	-0.004	-0.004	-0.002	0.001	0.002	0.002	-0.004	0.001
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.001)
(Log) Episode duration	0.012	0.074***	0.030**	0.058***	-0.017	0.041***	0.016	-0.001
	(0.014)	(0.012)	(0.013)	(0.014)	(0.014)	(0.014)	(0.014)	(0.005)
Episode with other	0.213***	0.212***	-0.099***	-0.051**	0.042	-0.001	0.191***	-0.035***
	(0.027)	(0.023)	(0.027)	(0.026)	(0.025)	(0.026)	(0.025)	(0.010)
Episode at home	-0.036	0.239***	-0.032	0.007	0.040	0.028	0.082**	-0.025**
	(0.036)	(0.034)	(0.031)	(0.034)	(0.034)	(0.033)	(0.034)	(0.012)
Episode outdoors	-0.009	0.284***	0.070	0.122**	-0.040	0.085	0.079	-0.039**
	(0.065)	(0.048)	(0.054)	(0.059)	(0.055)	(0.058)	(0.058)	(0.016)
Episode indoors	0.044	0.183***	-0.042	-0.026	-0.090**	0.015	0.129***	-0.028**
	(0.039)	(0.037)	(0.035)	(0.038)	(0.039)	(0.037)	(0.038)	(0.014)
Age	-0.006	0.028***	0.030***	0.028***	0.014***	0.045***	-0.013***	0.003*
	(0.004)	(0.004)	(0.005)	(0.005)	(0.004)	(0.005)	(0.004)	(0.001)
Age squared/100	0.011**	-0.020***	-0.029***	-0.034***	-0.020***	-0.039***	0.019***	-0.004***
	(0.004)	(0.004)	(0.005)	(0.005)	(0.004)	(0.005)	(0.005)	(0.002)
Native citizen	-0.118***	-0.109***	-0.102***	0.061*	0.065*	0.025	-0.110***	0.043***
	(0.035)	(0.029)	(0.037)	(0.035)	(0.036)	(0.039)	(0.035)	(0.011)
Secondary education	0.074	0.033	-0.116**	-0.051	-0.115**	-0.168***	0.132***	-0.030**
	(0.048)	(0.041)	(0.048)	(0.049)	(0.049)	(0.053)	(0.046)	(0.013)
University education	0.012	0.033	-0.218***	0.000	-0.152***	-0.258***	0.141***	-0.012
	(0.045)	(0.038)	(0.044)	(0.045)	(0.047)	(0.050)	(0.043)	(0.014)
Employed	0.078***	0.024	-0.069**	-0.121***	0.099***	-0.106***	0.073**	-0.013
	(0.029)	(0.026)	(0.028)	(0.028)	(0.029)	(0.031)	(0.029)	(0.009)
Married or cohabiting	0.091***	-0.007	-0.098***	-0.110***	-0.060*	-0.090***	0.102***	-0.014
	(0.030)	(0.025)	(0.031)	(0.033)	(0.031)	(0.033)	(0.030)	(0.011)
Number of household members	0.038**	0.035***	-0.014	-0.009	-0.004	0.026*	0.030**	-0.006
	(0.015)	(0.013)	(0.013)	(0.016)	(0.015)	(0.014)	(0.014)	(0.005)
Number of children	-0.002	0.001	-0.033*	-0.006	0.017	-0.069***	0.015	-0.005
	(0.019)	(0.018)	(0.017)	(0.020)	(0.019)	(0.020)	(0.019)	(0.006)
(Log) Family income	-0.054***	-0.095***	-0.054***	-0.027	-0.001	-0.155***	-0.018	0.004
	(0.018)	(0.015)	(0.016)	(0.020)	(0.018)	(0.020)	(0.019)	(0.006)
Weekend day	0.041*	-0.017	-0.019	-0.112***	-0.114***	-0.055**	0.072***	-0.012
	(0.025)	(0.022)	(0.026)	(0.026)	(0.026)	(0.028)	(0.025)	(0.008)
Holiday	0.068	0.036	0.137	-0.162**	-0.098	-0.116	0.100	-0.046***
	(0.083)	(0.098)	(0.105)	(0.071)	(0.072)	(0.076)	(0.089)	(0.017)
Constant	1.807***	0.551**	-0.380	-0.061	0.505	1.631***	0.554*	-0.126
	(0.289)	(0.278)	(0.271)	(0.310)	(0.307)	(0.298)	(0.302)	(0.100)
F-test on temperature bins	0.43	1.26	1.14	0.63	0.65	2.29**	1.47	0.46
Activity categories	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of episodes	50,520	50,520	50,520	50,520	50,520	50,520	50,520	50,520
Number of individuals	12,692	12,692	12,692	12,692	12,692	12,692	12,692	12,692
R-squared	0.140	0.196	0.105	0.191	0.107	0.145	0.172	0.110

Notes: Clustered standard errors at the individual level in parentheses. Data come from the 2010, 2012, 2013 and 2021 ATUS WB-Module. Estimation method for models is OLS. Dependent variables in columns (1-7) are standardized. Omitted category is maximum temperature 70 – 80°F. Estimates are weighted using sampling demographic weights at the activity level. The *F*-tests report the *F*-statistics for the joint significance of the six temperature bin coefficients. All models control for activity categories, month, year and county fixed effects, but not shown for brevity.

* $p < 0.1$
** $p < 0.05$
*** $p < 0.01$.

to a decrease of 0.202 standard deviations in the net affect and an increase of 3.9 percentage points in the U-index among men. Comparing these marginal effects to some other determinants of well-being, we observe that daily temperature bins exert a larger correlation with instant emotions than standard socio-demographic factors such as age, employment status, education level, marital status, and family income, as well as episode characteristics like activity duration. For example, a day with a maximum temperature equal of 90°F or higher is associated with a decrease of 0.202 standard deviations in net affect, whereas being employed or living with a partner corresponds to increases of 0.120 and 0.069 standard deviations, respectively. In contrast, such hot days are linked to a 3.9 percentage point increase in the U-index, whereas a one percent increase in family income is associated with a 0.015 percentage point decrease. All these differences are statistically significant at the 1% level.

In contrast, for women in Table 3, higher maximum temperatures are not related to changes in individual well-being.[15] In addition, although some specific temperature bins display statistically significant values, after applying the Romano-Wolf multiple-hypothesis correction (Clarke et al., 2020; Romano and Wolf, 2016) to explicitly control for the familywise error rate and enhance the power to correctly reject false null hypotheses, the results for women are no longer statistically significant, whereas the results for men remain unaffected. Appendix B Tables B1 and B2 present the adjusted *p*-values obtained by computing Romano-Wolf *p*-values with 300 replications, which control for the familywise error rate and correct for testing multiple hypotheses across outcomes. Additionally, we compare them to the original *p*-values reported in Tables 2 and 3.

Overall, our results indicate gender differences in the relationship between maximum temperatures and instant well-being, with men exhibiting greater sensitivity to higher temperatures. Specifically, extreme heat appears to reduce men's reported levels of meaningfulness while increasing their levels of tiredness. These gender-specific patterns contrast with previous research on affective measures by gender (Connolly, 2013). Connolly's study suggests that only the affective well-being of women, and not men, is influenced by daily temperatures. However, her dataset, although based in the US and analyzing similar measures, is not directly comparable to ours, as it lacks full-year representativeness and covers only the summer of 2006. Additionally, her analysis accounts for regional heterogeneity only at the state level, which may introduce bias in her estimates. Our findings qualitatively align with those of Noelke et al. (2016) and Frijters et al. (2020), who report that higher temperatures reduce well-being in the US. While these studies do not explicitly examine gender differences or distinguish the intensity of emotional responses, they similarly find that higher temperatures increase negative emotions and decrease positive ones.

To explore whether the differences in the estimates according to gender are statistically significant, in Table 4 we show the results of a Wald-type test of equality of coefficients between men and women. We observe statistically significant differences between male and female estimates. Specifically, we observe that for the upper tail of maximum temperature, the differences between happiness, meaningfulness, tiredness, net affect and the U-index on days with maximum temperatures around 80 – 90°F are statistically significant at the 5% level, so these days are related to an increase (a decrease) of tiredness and the U-index (happiness, meaningfulness and net affect) for men, in comparison to women. Days with maximum temperatures above 90°F are also associated with lower levels of meaningfulness and net affect for men and the differences are statistically significant at the 1% percent level, whereas the differences between stress and fatigue in men and women are also statistically significant at the 5% level. All in all, gender differences exist and men declare greater intensities of tiredness and stress and lower intensities of happiness and meaningfulness during days with higher maximum temperatures, leading to a decrease in the overall net affect for those days among men.

In Appendix B, we present Tables B3 and B4, providing estimates separated by gender, after incorporating additional controls for other meteorological variables that are correlated with temperature. Specifically, we include variables such as precipitation and snowfall intensity on the diary day, as well as the difference in maximum temperature, precipitation, and snowfall from the previous day.[16] We include these estimates in Appendix B because we did not identify substantial differences across gender, and the main results related to maximum temperature remain robust. However, we find that extreme cold days are related to an increase of 8.4 percentage points in the U-index for women, which suggests that those days are related to the predominance of negative emotions for women. Similarly, we also consider the inclusion of a control for air pollution in Tables B5 and B6, through the Air Quality Index (AQI) of the Environmental Protection Agency (EPA), and obtain robust estimates too.

Alternatively, in Tables B7 and B8 we estimate a specification that is similar to Eq. (1) but excludes the set of episode characteristics (i.e., episode duration, activity category, location, presence of others) and the main results do not change if we do not include the extensive set of controls at the episode level. Similarly, by comparing coefficient estimates with and without individual and episode-level controls in Tables B9 and B10, we find that the significant coefficients for the temperature bins remain largely unchanged relative to the main estimates. This suggests that our results are not driven by over-controlling issues (Dell et al., 2014) or endogeneity concerns. (The number of observations is slightly higher, as household income contains missing values for some respondents.)

One potential confounder in our specification is sunlight, which is correlated with temperature and has been shown to affect time allocation (Costa-Font et al., 2024a; Gibson and Shrader, 2018; Giuntella and Mazzonna, 2019; Jagnani, 2024; Jin and Ziebarth, 2020; Nguyen et al., 2024) and mood (Baylis et al., 2018; Beecher et al., 2016; Costa-Font et al., 2024a, 2024b; Denissen et al., 2008; Feddersen et al., 2016; Kämpfer and Mutz, 2013; Kent et al., 2009; Lucas and Lawless, 2013; Oyane et al., 2008). Unfortunately, this information is missing in most weather stations, preventing direct inclusion in our analysis. However, as shown in Tables B11 and B12, our results are robust when including county-season fixed effects (Graff Zivin and Neidell, 2014), which capture seasonal differences across counties, including sunlight patterns. Additionally, including state-month fixed effects also had little impact on our estimates.

Finally, in Tables B13 and B14, we consider a more flexible specification for maximum temperature, and include fourteen maximum temperature bins with a width of 5°F, using the maximum temperature bin of 70 – 75°F as the reference category. Additionally, we set the upper maximum temperature bin to days of 95°F or more, whereas the lower maximum temperature bin is set to days of less than 35°F. Results suggest that extremely hot days (i.e., days with maximum temperatures of 95°F or more) are related to an increase of 0.301 standard deviations in tiredness and a decrease of 0.280 standard deviations in meaningfulness among males, leading to a decrease of 0.319 standard deviations in the net affect and to an increase of 7.7 percentage points in the U-index.[17]

[15] We perform a Blinder-Oaxaca decomposition and find that most of the observed differences in the gender well-being gap are due to unobserved characteristics.

[16] By including the change in maximum temperature from the prior day we control for the adaptive behavior role.

[17] To investigate potential mechanisms underlying our main estimates in Tables 2 and 3, we analyze additional outcomes available in our data, including general health status, life satisfaction, sleep duration, and sleep quality. However, none of these estimates yield statistically significant results.

Table 4
Comparison of the main coefficients, men vs. women.

	TMAX < 40°F	TMAX = 40°F – 50°F	TMAX = 50°F – 60°F	TMAX = 60°F – 70°F	TMAX = 80°F – 90°F	TMAX ≥ 90°F
Happy	0.089 (0.58)	0.012 (0.02)	0.079 (1.04)	-0.081 (1.51)	-0.150** (5.75)	-0.161* (3.72)
Meaningful	0.147 (1.78)	-0.006 (0.00)	-0.074 (1.02)	-0.102* (3.15)	-0.211*** (13.96)	-0.255*** (10.68)
Sad	0.028 (0.05)	-0.170 (2.48)	-0.008 (0.01)	0.003 (0.00)	0.075 (1.38)	0.125 (1.99)
Stress	-0.204* (2.85)	-0.083 (0.70)	-0.034 (0.17)	0.000 (0.00)	0.099 (2.32)	0.176** (4.03)
Tired	-0.031 (0.07)	-0.097 (1.02)	-0.060 (0.58)	0.023 (0.13)	0.171*** (8.11)	0.176** (4.75)
Pain	-0.185 (2.09)	-0.119 (1.27)	-0.105 (1.52)	0.085 (1.71)	0.116* (3.62)	0.046 (0.29)
Net affect	0.181 (2.27)	0.091 (0.83)	0.038 (0.23)	-0.100 (2.36)	-0.249*** (16.08)	-0.286*** (11.27)
U-index	-0.064 (2.62)	-0.036 (1.23)	-0.016 (0.34)	0.005 (0.06)	0.046** (5.28)	0.033 (1.64)

Notes: Differences between coefficients (men – women) are reported in figures, chi-squared statistics are reported in parentheses. Standard errors are clustered at the individual level. Data come from the 2010, 2012, 2013 and 2021 ATUS WB-Module. Omitted category is maximum temperature 70 – 80 °F. Estimates are weighted using sampling demographic weights at the activity level. All models control for activity categories, month, year and county fixed effects, but not shown for brevity.
* $p < 0.1$
** $p < 0.05$
*** $p < 0.01$.\

5.2. Heterogeneity analysis

The individual well-being data is provided at the activity level by the ATUS WB-Module. So far, we have examined the correlation between daily maximum temperature and individual well-being without differentiation based on activity-related characteristics. This involves pooling all episodes with well-being information collected by the survey and controlling for these features through the vector $E_{ijk,t}$ in Eq. (1). In this subsection, we move beyond conditional correlations between temperature and individual well-being, and focus on these relationships across various time uses. This additional check enables us to elucidate potential mechanisms that may explain prior estimates on time use in relation to weather conditions.

This literature stems from Connolly (2008), who estimates the intertemporal relationship between rainy days and leisure and working time using data from the ATUS 2003-2004. In the context of temperature and time allocation, Graff Zivin and Neidell (2014) use data from the ATUS 2003-2006 to demonstrate that extreme temperature days are related to a reduction of 59 minutes spent working in heat-exposed industries, while also resulting in a shift from outdoor to indoor leisure activities. Similar conclusions are drawn by Neidell et al. (2021), who extend the survey period by incorporating data from the ATUS up to 2018. Within this framework, the granularity of our dataset enables us to delve deeper and explore the individual well-being reported by workers during their work-related activities.

To study the relationship between temperature and individual well-being while at work, leveraging the unit of analysis of our dependent variables, we alternatively estimate Eq. (1), separately by gender, for working and non-working episodes (refer to Appendix Table A3 for a summary of the activities considered in each sub-sample). Tables 5 and 6 display the main results separately for men and women, respectively, and controlling for occupation and industry characteristics in episodes of market work which are available in our data (22 and 51 categories, respectively). These latter controls are important to capture the temperature exposure experienced by industries and occupations (Dillender, 2021; Graff Zivin and Neidell, 2014).

For men during market work episodes (Columns (1-8) of Table 5), we observe that extremely hot days (i.e., days with maximum temperatures over 90°F), in comparison to days with maximum temperatures of 70 – 80 °F, are linked to a decrease of 0.266 and 0.376 standard deviations in happiness and meaningfulness, while they are associated with an increase of 0.224, 0.413 and 0.313 standard deviations in sadness, stress and tiredness, respectively. In aggregate, days with maximum temperatures exceeding 90°F relate to a decrease of 0.504 standard deviations in net affect and an increase of 12 percentage points in the U-index. Conversely, during non-market work episodes, days with maximum temperatures over 90°F are not related to men's well-being at standard significance levels ($p > 0.05$).

In summary, our overall estimates for men, as shown in Table 2, are primarily influenced by market work episodes. Men report lower levels of happiness and meaningfulness and higher levels of sadness, stress and fatigue during extremely hot days, resulting in a decrease in net affect and a prevalence of negative emotions during those days in market work episodes. By contrast, from the estimates of Table 6 for women, we find a positive association between days with maximum temperatures lower than 40°F and stress during market work episodes, which suggests that days with maximum temperatures lower than 40°F are linked to an increase of 0.410 standard deviations in stress among women during market work episodes. In contrast, days with maximum temperatures exceeding 90°F are related to an increase of 11.5 percentage points in the U-index during market work episodes among women, and they are also linked to a decrease of 0.127 standard deviations in stress during non-market work episodes.[18]

These findings from the heterogeneity analysis of the relationship between maximum temperature and individual well-being provide new insights into the connection between temperature and work activities. Existing evidence has consistently shown that higher temperatures are negatively linked to working hours across various contexts (Garg et al., 2020; Graff Zivin and Neidell, 2014; Neidell et al., 2021) but the underlying mechanisms have remained unexplored. Moreover, these results are significant considering that positive emotions such as higher happiness levels and perceptions of meaningful work enhance work effort and productivity (Asuyama, 2021; Chandler and Kapelner, 2013; Kosfeld et al., 2017; Lapalme et al., 2023; Nikolova and Cnossen, 2020; Oswald et al. 2015). Therefore, these results may suggest that days with higher temperatures may not only be negatively associated with workers' working hours but also with their productivity while at work. These findings for market work episodes also align with extensive research suggesting that extreme temperature days are associated with lower work performance (Cai et al., 2018; Fesselmeyer, 2021; LoPalo, 2023; Picchio and van Ours, 2024), work absenteeism (Heyes and Saberian, 2022; Somanathan et al., 2021), and elevated workplace accidents (Dillender, 2021; Drescher and Janzen, 2025; Filomena and Picchio, 2024; Ireland et al., 2023).

6. Conclusions

This paper explores the relationship between daily temperatures and individuals' well-being, utilizing nationally representative data from the American Time Use Survey (ATUS) and weather information from the National Climatic Data Center (NCDC). Drawing from special

[18] Appendix Table B15 shows similar results when we only categorize as market work episodes those related to "Work, main job" (activity code 50101) and control for the hours usually worked per week.

Table 5
Heterogeneity analysis by market work episodes, men.

	Market work episodes								Non-market work episodes							
	Happy (1)	Meaningful (2)	Sad (3)	Stress (4)	Tired (5)	Pain (6)	Net affect (7)	U-index (8)	Happy (9)	Meaningful (10)	Sad (11)	Stress (12)	Tired (13)	Pain (14)	Net affect (15)	U-index (16)
TMAX < 40°F	0.127	0.422***	0.207	-0.209	-0.092	-0.257	0.332*	-0.108*	0.021	-0.065	-0.087	-0.149*	-0.115	-0.003	0.045	-0.015
	(0.175)	(0.155)	(0.192)	(0.177)	(0.155)	(0.175)	(0.182)	(0.064)	(0.084)	(0.081)	(0.104)	(0.086)	(0.087)	(0.093)	(0.087)	(0.025)
TMAX = 40°F – 50°F	0.028	0.097	0.042	0.024	-0.029	-0.161	0.080	-0.068	0.044	-0.147**	-0.117	-0.045	-0.111	0.061	-0.013	-0.012
	(0.145)	(0.138)	(0.138)	(0.136)	(0.125)	(0.136)	(0.158)	(0.052)	(0.070)	(0.073)	(0.085)	(0.074)	(0.073)	(0.080)	(0.075)	(0.021)
TMAX = 50°F – 60°F	-0.018	-0.084	0.036	0.016	0.002	-0.019	-0.053	-0.015	0.073	-0.072	0.033	-0.032	-0.015	0.022	-0.005	-0.010
	(0.113)	(0.110)	(0.111)	(0.111)	(0.107)	(0.111)	(0.120)	(0.047)	(0.059)	(0.056)	(0.072)	(0.064)	(0.064)	(0.066)	(0.062)	(0.019)
TMAX = 60°F – 70°F	-0.208**	-0.065	0.127	0.139	0.083	0.073	-0.200**	0.022	-0.002	-0.050	-0.026	-0.046	-0.026	0.027	-0.011	-0.006
	(0.091)	(0.081)	(0.105)	(0.088)	(0.085)	(0.089)	(0.097)	(0.037)	(0.051)	(0.046)	(0.053)	(0.050)	(0.051)	(0.049)	(0.049)	(0.014)
TMAX = 80°F – 90°F	-0.212***	-0.331***	0.059	0.196**	0.122	0.051	-0.333***	0.128***	-0.072	-0.098**	0.036	0.009	0.136***	0.061	-0.124***	0.012
	(0.082)	(0.073)	(0.078)	(0.084)	(0.081)	(0.083)	(0.084)	(0.034)	(0.045)	(0.043)	(0.050)	(0.047)	(0.048)	(0.046)	(0.046)	(0.012)
TMAX ≥ 90°F	-0.266**	-0.376***	0.224**	0.413***	0.313***	0.088	-0.504***	0.120***	-0.072	-0.118*	0.006	-0.011	0.114*	-0.053	-0.100	0.006
	(0.112)	(0.105)	(0.111)	(0.107)	(0.110)	(0.112)	(0.117)	(0.044)	(0.061)	(0.062)	(0.071)	(0.061)	(0.062)	(0.059)	(0.063)	(0.017)
F-test on temperature bins	2.26**	6.01***	1.09	3.10***	1.48	1.03	5.04***	3.15***	1.04	1.70	0.74	0.76	2.11**	1.02	1.37	0.30
Socio-demographics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Activity characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Occupation F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	No	No	No	No	No	No	No
Industry F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	No	No	No	No	No	No	No
Month F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of episodes	5,507	5,507	5,507	5,507	5,507	5,507	5,507	5,507	35,393	35,393	35,393	35,393	35,393	35,393	35,393	35,393
Number of individuals	3,169	3,169	3,169	3,169	3,169	3,169	3,169	3,169	10,178	10,178	10,178	10,178	10,178	10,178	10,178	10,178
R-squared	0.313	0.344	0.276	0.320	0.276	0.292	0.326	0.319	0.155	0.204	0.122	0.110	0.106	0.162	0.176	0.077

Notes: Clustered standard errors at the individual level in parentheses. Data come from the 2010, 2012, 2013 and 2021 ATUS WB-Module. Estimation method for models is OLS. Dependent variables in columns (1-7) and (9-15) are standardized. Omitted category is maximum temperature 70 – 80°F. The *F*-tests report the *F*-statistics for the joint significance of the six temperature bin coefficients. Estimates are weighted using sampling demographic weights at the activity level. Additional coefficients available upon request.

* $p < 0.1$
** $p < 0.05$
*** $p < 0.01$

Table 6
Heterogeneity analysis by market work episodes, women.

	Market work episodes								Non-market work episodes							
	Happy (1)	Meaningful (2)	Sad (3)	Stress (4)	Tired (5)	Pain (6)	Net affect (7)	U-index (8)	Happy (9)	Meaningful (10)	Sad (11)	Stress (12)	Tired (13)	Pain (14)	Net affect (15)	U-index (16)
TMAX < 40°F	0.004	-0.128	0.189	0.410**	-0.070	0.285	-0.216	0.030	-0.063	-0.092	0.018	0.031	0.033	0.039	-0.090	0.034
	(0.191)	(0.160)	(0.169)	(0.187)	(0.179)	(0.189)	(0.169)	(0.082)	(0.079)	(0.068)	(0.076)	(0.079)	(0.082)	(0.093)	(0.082)	(0.025)
TMAX = 40°F – 50°F	0.189	-0.196	0.121	0.194	0.170	0.342**	-0.182	0.086	-0.079	-0.038	0.174**	0.132*	0.037	0.066	-0.124*	0.006
	(0.140)	(0.148)	(0.145)	(0.149)	(0.154)	(0.165)	(0.142)	(0.073)	(0.070)	(0.060)	(0.074)	(0.074)	(0.069)	(0.079)	(0.069)	(0.021)
TMAX = 50°F – 60°F	-0.050	-0.119	0.087	0.066	0.041	0.199*	-0.147	0.044	-0.077	-0.033	0.076	0.019	0.118**	0.109*	-0.110**	0.021
	(0.116)	(0.108)	(0.110)	(0.115)	(0.117)	(0.119)	(0.115)	(0.055)	(0.052)	(0.047)	(0.053)	(0.057)	(0.054)	(0.060)	(0.054)	(0.017)
TMAX = 60°F – 70°F	0.133	0.017	0.039	0.038	0.051	0.000	0.030	0.010	-0.032	0.028	-0.000	0.030	0.011	-0.082*	0.009	-0.010
	(0.089)	(0.087)	(0.094)	(0.098)	(0.096)	(0.104)	(0.090)	(0.049)	(0.045)	(0.036)	(0.046)	(0.047)	(0.045)	(0.044)	(0.042)	(0.012)
TMAX = 80°F – 90°F	-0.040	0.085	-0.095	-0.046	-0.015	0.064	0.041	0.038	0.012	0.016	-0.010	-0.060	-0.012	-0.053	0.039	0.000
	(0.094)	(0.082)	(0.098)	(0.091)	(0.088)	(0.094)	(0.089)	(0.040)	(0.040)	(0.036)	(0.042)	(0.043)	(0.042)	(0.045)	(0.040)	(0.012)
TMAX ≥ 90°F	0.026	0.040	-0.138	0.086	0.028	0.090	0.008	0.115**	0.013	0.001	-0.014	-0.127**	-0.024	-0.103*	0.060	-0.009
	(0.111)	(0.115)	(0.113)	(0.127)	(0.120)	(0.137)	(0.115)	(0.058)	(0.060)	(0.049)	(0.060)	(0.059)	(0.059)	(0.062)	(0.058)	(0.016)
F-test on temperature bins	1.25	0.76	0.49	1.29	0.54	1.48	0.75	1.16	0.46	0.76	1.67	1.54	1.15	2.78**	1.53	0.98
Socio-demographics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Activity characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Occupation F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	No	No	No	No	No	No	No
Industry F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	No	No	No	No	No	No	No
Month F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of episodes	4,753	4,753	4,753	4,753	4,753	4,753	4,753	4,753	45,767	45,767	45,767	45,767	45,767	45,767	45,767	45,767
Number of individuals	2,738	2,738	2,738	2,738	2,738	2,738	2,738	2,738	12,512	12,512	12,512	12,512	12,512	12,512	12,512	12,512
R-squared	0.358	0.400	0.379	0.372	0.353	0.396	0.390	0.343	0.128	0.212	0.104	0.114	0.115	0.153	0.166	0.096

Notes: Clustered standard errors at the individual level in parentheses. Data come from the 2010, 2012, 2013 and 2021 ATUS WB-Module. Estimation method for models is OLS. Dependent variables in columns (1-7) and (9-15) are standardized. Omitted category is maximum temperature 70 – 80°F. The *F*-tests report the *F*-statistics for the joint significance of the six temperature bin coefficients. Estimates are weighted using sampling demographic weights at the activity level. Additional coefficients available upon request.

* $p < 0.1$
** $p < 0.05$
*** $p < 0.01$.

supplements added to the ATUS in 2010, 2012, 2013, and 2021, the Well-Being Module, our study offers more comprehensive estimates by encompassing data from four entire years, in contrast to prior studies that centered on specific seasons due to data availability (Connolly, 2013), potentially introducing bias. Additionally, the survey captures the *intensity* of certain affective emotions during three random activities performed throughout the predecing day, against prior research based on dichotomic measures on the *full* preceding day (Frijters et al., 2020; Noelke et al., 2016).

The empirical analysis encompasses a sample of 23,131 individuals, comprising over 91,420 pooled observations, thereby contributing to the existing literature on the relationship between weather conditions and individuals' well-being, with a focus on gender and activity differences. Contrary to prior research by Connolly (2013), which suggests women are more affected by daily temperature fluctuations, and findings from Noelke et al. (2016) and Frijters et al. (2020), which cannot disentangle the intensity of distinct emotions and do not analyze gender differences, our study presents detailed conclusions. Our findings reveal gender-specific relationships between maximum temperatures and affective well-being, indicating a negative association between extremely hot days and well-being among men. Notably, the novel insight emerges that men appear to be more sensitive to extreme heat, while women may not be responsive to daily temperatures. This underscores the potential adverse *affective* well-being consequences for men amidst global climate change.

Furthermore, extremely hot days correlate with reduced feelings of happiness and meaningfulness among men workers during market work episodes, while they declare higher levels of sadness, stress and fatigue while at work. The finding that men's instant well-being at work is negatively related to extremely hot temperatures also poses significant challenges for firms. As climate change progresses and temperatures continue to rise, the frequency of extreme heat events is expected to increase. Tailored policies, such as the implementation of advanced air conditioning technologies or flexible work arrangements that enable workers to adjust their schedules to avoid peak heat periods throughout the day, are warranted to mitigate heat exposure. However, such measures may not be applicable to many workers who are inherently exposed to heat due to the nature of their occupations (Dillender, 2021).

Our study provides robust evidence that extreme temperatures are differentially associated with well-being depending on gender and activity. However, the limitations of our current study, including the inability to control for unobserved individual heterogeneity, underscore the need for future research. While the ATUS WB-Module reports individuals' well-being for three episodes, the daily-level nature of temperature prevents the use of individual fixed-effects models, so we interpret our results as conditional correlations subject to permanent individual heterogeneity. Subsequent studies should aim to obtain panel data that allow to account for individual fixed effects and validate our findings. Consequently, we call for further research identifying causal effects through alternative empirical strategies based on our correlational results. Importantly, our estimates are context specific. Most of the research has focused on the US, and future research is warranted to broaden and yield a more global perspective on how temperatures influence well-being. Specifically, researchers should focus on diverse geographical settings, such as rural areas, and incorporate a wide array of measures to provide a complete picture of individual well-being.

Finally, the specific reasons for gender differences in well-being responses to high temperatures remain unclear. Several mechanisms may contribute to our findings, including preferential differences, biological or physiological factors, social roles, or the gender division of labor. Prior research has documented that women adjust their time use in response to extreme hot temperatures more than men do (Garg et al., 2020; Heyes and Saberian, 2022; Jiao et al., 2021), while men are more likely to work in climate-exposed industries (Dillender, 2021; Filomena and Picchio, 2024; Jiao et al., 2021). In addition to differences in exposure and activities, biological or physiological factors may also explain such well-being responses to temperature (Karjalainen, 2012; Ormandy and Ezratty, 2012). Understanding these mechanisms is an important area for future research.

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CRediT authorship contribution statement

Ignacio Belloc: Writing – original draft, Investigation, Formal analysis, Data curation, Conceptualization. **José Ignacio Gimenez-Nadal:** Writing – review & editing, Validation, Supervision, Project administration, Methodology, Investigation, Funding acquisition. **José Alberto Molina:** Writing – review & editing, Resources, Project administration, Investigation, Funding acquisition, Conceptualization.

Declarations of competing interest

The authors declare that they have no conflict of interest.

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.socec.2025.102405.

Data availability

Data will be made available on request.

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