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Weather Conditions and Physical Activity: Insights for Climate Emergency Policies*

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Abstract

This study explores the link between daily weather conditions and individual engagement in physical activities within the context of the climate emergency. Using ATUS data from 2003-2022, alongside detailed daily-county weather data, the research investigates their correlations. Results highlight a significant positive relationship between extreme high temperatures and heightened participation in physical activities, coupled with increased time dedicated to such pursuits. Surprisingly, individuals in warmer regions exhibit no adaptation to higher temperatures, contradicting initial assumptions. Furthermore, this study discerns sustained effects over a week, with additional hot days positively impacting physical activity within the preceding seven days. These findings hold crucial implications, shedding light on voluntary responses to global warming. They provide essential insights for formulating effective mitigation and adaptive policies aimed at promoting physical activity across varying weather conditions amid the ongoing climate emergency.

Keywords: Physical activity, weather, extreme temperatures, health, time use, ATUS

JEL Codes: I12, J22, Q54

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1. Introduction

Physical exercise is widely acknowledged as the cornerstone of well-being, encompassing numerous positive impacts on health markers and overall quality of life (Kahneman et al., 2004a, 2004b; Krueger, 2007; Rasciute and Downward, 2010). Its correlation with favorable health outcomes, such as enhancing physical fitness, managing weight effectively (Sarma et al., 2014; Courtemanche et al., 2021), bolstering mental health (Huang and Humphreys, 2012), and preventing chronic illnesses (Humphreys et al., 2014), not only enhances individual well-being but also alleviates substantial healthcare burdens for governments (Sari, 2009). Encouraging physical activity is pivotal in enhancing health metrics and nurturing a healthier population, as emphasized by the World Health Organization (WHO, 2022). Nevertheless, in the current context of climate change, recent studies underscore the detrimental impact of global warming on health, ranging from increased depression (Mullins and White, 2019; Hua et al., 2023) and diminished well-being (Noelke et al., 2016; Belloc et al., 2023) to compromised fitness levels (Hou and Zhang, 2024), heightened mortality rates (Barreca et al., 2016; Otrachshenko et al., 2017; Yu et al., 2019; Nguyen, Nguyen and Nguyen, 2023), and substantial economic ramifications for businesses, due to absenteeism and healthcare expenses (Karlsson and Ziebarth, 2018; Mullins and White, 2019; Agarwal et al., 2021; Somanathan et al., 2021; Heyes and Saberian, 2022; Chen et al., 2023). The potential adverse effects of climate change on the ability to engage in physical exercise are a significant concern for individual and public health.

The aim of this paper is to discern whether extreme temperatures prompt shifts in time allocation, specifically towards physical exercise, within households, considering the finite nature of time and potential redistribution due to climate change effects. Amid the pressing issue of climate change and its profound impact on health indicators, this study examines the relationship between daily weather conditions and physical activity among individuals in the United States. Extreme temperatures, whether hot or cold, can significantly influence activity levels; in hotter climates, individuals may opt for less strenuous outdoor activities during peak heat but might still engage in water-based pursuits, while colder weather often leads to indoor exercises or winter sports. Precipitation, such as rain or snow, tends to deter outdoor activities, yet some individuals find enjoyment in activities like running in the rain or skiing in snowy conditions. Seasonal variations impact activity preferences, with warmer seasons encouraging

outdoor activities like hiking or swimming, while colder seasons tend to prompt indoor workouts or sports like skiing. Daylight duration plays a role as well; longer daylight hours in summer promote extended outdoor activities, while shorter daylight hours in winter can limit outdoor pursuits. Moreover, weather exerts a psychological influence, affecting mood and motivation; sunny days may inspire more outdoor activities while gloomy weather could reduce the motivation for physical exertion. These diverse factors contribute to the nuanced and multifaceted relationship between weather conditions and physical activity choices.

The literature has documented that extreme temperatures are negatively related to the amount of time spent on compulsory activities (Graff Zivin and Neidell, 2014; Neidell et al., 2021; Alberto et al., 2021; Belloc et al., 2022), but the substitution across time uses has not been considered. Individuals may opt to pursue certain activity categories on days with specific weather conditions, according to their preferences. In this context, if the reduction of time devoted to compulsory activities such as paid work, and the consequent greater availability of time, during extreme temperature days is compensated with an increase in the time devoted to physical exercise, this would suggest some potential health-related benefits from warmer temperatures.

Employing data from the American Time Use Survey (ATUS) alongside detailed county-level weather data, this study aims to investigate the correlation between weather conditions and physical activity. Our results suggest that extreme cold days are negatively related to participation in activities that involve physical effort, while extreme hot days are positively related to participation and, conditional on participation, the amount of time devoted to these activities. We find that a day with a maximum temperature below 40°F is related to a decrease of 3.3 percent in the probability of doing any physical activity, while days with maximum temperatures above 90°F are related to an increase of 5.2 percent. Conditional on participation, a day with a maximum temperature higher than 90°F is associated with an increase of 18.6 percent in the time devoted to physical exercise. Besides, we find no evidence for adaptation of individuals residing in warmer places, as their time use behaviors are sensitive to extreme hot temperatures. Finally, the results for the extensive margin appear to be consistent with a long-run analysis.

In this research, significant emphasis is placed on bridging existing gaps in the literature of climate change. Specifically, we delve into uncharted territory by scrutinizing the intricate relationship between physical activity and the nuances of daily weather

conditions. This unique approach sheds light on a relatively overlooked aspect, offering a fresh perspective that contributes to the broader discourse on climate change adaptation.

The study extends its scope by methodically testing for adaptation mechanisms. This includes an exploration of voluntary time use categories, providing a comprehensive understanding of how individuals adapt their activities in response to varying weather patterns. By dissecting and differentiating between contemporaneous relationships and potential adaptation responses across the span of a week, this research reveals nuanced insights into the behavioral dynamics of individuals when faced with diverse weather conditions.

The novelty of this approach lies in its attention to the micro-level dynamics of human behavior in the face of climatic variations. By dissecting the interplay between physical activity and daily weather conditions, while accounting for adaptive responses, this study not only fills crucial gaps in the existing literature, but also lays the groundwork for a more nuanced comprehension of how individuals interact with and adapt to changing environmental circumstances at a micro-level scale.

The rest of the paper is organized as follows. Section 2 discusses the related literature. Section 3 introduces the data sources, variables, and sample selection. Section 4 describes the econometric strategy, while Section 5 presents the main results. Finally, Section 6 concludes.

2. Related literature

We examine two interconnected branches, exploring the impact of weather conditions on daily activities and the health-related repercussions of global warming. The study of time use in relation to daily weather conditions traces back to Connolly (2008), who studies time allocation responses to rainy days, drawn from personal time diaries in the ATUS 2003-2004. She shows that men tend to work 30 more minutes on rainy days (defined as days with at least 0.1 inches of precipitation) and allocate 25 minutes less to leisure. However, the findings for women are inconclusive.

The exploration of the influence of weather on time use has expanded significantly since Connolly's research, notably over the past decade. Graff Zivin and Neidell (2014) expanded the field by examining extreme weather conditions, particularly extreme

temperature effects on daily working times. Their analysis, using ATUS data from 2003 to 2006, highlights a reduction of 59 minutes in working times for individuals in heat-exposed industries during higher extreme temperatures. Moreover, the authors identify distinct relationships between maximum daily temperatures and outdoor and indoor leisure, where individuals prefer indoor leisure activities for extreme hot days.

Subsequent work by Neidell et al. (2021) validated and broadened these findings by extending the sample period and including the later available ATUS waves from 2003 to 2018. Their analysis revealed similar patterns, particularly accentuated during prosperous economic cycles, attributing variations to employment dynamics during economic difficulties that may diminish workers' bargaining power. While much attention in the literature focuses on adults and their work-related activities during extreme temperatures (Jesoe et al., 2018; Krüger and Neugart, 2018; Garg et al., 2020; Huang et al., 2020; Jiao et al., 2021; Belloc et al., 2022; Cosaert et al., 2023a, 2023b), other studies explore a range of demographic groups and activities.

For instance, Garg et al. (2020) studied time use responses in China between 1989 and 2011, using data from 9 waves of the China Health and Nutrition Survey (CHNS), finding that both extreme cold and extreme hot days impact workers by reducing weekly working hours. Expanding the focus, Alberto et al. (2021) use the ATUS 2004-2017 and investigate college students' time allocation, indicating alterations in study and class time during extreme temperatures, with increased leisure activities on hot days. Nguyen et al. (2021) studied children in Australia and observed shifts from outdoor to indoor activities during cold, hot, and rainy days. Additionally, with a focus on gender differences and using the ATUS 2004-2017, Jiao et al. (2021) scrutinized gender differences, discovering that women adjust labor supply and leisure time more significantly than do men during extremely hot days, reinforcing traditional gender roles.

By examining the impact of daily weather conditions on physical activity, we contribute to a strand of the literature that studies the potential effects of climate change on health outcomes, through observed time use behaviors (Mullins and White, 2019; Belloc et al., 2023; Hua et al., 2023). All these studies pay attention to the impacts of extreme temperatures on sleeping measures, given sleep's well-known impact on general human health, to explain potential underlying channels through which higher temperatures may influence mental health and overall well-being, and showing that

warmer temperatures are related to a reduction in sleeping time (Mullins and White, 2019; Hua et al., 2023) and sleeping quality (Belloc et al., 2023).

3. Data and variables

We use data from the American Time Use Survey (ATUS) from 2003 to 2022. The ATUS is an annual, nationally representative study involving time diaries, continuously conducted by the US Census Bureau since January 2003 and sponsored by the Bureau of Labor Statistics. It is the official time use survey in the US, measuring the amount of time individuals aged 15 and above allocate to various activities. The households included in the survey are those that have completed their eighth (final) interview for the Current Population Survey (CPS). The ATUS stands out as the most comprehensive time use survey globally, as many other similar surveys are seldom conducted regularly on an annual basis.¹

The survey questionnaire focuses on selecting one individual aged 15 or older from each household, chosen randomly among the sampled households, to partake in the interview. Respondents complete a personal time-use diary through computer-assisted telephone interviewing (CATI), recording their activities for every minute of the day preceding the interview. This goes from 4 a.m. on the day before the interview to 4 a.m. on the day of the interview, commonly referred to as the "diary day" in the ATUS terminology. Information gathered from ATUS respondents reflects activities observed on a single day of the week, indicating the survey's cross-sectional nature. The survey collects data from one member per CPS household annually from 2003 onwards (excluding two months in 2020).²

In addition to specific variables regarding individual time use, such as location, company, and the timing (including start and end times) of activities, the survey also collects demographic information about respondents. Numerous studies have shown that time use data obtained through diary-based methods offer superior accuracy and precision

¹ For a recent summary detailing the history and characteristics of time use surveys we refer to Gimenez-Nadal and Molina (2022).

² The survey ensures an equal representation across the days of the week, dedicating 50 percent of the diary to weekdays and 50 percent to weekend days throughout the weeks of the corresponding year. However, to accurately represent each day of the week within the corresponding month, survey weights need to be applied.

compared to information gathered via individual standardized questionnaires (Bonke, 2005; Yee-Kan, 2008). This includes household panel surveys like the Panel Study of Income Dynamics (PSID) in the US or the UK Household Longitudinal Study (UKHLS) in the UK, as well as other cross-sectional health surveys, such as the Behavioral Risk Factor Surveillance System (BRFSS) in the US.³

For our analysis, we use the most recent available data, pooling the ATUS data from the survey years 2003 to 2022, excluding the 2020 survey.⁴ Physical exercise time is specifically defined by the activities categorized under code 130100 "Participating in Sports, Exercise, or Recreation". This definition excludes other activity codes found in categories 130200 "Attending Sports or Recreational Events", 130300 "Waiting Associated with Sports, Exercise, and Recreation", 130400 "Security Procedures Related to Sports, Exercise, and Recreation", 139900 "Sports, Exercise, and Recreation, n.e.c.", and 139999 "Sports, exercise, and recreation, n.e.c.". Given the documented health benefits associated with active forms of travel (Jacob et al., 2021; Echeverría et al., 2022a), we also include activities related to travel (category 180000 "Traveling") performed using active modes of transport, such as walking or cycling.⁵ We then consider all activities falling within the 130100 and 180000 sub-categories to calculate the total time allocated to physical activity within the diary day.⁶ From this variable, we create a

³ The BRFSS only includes information at the broad level regarding participation in any physical activity or exercise during the past month. In contrast, the PSID and UKHLS feature different stylized questions that focus on the frequency and typical duration of physical activities.

⁴ The 2020 survey year was significantly impacted by the COVID-19 outbreak, leading to a suspension of data collection from March 18 to May 9. As a result, the estimates derived from ATUS 2020 are not representative of the entire year. Therefore, we exclude this survey year from our analysis.

⁵ The personal time diary also gathers information regarding the location and the presence of others (if any) during the activity. For travel episodes, there is information about the mode of transport used while travelling. Hence, the nature of our dataset allows us to distinguish among different forms of travel. See Echeverría et al. (2022b) for a recent analysis of the determinants of active travel time in a cross-country setting, using time use surveys from a total of 9 countries.

⁶ The activity codes in the category 130100 include: "Playing sports with household children", "Doing aerobics", "Playing baseball", "Playing basketball", "Biking", "Playing billiards", "Boating", "Bowling", "Climbing, spelunking, caving", "Dancing", "Participating in equestrian sports", "Fencing", "Fishing", "Playing football", "Golfing", "Doing gymnastics", "Hiking", "Playing hockey", "Hunting", "Participating in martial arts", "Playing racquet sports", "Participating in rodeo competitions", "Rollerblading", "Playing rugby", "Running", "Skiing, ice skating, snowboarding", "Playing soccer", "Playing softball", "Using cardiovascular equipment", "Vehicle touring/racing", "Playing volleyball", "Walking", "Participating in water sports", "Weightlifting/strength training", "Working out, unspecified", "Wrestling", "Doing yoga" and "Playing sports n.e.c.". The activity codes included in the category 180000 refer to travelling for different purposes, such as travel related to work, childcare, leisure, housework, personal care... See https://www.atusdata.org/atus-action/variables/activity#codes_section for further details about the activities included (accessed in December 2023).

dummy variable that indicates participation in physical exercise on the diary day, with value 1 if the respondent allocates positive time to physical exercise and 0 otherwise. These two raw measures serve as our outcomes of interest.

The ATUS provides detailed geographic and diary-date information, driving numerous studies that combine ATUS data with specific geographical variables, as previously outlined in Section 2. The particularities of the dataset, including its geographical details and time-diary-based structure – where individuals record their activities minute by minute from the previous day – make it especially suitable for examining responses to weather conditions, which aligns with our research focus. In particular, the ATUS includes data on the county of residence of the respondent and the precise date of the diary. We use this information to link the ATUS dataset with external weather variables sourced from the National Climatic Data Center (NCDC), covering a total of 22,343 weather stations nationwide.⁷ The NCDC provides us with daily summaries of precipitation levels (in inches), snowfall (in inches), and maximum temperature (in degrees Fahrenheit, °F), all of which we incorporate into our primary analysis.⁸ Regrettably, county of residence information is unavailable for counties with populations of fewer than 100,000 inhabitants due to confidentiality constraints. As a result, following the matching process, our sample consists of 87,551 observations (respondents).⁹

The survey includes information about demographic characteristics that we utilize to define various respondent variables: gender (male), age, dummy variables for secondary and university education, employment status (indicated by a dummy variable), a control dummy for unemployed respondents, marital status (indicated by a dummy variable),

⁷ We aggregate the data from the daily weather station level to the daily county level, assigning equal weight to all stations. The count of stations per county varies from 4 to 667.

⁸ We possess an external (unbalanced) panel dataset concerning daily weather conditions at the county level, covering the period from 2002 to 2022. The unbalanced structure primarily results from missing precipitation and snowfall values for specific counties, throughout the entire timeframe. Information about weather conditions other than (maximum and minimum) temperature, precipitation, and snowfall is unavailable for the majority of counties; thus, we do not include them in our analysis.

⁹ Following the exclusion of respondents with missing data among our variables, our final sample comprises 214,111 respondents from ATUS data spanning 2003-2019, 2021-2022. County information is available for approximately 41 percent of these respondents. We employ the BACON algorithm, as described by Billor et al. (2000), to identify outliers in multivariate data. This process leads to the removal of 3 respondents exhibiting outliers at the 5 percent significance level. Other data sources in the US, such as the BRFSS, also has the disadvantage of missing county identifiers (Mullins and White, 2019), while other household datasets such as the PSID do not provide information regarding the county of residence in their public version.

total family size, number of children, the logarithm of family income, and a dummy variable for holidays.¹⁰ To handle family income, we use coded income brackets to minimize missing values. For each interval between two figures, we assign the midpoint as the family income value, while the last interval, not bounded within a range, is designated as \$150,000. These sociodemographic variables align with common inclusions in time use studies overall and specifically in studies related to physical activity (Mullahy and Robert, 2010; Sen, 2012; Huang and Humphreys, 2012; Humphreys et al., 2014; Roy and Orazem, 2021).

Table 1 presents the summary statistics of our sample. Approximately 30.6 percent of individuals in our sample allocate positive amounts of time to physical activity, with an average of 22.33 minutes per day. For participants, the average time dedicated to physical activity stands at about 74.21 minutes per day. In terms of weather conditions, the average daily precipitation is 9.81 inches, snowfall averages at 0.58 inches, and the mean maximum temperature is 69.42°F. Among the control variables in our analysis, 48.6 percent of our sample are men, with the average age of the respondents being 44 years. Roughly 25.9 percent have attained secondary education, and 57.4 percent hold a university education. Moreover, 63 percent of our sample are employed, while 5.5 percent are unemployed. Regarding household characteristics, 51.2 percent of our respondents are married, the average household size is 3 individuals, with an average of 0.776 children per household. The mean family income is recorded at \$69,130. Finally, nearly 1.7 percent of diary days correspond to holidays.

The correlation between daily weather conditions and participation in physical activity, and the total time allocated to such activities demonstrates statistical significance at standard levels. Precipitation and snowfall act as deterrents to physical activity. Conversely, days with higher maximum temperatures exhibit a positive association, correlating with an increased likelihood of engaging in physical activity and spending more time on such activities. Specifically, for precipitation, we observe correlations of -0.011 and -0.015 with participation and time spent on physical exercise, respectively. In contrast, snowfall demonstrates correlations of -0.012. Additionally, the correlation coefficients between maximum temperatures and participation, as well as time devoted to physical activity, range from 0.041 to 0.054.

¹⁰ The reference category for employment status is then “Not in labor force”.

4. Econometric strategy

We estimate the relationship between physical exercise and weather conditions using the Ordinary Least Squares (OLS) estimator, accounting for individual probability weights provided by the survey. Additionally, we adjust for standard errors clustered at the state level to control for potential correlation among counties in the same state over time. Furthermore, our model is robust to heteroskedasticity. Specifically, we estimate the following equation:

$$Y_{ijt} = \beta_0 + \sum_{k=1}^{k=6} \delta_k TMAXBin_{ijt} + \sum_{l=1}^{l=4} \alpha_l PRCPBin_{ijt} + \sum_{r=1}^{r=4} \gamma_r SNOWBin_{ijt} + X'_{ijt}\beta + \theta_j + \mu_t + \varepsilon_{ijt}, \quad (1)$$

Where i denotes individual, j is county of residence and t refers to characteristics of the diary day. The dependent variable, Y_{ijt} , refers to the physical exercise outcome of interest for individual i in county j on diary day t . We examine two distinct measures of physical activity: first, participation in activities involving physical effort on the diary day, represented by a binary variable that takes the value 1 if the individual spent more than 0 minutes on physical activities, and 0 otherwise. Second, we consider the logarithm of the duration (in minutes) spent on activities involving physical effort throughout the entire diary day.

We include three vectors regarding weather variables on the diary day (i.e., the day prior to the interview day and the day about which respondents report their time use), namely: maximum temperature ($TMAXBin_{ijt}$), precipitation ($PRCPBin_{ijt}$) and snowfall ($SNOWBin_{ijt}$). For both precipitation and snowfall, we categorize the original continuous variables into four precipitation- and snowfall-bins. These bins are assigned a value of 1 if, on the diary day, there was rainfall (snowfall) within the ranges of 0-0.1 inches, 0.1-0.5 inches, 0.5-1 inches, or over 1 inch, and 0 otherwise. Hence, our reference point remains the days with no precipitation or snowfall, respectively. Regarding maximum temperature, we segment the raw maximum temperature values into seven temperature-bins: less than 40°F (considered extreme cold days), 40-50°F, 60-70°F, 70-80°F, 80-90°F, and over 90°F (considered extreme hot days). Our reference point remains

the diary days with maximum temperatures around 50-60°F (Yu et al., 2019; Dillender, 2021).¹¹

Each coefficient estimated for precipitation- and snowfall-bins represents the change in the probability of participating in physical activities, or the time spent on physical activity on a day within a precipitation- or snowfall-bin, relative to a day without precipitation or snowfall. Conversely, for maximum temperature, each estimated coefficient gauges the change in the physical outcomes associated with a day having a maximum temperature within a specific maximum temperature-bin, relative to a day with a maximum temperature around 50-60°F.

For the rest of the specification, X'_{ijt} represents a vector of socio-demographics of individual i , including gender, age and age squared, secondary and university education, employment and unemployment status, marital status, household size, number of children, log of family income, and a dummy variable for whether the diary day was a holiday. Given the time dimension of our pooled cross-section data source, we control for time-specific fixed effects by μ_t and include day fixed effects, to control for any time schedule and differences in physical activity on each day of the week, month fixed effects, to control for any seasonality in physical activity, and year fixed effects to control for unobserved temporal issues, such as specific macroeconomic factors or survey issues (i.e., changes of the survey questionnaires). Further, θ_j denotes county fixed effects, which control for regional differences in physical activity and for any time-invariant characteristics of a respondent's location, such as the historical climate that may explain certain county-specific physical activity participation rates. Consequently, the variables of interest regarding weather conditions are identified from cross-county and within-county daily variations in weather. Finally, ε_{ijt} is the error term of the equation.

¹¹ This weather-binning approach has been used for different weather variables in many studies (Deschênes and Greenstone, 2011; Graff Zivin and Neidell, 2014; Ranson, 2014; Barreca et al., 2016; Otrachshenko et al., 2017, 2018; Karlsson and Ziebarth, 2018; Krüger and Neugart, 2018; Mullins and White, 2019; Garg et al., 2020; Liu and Hirsch, 2021; Belloc et al., 2022, 2023; Heyes and Saberian, 2022; Cosaert et al., 2023a, 2023b). Summary statistics of daily weather conditions by bins is available in Appendix Table A1.

5. Results

The main estimates from Eq. (1) are presented in Table 2, highlighting significant connections between daily maximum temperatures, precipitation, and engagement in physical activities. Lower temperatures are associated with a reduced likelihood of participating in physical activities, while higher temperatures show a positive association with participation, with this relationship becoming stronger as temperatures rise. Precipitation, on the other hand, tends to reduce engagement in physical activities. Overall, these results indicate that daily temperatures act as an incentive for participation and influence the time spent on physical activity. Conversely, rainy days discourage participation, likely due to the outdoor nature of many physical activities. Essentially, individuals perceive days with higher temperatures as favorable for physical activity and view rainy days negatively when engaging in exercise.

Column (1) of Table 2 shows statistically significant correlations between daily maximum temperatures, precipitation, and engagement in physical activities. In particular, lower maximum temperatures, below 40°F, correlate with a 3.3 percent decrease in the probability of participating in physical activities, compared to days with a maximum temperature of 50-60°F. Similarly, days with temperatures between 40-50°F show a 2.1 percent reduction in the likelihood of engaging in physical activity. Days with temperatures of 60-70°F are associated with a 1.9 percent increase in physical activity engagement, while days between 70-80°F and 80-90°F show increases of 2.4 percent and 4.5 percent, respectively. Additionally, days exceeding 90°F (considered extreme hot days) are associated with a 5.2 percent increase in the likelihood of physical activity engagement. Days with over 1 inch of precipitation exhibit a 1.3 percent decrease in the probability of participating in physical activities compared to days without rain.

Column (2) in Table 2 presents the results of estimating Eq. (1) for the time allocated to physical activity, contingent upon participation (i.e., positive durations of physical activity), indicating that temperature correlates with physical activities, as higher maximum temperatures are associated with increased time spent on physical activity. Conversely, rainy and snowy days, regardless of their intensity, show no statistically significant impact on physical activity time compared to days without rain or snow. Notably, higher maximum temperatures, in contrast to temperatures between 50-60°F, display a significant correlation with increased time dedicated to physical activity.

Specifically, days with maximum temperatures of 70-80°F are linked to a 12 percent increase in physical activity time, while those with 80-90°F of maximum temperatures correspond to a 15.7 percent rise in physical activity duration. Moreover, extreme hot days exhibit an 18.6 percent increase in the time devoted to physical activity. Conversely, there are no statistically significant coefficients for rainy and snowy days, regardless of their intensity, compared to days without rain or snow, respectively.

The effects of weather conditions on physical activity vary due to individual differences in preferences, health, available resources, and cultural adaptation to specific climates. These combined factors influence how different population groups respond to and are affected by weather conditions during exercise. For instance, individuals may have preferences for certain weather conditions when engaging in physical activity—some may enjoy warmer climates, while others prefer cooler temperatures. Additionally, weather conditions, such as rain or snow, can restrict access to outdoor exercise facilities, hindering the use of parks or trails for activities like running or walking. Extreme weather poses risks for specific groups, like older individuals or those with respiratory issues, with high temperatures being challenging for people with existing health problems. Moreover, certain communities or cultures may find particular weather conditions more suitable or customary for physical activity. For example, regions with lengthy winters may have more prevalent winter activities. In extreme climates, individuals may limit the time spent exercising outdoors, which impacts their participation in physical activities.

We now analyze how different groups within the sample might react differently to weather conditions.¹² Specifically, we explore the hypothesis that individuals in warmer regions, accustomed to higher temperatures, might not alter their behavior in response to extreme heat. To test this, the sample was divided into warmer and colder areas based on the average maximum temperature from 2003 to 2022. Counties with an average maximum temperature above the overall mean were categorized as warmer areas, while the rest were considered colder areas. Table 3 presents the findings of Equation (1) estimations for warmer and colder areas. Surprisingly, individuals in warmer areas do not

¹² We conducted various checks on heterogeneity concerning time use constraints based on socio-demographics that could potentially restrict individuals from altering their physical activity behavior. However, we do not find any distinct relationship based on employment status, weekdays versus weekends, or the presence of children in the household. Table A2 displays the main results after controlling for the Air Quality Index (AQI), obtained from the Environmental Protection Agency (EPA) at the daily-county level, from 2003 to 2022, and indicates similar findings.

seem acclimated to more frequent higher temperatures, as temperatures above 90°F positively correlate with increased time spent in physical activities in warmer places, while no such relationship appears in colder areas.

The current analysis has primarily looked at the immediate links between weather and daily activities. However, our study highlights the likelihood of people adapting their behavior over time due to prior experiences with weather. For instance, individuals in consistently hot areas may be accustomed to exercising in such conditions, leading to less change in their physical activity during extreme heat. Likewise, seasonal shifts could prompt different activities between summer and winter. Essentially, the connection between weather and physical activity may change as people adjust their behavior based on past experiences, location, and the seasonal context of their activities. Adaptation involves individuals modifying their actions in response to past weather conditions, considering factors like location, prior weather experiences, and the specific season they are in when conducting activities

The ATUS was designed to expand its scope across survey years by integrating various time-use-specific modules at the end of the survey, aiming to dig deeper into social and economic issues associated with time use. During the periods of 2006-2018, 2014-2016, and 2022, it introduced a set of inquiries related to eating habits, dietary patterns, and individual health status, under the umbrella of the “Eating and Health (EH) Module”. Specifically, within this module, we leverage data from the survey years 2014-2016 and 2022, which encompass specific information about the frequency of physical activity in the past seven days. This data is gathered through the question: “During the past seven days, did you participate in any leisure time physical activities or exercises for fitness and health such as running, bicycling, working out in a gym, walking for exercise, or playing sports?” The possible responses to this inquiry include “Yes” or “No.” Consequently, we define a binary variable that equals 1 for “Yes” and 0 otherwise.

We now examine a 7-day rolling time frame, considering various weather variables like snowfall, precipitation, and maximum temperatures, to uncover potential delayed effects on physical activity. The results displayed in Table 4 reaffirm the relationship between weather conditions and physical activity, suggesting that specific temperature ranges may influence the likelihood of engaging in physical activities within a week-long

timeframe.¹³ For instance, additional days with maximum temperatures of 70-80°F or exceeding 90°F exhibit increased probabilities of engaging in physical activities compared to days with temperatures between 50-60°F. Specifically, an extra day with a maximum temperature of 70-80°F shows a 1.2 percent increase in the likelihood of participating in any physical activity during the past seven days, relative to an additional day with a maximum temperature of 50-60°F. Additionally, a day with maximum temperatures surpassing 90°F is associated with a 1.4 percent rise in the probability of engaging in any physical activity within the past 7 days compared to a day with a maximum temperature of 50-60°F.¹⁴

6. Conclusions

This paper explores the correlation between daily weather conditions and physical activity, a novel approach in research. Using data from the American Time Use Survey (ATUS) across 19 waves from 2003 to 2022, coupled with detailed county-level weather information, our analysis reveals notable associations. Extreme cold days decrease the likelihood of physical activity, while higher temperatures correspond to increased participation. Specifically, days with maximum temperatures below 40°F are linked to a 3.3 percent reduction in physical activity probability, whereas temperatures exceeding 90°F relate to a 5.2 percent increase. Moreover, extreme hot days significantly increase the time allocated to physical activity by approximately 18.6 percent among participants. Importantly, these findings hold over longer periods, as an extra day with temperatures surpassing 90°F within the previous week is associated with a 1.4 percent rise in the probability of engaging in physical activity over the past 7 days.

The results suggest that warmer temperatures could positively impact physical activity levels, potentially enhancing overall population health. While controversial in climate change health literature, these findings align with the idea that higher temperatures might correlate with more favorable weather, prompting individuals to engage in such health-

¹³ Considering the 7-day time frame, we can interpret these estimates as accounting for climate adaptation during the week. However, when we include past weather conditions (lagged by one and two diary days) in our primary estimates for ATUS 03-22 in Table 2, we still obtain similar estimates.

¹⁴ Because the dependent variables related to physical activity participation often contain numerous zero values, we employ the Poisson Pseudo-Maximum Likelihood (PPML) estimator. The obtained results are qualitatively robust, and the detailed outcomes can be provided upon request.

promoting activities as exercise. This insight could guide public action, advocating for initiatives promoting physical activity during warm weather. Strategies could involve public health campaigns, infrastructure development for active transportation, education on the benefits of exercise, workplace adaptations for heat-exposed workers, and continued research to understand and target interventions effectively. These actions aim to foster greater physical activity during warmer temperatures, ultimately improving population health and well-being.

One limitation of this paper is the unavailability of geographic information for counties with fewer than 100,000 inhabitants, a common issue in many surveys due to confidentiality concerns. This implies a significant number of rural areas being omitted from our analysis, resulting in a bias toward urban areas. Future research should take into account these specific geographic locations by utilizing appropriate datasets. However, it is important to note that we are unaware of any time-use survey offering such detailed geographic information.

Furthermore, while daily weather conditions are external variables beyond individuals' control, we refrain from discussing effects and causal relationships based on the estimates, due to our reliance on only one observation per respondent and diary day. This limitation also restricts our ability to study the impact of weather conditions on regular exercise among individuals. Considering this, climate might significantly influence migration decisions (Rappaport, 2009; Belloc et al., 2023), potentially affecting our results. Given individual mobility, populations can modify their exposure to specific weather conditions through migration. Hence, we propose further research to examine whether weather, including extreme weather conditions, can elucidate patterns of individual migration.

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References

- Agarwal, S., Qin, Y., Shi, L., Wei, G., & Zhu, H. (2021). Impact of temperature on morbidity: New evidence from China. *Journal of Environmental Economics and Management*, 109, 102495. <https://doi.org/10.1016/j.jeem.2021.102495>
- Alberto, I. C., Jiao, Y., & Zhang, X. (2021). Too hot or too cold to study? The effect of temperature on student time allocation. *Economics of Education Review*, 84, 102152. <https://doi.org/10.1016/j.econedurev.2021.102152>
- Barreca, A., Clay, K., Deschenes, O., Greenstone, M., & Shapiro, J. S. (2016). Adapting to climate change: The remarkable decline in the US temperature-mortality relationship over the twentieth century. *Journal of Political Economy*, 124(1), 105-159. <https://doi.org/10.1086/684582>
- Belloc, I., Gimenez-Nadal, J. I., & Molina, J. A. (2022). Weather Conditions and Daily Commuting. IZA DP No. 15661.
- Belloc, I., Gimenez-Nadal, J. I., & Molina, J. A. (2023). Extreme temperatures: Gender differences in well-being. Boston College Working Papers in Economics No. 1060.
- Billor, N., Hadi, A. S., & Velleman, P. F. (2000). BACON: blocked adaptive computationally efficient outlier nominators. *Computational Statistics & Data Analysis*, 34(3), 279-298. [https://doi.org/10.1016/S0167-9473\(99\)00101-2](https://doi.org/10.1016/S0167-9473(99)00101-2)
- Bonke, J. (2005). Paid work and unpaid work: Diary information versus questionnaire information. *Social Indicators Research*, 70, 349-368. <https://doi.org/10.1007/s11205-004-1547-6>
- Chen, F., Zhang, X., & Chen, Z. (2023). Behind climate change: Extreme heat and health cost. *Structural Change and Economic Dynamics*, 64, 101-110. <https://doi.org/10.1016/j.strueco.2022.12.007>

- Connolly, M. (2008). Here comes the rain again: Weather and the intertemporal substitution of leisure. *Journal of Labor Economics*, 26(1), 73-100. <https://doi.org/10.1086/522067>
- Cosaert, S., Nieto, A., & Tatsiramos, K. (2023a). Temperature and Joint Time Use. IZA DP No. 16175.
- Cosaert, S., Nieto, A., & Tatsiramos, K. (2023b). Temperature and the Timing of Work. IZA DP No. 16480.
- Courtemanche, C., Pinkston, J. C., & Stewart, J. (2021). Time spent exercising and obesity: An application of Lewbel's instrumental variables method. *Economics & Human Biology*, 41, 100940. <https://doi.org/10.1016/j.ehb.2020.100940>
- Deschênes, O., & Greenstone, M. (2011). Climate change, mortality, and adaptation: Evidence from annual fluctuations in weather in the US. *American Economic Journal: Applied Economics*, 3(4), 152-185. <https://doi.org/10.1257/app.3.4.152>
- Dillender, M. (2021). Climate change and occupational health: Are there limits to our ability to adapt?. *Journal of Human Resources*, 56(1), 184-224. <https://doi.org/10.3368/jhr.56.1.0718-9594R3>
- Echeverría, L., Gimenez-Nadal, J. I., & Molina, J. A. (2022a). Green mobility and well-being. *Ecological Economics*, 195, 107368. <https://doi.org/10.1016/j.ecolecon.2022.107368>
- Echeverría, L., Gimenez-Nadal, J. I., & Molina, J. A. (2022b). Who uses green mobility? Exploring profiles in developed countries. *Transportation Research Part A: Policy and Practice*, 163, 247-265. <https://doi.org/10.1016/j.tra.2022.07.008>
- Garg, T., Gibson, M., & Sun, F. (2020). Extreme temperatures and time use in China. *Journal of Economic Behavior & Organization*, 180, 309-324. <https://doi.org/10.1016/j.jebo.2020.10.016>
- Gimenez-Nadal, J.I., Molina, J.A. (2022). Time Use Surveys. Handbook of Labor, Human Resources and Population Economics. https://doi.org/10.1007/978-3-319-57365-6_270-1
- Graff Zivin, J., & Neidell, M. (2014). Temperature and the allocation of time: Implications for climate change. *Journal of Labor Economics*, 32(1), 1-26. <https://doi.org/10.1086/671766>

- Heyes, A., & Saberian, S. (2022). Hot Days, the ability to Work and climate resilience: Evidence from a representative sample of 42,152 Indian households. *Journal of Development Economics*, 155, 102786. <https://doi.org/10.1016/j.jdevco.2021.102786>
- Hou, X., & Zhang, X. (2024). Effects of temperature anomaly on health: A perspective from individual adaptation. *Structural Change and Economic Dynamics*, 68, 62-74. <https://doi.org/10.1016/j.strueco.2023.10.007>
- Hua, Y., Qiu, Y., & Tan, X. (2023). The effects of temperature on mental health: evidence from China. *Journal of Population Economics*, 36(3), 1293-1332. <https://doi.org/10.1007/s00148-022-00932-y>
- Huang, H., & Humphreys, B. R. (2012). Sports participation and happiness: Evidence from US microdata. *Journal of Economic Psychology*, 33(4), 776-793. <https://doi.org/10.1016/j.joep.2012.02.007>
- Huang, K., Zhao, H., Huang, J., Wang, J., & Findlay, C. (2020). The impact of climate change on the labor allocation: Empirical evidence from China. *Journal of Environmental Economics and Management*, 104, 102376. <https://doi.org/10.1016/j.jeem.2020.102376>
- Humphreys, B. R., McLeod, L., & Ruseski, J. E. (2014). Physical activity and health outcomes: evidence from Canada. *Health Economics*, 23(1), 33-54. <https://doi.org/10.1002/hec.2900>
- Jacob, N., Munford, L., Rice, N., & Roberts, J. (2021). Does commuting mode choice impact health?. *Health Economics*, 30(2), 207-230. <https://doi.org/10.1002/hec.4184>
- Jessoe, K., Manning, D. T., & Taylor, J. E. (2018). Climate change and labour allocation in rural Mexico: Evidence from annual fluctuations in weather. *The Economic Journal*, 128(608), 230-261. <https://doi.org/10.1111/eoj.12448>
- Jiao, Y., Li, Y., & Liu, M. (2021). Widening the gap? temperature and time allocation between men and women. *Applied Economics*, 53(5), 595-627. <https://doi.org/10.1080/00036846.2020.1808575>
- Kahneman, D., Krueger, A. B., Schkade, D. A., Schwarz, N., & Stone, A. A. (2004a). A survey method for characterizing daily life experience: The day reconstruction method. *Science*, 306(5702), 1776-1780. <https://doi.org/10.1126/science.1103572>

- Kahneman, D., Krueger, A. B., Schkade, D., Schwarz, N., & Stone, A. (2004b). Toward national well-being accounts. *American Economic Review*, 94(2), 429-434. <https://doi.org/10.1257/0002828041301713>
- Karlsson, M., & Ziebarth, N. R. (2018). Population health effects and health-related costs of extreme temperatures: Comprehensive evidence from Germany. *Journal of Environmental Economics and Management*, 91, 93-117. <https://doi.org/10.1016/j.jeem.2018.06.004>
- Krueger, A. B. (2007). Are we having more fun yet? Categorizing and evaluating changes in time allocation. *Brookings Papers on Economic Activity*, 2007(2), 193-215.
- Krüger, J. J., & Neugart, M. (2018). Weather and Intertemporal Labor Supply: Results from German Time-Use Data. *Labour*, 32(1), 112-140. <https://doi.org/10.1111/labr.12105>
- Liu, B., & Hirsch, B. T. (2021). Winter weather and work hours: Heterogeneous effects and regional adaptation. *Contemporary Economic Policy*, 39(4), 867-881. <https://doi.org/10.1111/coep.12516>
- Mullahy, J., & Robert, S. A. (2010). No time to lose: Time constraints and physical activity in the production of health. *Review of Economics of the Household*, 8, 409-432. <https://doi.org/10.1007/s11150-010-9091-4>
- Mullins, J. T., & White, C. (2019). Temperature and mental health: Evidence from the spectrum of mental health outcomes. *Journal of Health Economics*, 68, 102240. <https://doi.org/10.1016/j.jhealeco.2019.102240>
- Neidell, M., Graff Zivin, J., Sheahan, M., Willwerth, J., Fant, C., Sarofim, M., & Martinich, J. (2021). Temperature and work: Time allocated to work under varying climate and labor market conditions. *PLOS ONE*, 16(8), e0254224. <https://doi.org/10.1371/journal.pone.0254224>
- Nguyen, H. T., Le, H. T., & Connelly, L. B. (2021). Weather and children's time allocation. *Health Economics*, 30(7), 1559-1579. <https://doi.org/10.1002/hec.4264>
- Nguyen, C. V., Nguyen, M. H., & Nguyen, T. T. (2023). The impact of cold waves and heat waves on mortality: Evidence from a lower middle-income country. *Health Economics*, 32(6), 1220-1243. <https://doi.org/10.1002/hec.4663>

- Noelke, C., McGovern, M., Corsi, D. J., Jimenez, M. P., Stern, A., Wing, I. S., & Berkman, L. (2016). Increasing ambient temperature reduces emotional well-being. *Environmental Research*, 151, 124-129. <https://doi.org/10.1016/j.envres.2016.06.045>
- Otrachshenko, V., Popova, O., & Solomin, P. (2017). Health consequences of the Russian weather. *Ecological Economics*, 132, 290-306. <https://doi.org/10.1016/j.ecolecon.2016.10.021>
- Otrachshenko, V., Popova, O., & Solomin, P. (2018). Misfortunes never come singly: Consecutive weather shocks and mortality in Russia. *Economics & Human Biology*, 31, 249-258. <https://doi.org/10.1016/j.ehb.2018.08.008>
- Ranson, M. (2014). Crime, weather, and climate change. *Journal of Environmental Economics and Management*, 67(3), 274-302. <https://doi.org/10.1016/j.jeem.2013.11.008>
- Rappaport, J. (2009). Moving to nice weather. *Environmental amenities and regional economic development*.
- Rasciute, S., & Downward, P. (2010). Health or happiness? What is the impact of physical activity on the individual?. *Kyklos*, 63(2), 256-270. <https://doi.org/10.1111/j.1467-6435.2010.00472.x>
- Roy, S., & Orazem, P. F. (2021). Active leisure, passive leisure and health. *Economics & Human Biology*, 43, 101053. <https://doi.org/10.1016/j.ehb.2021.101053>
- Sari, N. (2009). Physical inactivity and its impact on healthcare utilization. *Health Economics*, 18(8), 885-901. <https://doi.org/10.1002/hec.1408>
- Sarma, S., Zaric, G. S., Campbell, M. K., & Gilliland, J. (2014). The effect of physical activity on adult obesity: Evidence from the Canadian NPHS panel. *Economics & Human Biology*, 14, 1-21. <https://doi.org/10.1016/j.ehb.2014.03.002>
- Sen, B. (2012). Is There an Association Between Gasoline Prices and Physical Activity? Evidence from A merican Time Use Data. *Journal of Policy Analysis and Management*, 31(2), 338-366. <https://doi.org/10.1002/pam.21601>
- Somanathan, E., Somanathan, R., Sudarshan, A., & Tewari, M. (2021). The impact of temperature on productivity and labor supply: Evidence from Indian manufacturing. *Journal of Political Economy*, 129(6), 1797-1827. Retrieved from

<https://www.who.int/news-room/fact-sheets/detail/physical-activity>. Accessed 19 December 2023.

WHO (2022). Physical activity. Available online in <https://www.who.int/news-room/fact-sheets/detail/physical-activity>. Accessed 19 December 2023.

Yee-Kan, M. (2008). Measuring housework participation: The gap between “stylised” questionnaire estimates and diary-based estimates. *Social Indicators Research*, 86, 381-400. <https://doi.org/10.1007/s11205-007-9184-5>

Yu, X., Lei, X., & Wang, M. (2019). Temperature effects on mortality and household adaptation: Evidence from China. *Journal of Environmental Economics and Management*, 96, 195-212. <https://doi.org/10.1016/j.jeem.2019.05.004>

Table 1. Summary statistics

	Mean	Std. Dev.
<i>Dependent variables</i>		
Participation	0.306	0.461
Physical activity time	22.330	55.012
Physical activity time (conditional on time > 0)	74.212	83.076
<i>Daily weather conditions</i>		
Amount of precipitation	9.813	26.726
Amount of snowfall	0.580	4.760
Maximum temperature	69.415	18.561
<i>Socio-demographic variables</i>		
Male	0.486	0.500
Age	44.458	18.453
Primary education	0.166	0.373
Secondary education	0.259	0.438
University education	0.574	0.494
Employed	0.629	0.483
Unemployed	0.055	0.228
Married	0.512	0.500
Household size	3.064	1.619
Number of children	0.776	1.149
Family income	69,130	45,304.270
Holiday	0.017	0.129
Number of observations	87,551	

Notes: Data come from the ATUS 2003-2019, 2022-2023. Summary statistics are sample weighted. Physical activity time is calculated in minutes per day.

Table 2. Main results

	Likelihood(Participation)	log(Physical activity time)
TMAX < 40	-0.033*** (0.009)	0.001 (0.059)
40 ≤ TMAX < 50	-0.021** (0.010)	0.050 (0.037)
60 ≤ TMAX < 70	0.019** (0.008)	0.075* (0.042)
70 ≤ TMAX < 80	0.024*** (0.008)	0.120*** (0.034)
80 ≤ TMAX < 90	0.045*** (0.012)	0.157*** (0.044)
TMAX ≥ 90	0.052*** (0.013)	0.186*** (0.059)
0 < PRCP < 0.1	-0.005 (0.008)	-0.008 (0.046)
0.1 ≤ PRCP < 0.5	-0.002 (0.010)	0.033 (0.032)
0.5 ≤ PRCP < 1	-0.003 (0.015)	0.070 (0.043)
PRCP ≥ 1	-0.013*** (0.004)	-0.025 (0.018)
0 < SNOW < 0.1	0.034 (0.032)	0.122 (0.113)
0.1 ≤ SNOW < 0.5	0.025 (0.031)	0.027 (0.127)
0.5 ≤ SNOW < 1	0.021 (0.026)	-0.241 (0.166)
SNOW ≥ 1	0.003 (0.013)	0.007 (0.053)
Male	0.045*** (0.005)	0.294*** (0.027)
Age	-0.007*** (0.001)	-0.012*** (0.003)
Age squared/100	0.005*** (0.001)	0.008** (0.003)
Secondary education	-0.054*** (0.008)	-0.057** (0.026)
University education	0.020*** (0.006)	0.012 (0.032)
Employed	-0.064*** (0.008)	-0.223*** (0.026)
Unemployed	0.009 (0.013)	0.007 (0.038)
Married	-0.013** (0.005)	-0.004 (0.022)
Household size	-0.013*** (0.004)	0.004 (0.009)
Number of children	0.010* (0.005)	-0.033** (0.014)
Log of family income	0.024*** (0.004)	0.103*** (0.018)
Holiday	-0.035* (0.018)	0.167** (0.076)
Constant	-0.008	3.462***

	(0.047)	(0.233)
Observations	87,551	25,504
R-squared	0.069	0.080

Notes: OLS estimates using survey demographic weights. Robust standard errors, clustered at the state level, in parentheses. Estimates also include day, month, year and county fixed effects, but are not shown for brevity. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 3. Heterogeneity analysis: warmer vs. colder places

	Likelihood(Participation)		log(Physical activity time)	
	Warmer	Colder	Warmer	Colder
TMAX < 40	-0.035 (0.035)	-0.024*** (0.009)	0.061 (0.140)	0.080 (0.064)
40 ≤ TMAX < 50	-0.038** (0.017)	-0.009 (0.011)	-0.058 (0.077)	0.110*** (0.035)
60 ≤ TMAX < 70	0.000 (0.009)	0.026** (0.013)	0.088* (0.048)	0.038 (0.068)
70 ≤ TMAX < 80	0.005 (0.010)	0.027* (0.014)	0.143*** (0.039)	0.069 (0.053)
80 ≤ TMAX < 90	0.018 (0.013)	0.060*** (0.013)	0.182*** (0.048)	0.123* (0.062)
TMAX ≥ 90	0.037** (0.015)	0.052** (0.021)	0.282*** (0.049)	0.059 (0.102)
Observations	44,895	42,656	12,548	12,956
R-squared	0.051	0.090	0.076	0.092

Notes: OLS estimates using survey demographic weights. Robust standard errors, clustered at the state level, in parentheses. Estimates also include precipitation- and snowfall-bins, socio-demographics, and day, month, year and county fixed effects, but are not shown for brevity. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 4. Participation in physical activities past 7 days, ATUS EH Module (2014-2016, 2022)

	Likelihood(Participation past 7 days)
Number of days TMAX < 40	-0.006 (0.009)
Number of days $40 \leq \text{TMAX} < 50$	-0.001 (0.008)
Number of days $60 \leq \text{TMAX} < 70$	0.009 (0.006)
Number of days $70 \leq \text{TMAX} < 80$	0.012*** (0.004)
Number of days $80 \leq \text{TMAX} < 90$	0.006 (0.004)
Number of days TMAX ≥ 90	0.014** (0.006)
Number of days $0 < \text{PRCP} < 0.1$	0.006 (0.009)
Number of days $0.1 \leq \text{PRCP} < 0.5$	0.001 (0.007)
Number of days $0.5 \leq \text{PRCP} < 1$	0.003 (0.010)
Number of days PRCP ≥ 1	-0.003 (0.003)
Number of days $0 < \text{SNOW} < 0.1$	0.033 (0.026)
Number of days $0.1 \leq \text{SNOW} < 0.5$	0.017 (0.023)
Number of days $0.5 \leq \text{SNOW} < 1$	-0.003 (0.022)
SNOW ≥ 1	-0.001 (0.008)
Male	0.017* (0.009)
Age	-0.009*** (0.002)
Age squared/100	0.006*** (0.002)
Secondary education	-0.017 (0.015)
University education	0.102*** (0.018)
Employed	-0.073*** (0.009)
Unemployed	0.071*** (0.020)
Married	0.013 (0.012)
Household size	-0.032*** (0.005)
Number of children	0.017** (0.008)
Log of family income	0.067*** (0.010)
Holiday	-0.131*** (0.042)
Constant	-0.188

(0.141)

Observations

16,060

R-squared

0.115

Notes: OLS estimates using survey demographic weights. Robust standard errors, clustered at the state level, in parentheses. Estimates also include day, month, year and county fixed effects, but are not shown for brevity. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

SUPPLEMENTARY MATERIAL

Table A1. Summary statistics, weather-binning variables

	Mean	Std. Dev.
TMAX < 40	0.081	0.273
40 ≤ TMAX < 50	0.085	0.279
50 ≤ TMAX < 60	0.121	0.326
60 ≤ TMAX < 70	0.162	0.368
70 ≤ TMAX < 80	0.202	0.401
80 ≤ TMAX < 90	0.233	0.423
TMAX ≥ 90	0.116	0.321
No PRCP	0.483	0.500
0 < PRCP < 0.1	0.038	0.191
0.1 ≤ PRCP < 0.5	0.065	0.246
0.5 ≤ PRCP < 1	0.036	0.186
PRCP ≥ 1	0.378	0.485
No SNOW	0.944	0.229
0 < SNOW < 0.1	0.002	0.044
0.1 ≤ SNOW < 0.5	0.007	0.080
0.5 ≤ SNOW < 1	0.005	0.072
SNOW ≥ 1	0.042	0.201

Table A2. Robustness check including AQI

	Likelihood(Participation)	log(Physical activity time)
TMAX < 40	-0.039*** (0.009)	-0.009 (0.067)
40 ≤ TMAX < 50	-0.021* (0.010)	0.053 (0.041)
60 ≤ TMAX < 70	0.020** (0.009)	0.076* (0.044)
70 ≤ TMAX < 80	0.025*** (0.009)	0.116*** (0.036)
80 ≤ TMAX < 90	0.051*** (0.012)	0.141*** (0.047)
TMAX ≥ 90	0.059*** (0.014)	0.155** (0.062)
0 < PRCP < 0.1	-0.005 (0.008)	-0.017 (0.044)
0.1 ≤ PRCP < 0.5	-0.003 (0.010)	0.027 (0.034)
0.5 ≤ PRCP < 1	-0.002 (0.015)	0.085* (0.046)
PRCP ≥ 1	-0.013*** (0.004)	-0.019 (0.019)
0 < SNOW < 0.1	0.034 (0.032)	0.126 (0.111)
0.1 ≤ SNOW < 0.5	0.026 (0.034)	0.047 (0.131)
0.5 ≤ SNOW < 1	0.028 (0.028)	-0.222 (0.171)
SNOW ≥ 1	0.008 (0.014)	0.011 (0.056)
AQI	-0.000 (0.000)	0.001** (0.000)
Observations	80,587	23,919
R-squared	0.068	0.078

Notes: OLS estimates using survey demographic weights. Robust standard errors, clustered at the state level, in parentheses. Estimates also include socio-demographics, and day, month, year and county fixed effects, but are not shown for brevity. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.