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Temperature exposure and sleep duration: evidence from time use surveys

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ABSTRACT
The Earth's climate is projected to warm significantly in the 21st century, and this will affect human societies in many ways. Since sleep is a basic human need and part of everyone's life, the question of how temperature affects human sleep naturally arises. This paper examines the effect of daily mean temperature on sleep duration using nationally representative Hungarian time use surveys between 1976 and 2010. Compared to a mild temperature (5-10 °C), colder temperatures do not influence sleep duration. However, as daily mean temperatures rise, sleep duration starts to strongly decline. The effect of a hot (>25 °C) day is −12.4 minutes. The estimated sleep loss is especially large on weekends and public holidays, for older individuals, and for men. Combining the estimated effects with temperature projections of twenty-four climate models under four climate change scenarios shows that the warming climate will substantially decrease sleep duration. The projected impacts are especially large when taking into account of the effects of heatwave days. This study also shows that different groups in society are likely to be affected in significantly different ways by a warming climate.

JEL codes: I12, Q54
Keywords: temperature; climate change; sleep; time use survey; Hungary

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A hőmérséklet és alvásmennyiség kapcsolta időmérleg-felmérések adatai alapján

HAJDU TAMÁS

ÖSSZEFOGLALÓ
Az előrejelzések szerint a Föld éghajlata jelentősen melegszik a 21. században, és ez sokféleképpen érinti majd az emberiséget. Mivel az alvás olyan alapvető emberi szükséglet, ami mindenki életének szerves része, természetesen felmerül a kérdés, hogy a hőmérséklet hogyan befolyásolja az alvásmennyiséget. Ez a tanulmány a napi középhőmérsékletnek az alvás időtartamára gyakorolt hatását vizsgálja 1976 és 2010 közötti országos reprezentatív időmérleg-felmérések segítségével. Az enyhe hőmérséklethez képest (amikor a napi középhőmérséklet 5-10°C) a hidegebb hőmérséklet nem befolyásolja az alvás időtartamát. A napi középhőmérséklet emelkedésével azonban az alvás időtartama erőteljesen csökkenni kezd. Egy forró (>25°C) nap hatása –12,4 perc. Az alvásveszteség különösen nagy a hétvégeken és ünnepnapokon, az idősebbek és a férfiak esetében. A becsült hőmérsékleti hatások és huszonnégy klímamodell által négy éghajlatváltozási forgatókönyvre készített hőmérsékleti előrejelzések kombinálása azt mutatja, hogy a melegedő éghajlat jelentősen csökkenteni fogja az alvás időtartamát. A hatások különösen nagyok, ha figyelembe vesszük a hőhullámos napok hatásait. A tanulmány azt is mutatja, hogy a társadalom különböző csoportjait valószínűleg jelentősen eltérően érinti majd a felmelegedő éghajlat.

JEL: I12, Q54
Kulcsszavak: hőmérséklet; klímaváltozás; alvás; időmérleg-felmérés; Magyarország

Temperature exposure and sleep duration: evidence from time use surveys

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Abstract

The Earth's climate is projected to warm significantly in the 21st century, and this will affect human societies in many ways. Since sleep is a basic human need and part of everyone's life, the question of how temperature affects human sleep naturally arises. This paper examines the effect of daily mean temperature on sleep duration using nationally representative Hungarian time use surveys between 1976 and 2010. Compared to a mild temperature (5-10 °C), colder temperatures do not influence sleep duration. However, as daily mean temperatures rise, sleep duration starts to strongly decline. The effect of a hot (>25 °C) day is −12.4 minutes. The estimated sleep loss is especially large on weekends and public holidays, for older individuals, and for men. Combining the estimated effects with temperature projections of twenty-four climate models under four climate change scenarios shows that the warming climate will substantially decrease sleep duration. The projected impacts are especially large when taking into account of the effects of heatwave days. This study also shows that different groups in society are likely to be affected in significantly different ways by a warming climate.

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1. Introduction

Sleep is essential for humans and other animals (Cirelli and Tononi 2008). Insufficient sleep and sleep disturbances are associated with negative physical, cognitive, emotional, and social consequences. The short duration of sleep is associated with higher mortality risk, health complications, and diseases, including hypertension, cardiovascular disease, and stroke (Cappuccio et al. 2010; Itani et al. 2017; Tobaldini et al. 2019). Sleep plays an essential role in maintaining a healthy immune system (Besedovsky, Lange, and Haack 2019). Disrupted, inadequate sleep or reduced sleep quality leads to negative mode, anxiety, greater interpersonal conflict, and social withdrawal (Ben Simon et al. 2020; Ben Simon and Walker 2018; Tomaso, Johnson, and Nelson 2021). Sleep deprivation has also a deleterious effect on cognitive performance (Lim and Dinges 2010; Krause et al. 2017; Lowe, Safati, and Hall 2017).

Given the importance of sleep, there is an extensive literature on the factors that influence sleep. An important strand of this literature investigates how environmental factors affect human sleep. Among others, it includes studies on noise (Muzet 2007; Basner and McGuire 2018), artificial light (Paksarian et al. 2020; Boslett et al. 2021), air pollution (Liu et al. 2020; Cao, Chen, and McIntyre 2021), and exposure to green spaces (Shin et al. 2020; Stenfors et al. 2023).

As climate change is considered one of the greatest threats to humanity in the 21st century, the question naturally arises of how temperature and a warming climate affect human sleep. Previous studies on the effect of temperature on sleep consist mainly of laboratory experiments. These studies show that both cold and heat decrease sleep quality and increase wakefulness (Haskell et al. 1981; Fletcher, van den Heuvel, and Dawson 1999; Tsuzuki, Okamoto-Mizuno, and Mizuno 2004; Okamoto-Mizuno et al. 2005; Okamoto-Mizuno and Mizuno 2012; Lan et al. 2017; Rifkin, Long, and Perry 2018). However, large-scale studies in real-world settings that examine the effects of ambient temperatures and are able to provide quantitative information on the potential impacts of climate change for policymakers are extremely rare.

Such a unique example is the study that uses U.S. survey data from more than 750,000 respondents over a 10-year-long period (Obradovich et al. 2017). It examines the effect of ambient temperature on the number of days of insufficient rest or sleep over the past 30 days (measured by a single retrospective question). It finds that an increase of 1 °C in the 30-day average of daily minimum temperature deviations from their long-term mean causes nearly 3 days of insufficient rest/sleep per 100 individuals per month. Assuming a worst-case climate scenario (RCP 8.5), the study predicts that 14 additional days of insufficient rest/sleep per 100 individuals will be expected in the U.S. by 2099, compared to 2010. Another paper used data from sleep-tracking wristbands (Minor et al. 2022). This dataset consists of more than 7 million daily sleep records of 47,628 individuals over a two-year period across 68 countries. The paper concludes that the higher the daily minimum temperature the shorter the sleep duration. The relationship is monotone, but the marginal effect of temperature is increasing. The impact of increasing minimum temperature by 1 °C is much stronger above a temperature baseline of 5-10 °C. The observed relationship means that the warming climate will cause an average of 6 hours of sleep loss per person by 2099 (compared to 2010) under the RCP 4.5 scenario, whereas the projected sleep loss is 14 hours under the RCP 8.5 scenario. Mullins and White (2019) examine the effect of temperature on mental health and identify changes in sleep quantity as a potential mechanism. Based on data from the US Time Use Survey, they found that warmer temperatures reduce the number of minutes slept.

The present study examines the effect of ambient temperature on sleep duration. It uses nationally representative Hungarian time use surveys between 1976 and 2010, fine spatial resolution meteorological data, and temperature projections of state-of-the-art climate models. Meteorological data is linked to the almost 122,000 time use diaries to investigate the effect of daily mean temperature on sleep duration. The empirical approach is based on the recent climate econometrics literature (Dell, Jones, and Olken 2014; S. Hsiang 2016). A nonlinear relationship between temperature and sleep duration is allowed by using temperature categories representing different daily mean temperatures. The baseline model includes controls for precipitation, humidity, socio-economic background, day-of-week, and public holidays, but an individual fixed effects model is also estimated. As county-by-year-by-month fixed effects are also included, the effects of temperature are identified from the random variation in daily temperatures within a given county and a given month. The analysis shows that as the daily mean temperature increases, sleep duration decreases. On a day of 20-25 °C, the average sleep duration is 6.3 minutes shorter than on a mild (5-10 °C) day. The effect of an extremely hot (>25 °C) day is −12.4 minutes. However, the effects are much stronger for certain groups in society, especially among older people. It is also shown by this paper that the effect of heatwave days (hot days preceded by other hot days) is much stronger than "simple" hot days.

Coupling the obtained relationship with the outputs of climate models, the impact of climate change is projected under four SSP (Shared Socio-Economic Pathway) scenarios. The warming climate will decrease sleep duration during the 21st century. The median projections for the last decade of the century range between 3.7 (SSP 1-2.6 scenario) and 14.0 hours (SSP 5-8.5

scenario) per person per year, while they range between −4.7 and −22.7 hours when taking into account the effect of heatwave days and their future increase. Importantly, most of this loss is concentrated in the summer and early autumn.

This study makes important contributions to the literature. Despite the growing evidence on the relationship between ambient temperature and sleep from large-scale data collected in real-world settings, limitations remain in terms of (i) measurement of sleep, (ii) data collection strategy, and (iii) understanding the potential impact of climate change. First, some research measures sleep in terms of days of insufficient sleep, which is helpful for providing evidence about subjective sleep quality but limited in its ability to tell us about the effect of temperature on an objective measure of sleep duration. Second, of those that do monitor sleep duration, some of the previous research has relied on data collected from users of sleep-tracking wristbands, which are prone to selection bias. In a high-quality paper, Minor et al. (2022) use a sample that was overrepresented by middle-aged males. On the one hand, people of higher social status may make defensive efforts, which may lead to effects different from those in a general population. On the other hand, these demographic groups and study participants using sleep-tracking technology may also be more prone to sleep disruption and sleep-related anxiety. Again, this makes it more difficult to generalize the results. The heterogeneity of the effects also needs to be investigated in more detail to get a full picture of the impact of temperature on sleep, and this can only be done using data covering the whole of society. This is important, for example, because the world's population is growing rapidly, so understanding the differences between age groups can provide useful information for public policy. Finally, long-term databases spanning several decades are needed to examine possible adaptation. This has not been possible in previous research due to a lack of suitable data but is essential to predict and assess the potential impacts of climate change. Although not explored in previous studies, understanding the effects of heatwaves, which will become more frequent in the future, is also essential. This study addresses these gaps by using a large number of time-use diaries over a thirty-five-year period, which addresses prior concerns regarding measurement and generalizability and also provides an opportunity for an in-depth examination of heterogeneities, changes over time, and the impacts of heatwaves.

2. Data

2.1. Time use surveys

Data on sleep duration are from five waves of the Hungarian Time Use Survey (HTUS) administered by the Hungarian Central Statistical Office. HTUS is a nationally representative time use data collection. During a face-to-face interview, one respondent per household completes a time diary in which they report their activities for the previous day (24 hours).[1] The waves used in this paper are from 1976/1977, 1986/1987, 1993, 1999/2000, and 2009/2010. All waves follow an open diary design and, with the exception of the 1993 wave, covered a one-year period. In three out of the five waves of the HTUS (1976/1977, 1986/1987, and 1999/2000), each respondent completed four diaries (one per season). Table A1 in Supplementary Materials summarizes some important characteristics of the surveys.

The analysis sample is restricted to adults (aged 18 and over). A few observations with missing information on the exact date of the diary, education level, or labor force status are excluded. In addition, as the effect of temperatures is identified from the variation in temperature exposure within a particular county and calendar month, observations in county-by-year-by-month "cells" with less than 10 diaries are also excluded. The final sample covers 121,670 diaries of 46,586 individuals (Table A2, Supplementary Materials). Table A3 in Supplementary Materials provides a step-by-step summary of the sample selection process.

The main dependent variable is the sleep duration (measured in minutes) which includes all sleep and nap periods of the 24 hours. It has an average of 513 minutes in the sample (Table A4, Supplementary Materials). Two additional dependent variables are defined: (i) the time of falling asleep and (ii) the wake-up time. The first one is the start of the first sleep period after 19:00, the second one is the end of the last sleep period before 11:00.

2.2. Historical temperature observations

Information on ambient temperature is drawn from the European Climate Assessment & Dataset project (Cornes et al. 2018). The E–OBS 27.0e dataset provides information on daily (mean, minimum, and maximum) temperatures and other weather data for Europe with a spacing of 0.1° × 0.1° in regular latitude/longitude coordinates starting from 1950. The gridded data are aggregated to the county (NUTS 3 region) level by averaging the observed temperature

[1] The selection of the person to be sampled from the household was done differently in each wave of the survey, usually either by random selection by interviewers or by selecting a person with a predefined characteristic.

measures.[2] For the main analysis, the following temperature categories were constructed from the daily mean temperatures: ≤−5 °C, −5–0 °C, 0–5 °C, 5–10 °C, 10–15 °C, 15–20 °C, 20–25 °C, >25 °C.

2.3. Temperature change in the 21st century

Information on the change in temperatures during the 21st century is from the latest version of the NASA Earth Exchange Global Daily Downscaled Projections (NEX-GDDP-CMIP6) (Thrasher et al. 2022). This dataset provides daily temperature projections for 2015-2100 and retrospectively simulated historical data for the period 1950-2014 based on output from Phase 6 of the Climate Model Intercomparison Project (CMIP6). The spatial resolution of the projections is 0.25° × 0.25°.

Projected temperature changes under four climate change scenarios are considered: SSP1-2.6, SSP2-4.5, SSP3-7.0, and SSP5-8.5 scenarios (O'Neill et al. 2016). SSP1-2.6 assumes that CO_2 emission will be cut severely declining to net zero in the 2070s. This scenario is consistent with limiting warming to 2°C by the end of the 21st century (relative to 1850–1900). SSP2-4.5 is often labeled as a "middle-of-the-road" scenario. It assumes that climate protection measures will be taken, but the CO_2 emission will decline only after the middle of the century. SSP3-7.0 is a scenario with increasing CO_2 emission during the 21st century, whereas SSP5-8.5 is a worst-case scenario that assumes very high greenhouse gas emissions and a fossil-fuel-based development. Projections of twenty-four climate models are used: ACCESS-CM2, ACCESS-ESM1-5, BCC-CSM2-MR, CanESM5, CESM2, CMCC-ESM2, CNRM-CM6-1, CNRM-ESM2-1, EC-Earth3, EC-Earth3-Veg-LR, FGOALS-g3, GFDL-ESM4, GISS-E2-1-G, IITM-ESM, INM-CM4-8, INM-CM5-0, IPSL-CM6A-LR, MIROC6, MIROC-ES2L, MPI-ESM1-2-HR, MPI-ESM1-2-LR, MRI-ESM2-0, NorESM2-LM, NorESM2-MM.

To project the impact of climate change, within-model changes in the temperature distribution are calculated for each decade between 2020 and 2099 using 1990-2014 as a baseline. In the first step, daily temperature data are calculated by averaging the mean temperature for each day over grid points within Hungary. Next, the annual distribution of the main temperature categories (≤−5 °C, −5–0 °C, 0–5 °C, 5–10 °C, 10–15 °C, 15–20 °C, 20–25 °C, >25 °C) is determined for each decade and compared to the temperature distribution of the baseline period:

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[2] According to the NUTS classification system, Budapest (the capital of Hungary) is a county in its own right, so the country is divided into 20 counties.

$$\Delta T^{j}_{olg} = T^{j}_{olg} - \widehat{T}^{j}_{ol} \tag{1}$$

where *o* stands for the SSP scenario (SSP1-2.6, SSP2-4.5, SSP3-7.0, and SSP5-8.5), *l* denotes the climate model, and *g* denotes the decade (from the 2020s to the 2090s). T is the annual number of days when the daily mean temperature falls into temperature category *j*, whereas $\widehat{T}$ denotes the baseline annual value from the 1990-2014 period.

3. Methods

3.1. The effect of daily mean temperature

To identify the effect of daily mean temperatures on sleep duration, the following equation is estimated:

$$S_{icymd} = \sum_j \beta^j T^{j}_{cymd} + \sum_k \gamma^k P^{k}_{cymd} + \sum_l \pi^l H^{l}_{cymd} + \delta X_{icymd} + \rho_{cym} + \varepsilon_{icymd} \tag{2}$$

S is the sleep duration (in minutes) of individual *i* in county *c*, in year *y*, month *m*, and day *d*. T stands for temperature bins. β^j is the coefficient of interest and shows the effect of daily mean temperature falling in temperature bin *j* on the sleep duration. In the main specification, the effects of seven temperature categories are estimated (≤−5 °C, −5–0 °C, 0–5 °C, 10–15 °C, 15–20 °C, 20–25 °C, >25 °C) compared to a 5–10 °C day. This is a flexible estimation strategy. The only restriction is that the effect of temperature is the same within the 5 °C-wide temperature bins.

P denotes the daily amount of precipitation (0 mm, 0-3 mm, 3-5 mm, 5-10 mm, >10 mm), while H stands for relative humidity (≤50%, 50-60%, 60-70%, 70-80%, >80%). A series of characteristics of the respondent and the interview day is also included (X): gender, age category (<20, 21-30, 31-40, 41-50, 51-60, 61-70, 71-), education (primary, vocational, high school, tertiary), labor market status (employed, unemployed, on maternity leave, student, retired, other), household size (1, 2, 3, 4, 5, 6+), day-of-week (Monday, Tuesday, Wednesday, Thursday, Friday, Saturday, Sunday), and an indicator of public holidays. County-by-year-by-month fixed effects (ρ) controls for unobserved location-by-time-specific factors that influence sleep. It effectively means that each county is allowed its own level, nonlinear trend, and seasonality in sleep duration. Thus, the effects of temperatures are identified from the variation in daily temperatures within a county and month.

The regression is estimated using an individual weight that adjusts for the unequal inclusion probabilities (provided by the HTUS) combined with another weight that transforms every wave's N equal. The standard errors are clustered at the county and individual levels (two-way clustering).

3.2. The effect of climate change

The effects of climate change are calculated by multiplying the β coefficients from Eq. (2) by the projected within-model temperature changes from Eq. (1) (ΔT). Uncertainty in the relationship between temperatures and sleep duration is captured by bootstrapping the β coefficient estimates (200 times, sampling with replacement) (Burke et al. 2015). As a result, several projections are calculated as follows:

$$\Delta S_{bolg} = \sum_j \beta_b^j \Delta T_{olg}^j \quad (3)$$

where *b* stands for the bootstrap sample (1-200), *o* stands for the SSP scenario (SSP1-2.6, SSP2-4.5, SSP3-7.0, and SSP5-8.5), *l* denotes the climate model (24 in total), and *g* denotes the decade (from the 2020s to the 2090s). That is, the ΔSs show the projected change in sleep duration per person per year due to changes in temperature distribution compared to 1990-2014. The results are presented separately for SSP scenario-decade pairs, so for each SSP scenario-decade pair, 4,800 possible projections (24 climate models × 200 estimates of the temperature-sleep relationship) are analyzed, thus capturing both climate uncertainty and regression uncertainty. In the empirical analysis, the median, the interquartile range, and the middle 95% of these 4,800 projections are calculated for each SSP scenario and decade.

The impacts by calendar month are examined by using projected temperature changes for each month:

$$\Delta S_{bolgm} = \sum_j \beta_b^j \Delta T_{olgm}^j \quad (4)$$

where *b* stands for the bootstrap sample, *o* stands for the SSP scenario, *l* denotes the climate model, *g* denotes the decade, and *m* denotes the calendar month.

4. Results

4.1. Main results and robustness

Figure 1 shows the effects of daily mean temperature on sleep duration. Compared to the reference temperature (5–10 °C), colder temperatures do not influence sleep duration. However, hot temperatures have detrimental effects, especially beyond 15-20 °C. The effect of a 20–25 °C is −6.3 minutes, whereas the effect of a >25 °C day is −12.4 minutes. Compared to the average sleep duration of 513.2 minutes (Table A4, Supplementary Materials), these values represent a decrease of 1.2% and 2.4%. The pattern of the temperature coefficients suggests that the marginal effect of temperature is increasing. Compared to the 10–20 °C range where a 1 °C increase in temperature decreases sleep duration by approximately 0.25 minutes, the marginal effect increases fourfold beyond 20 °C.

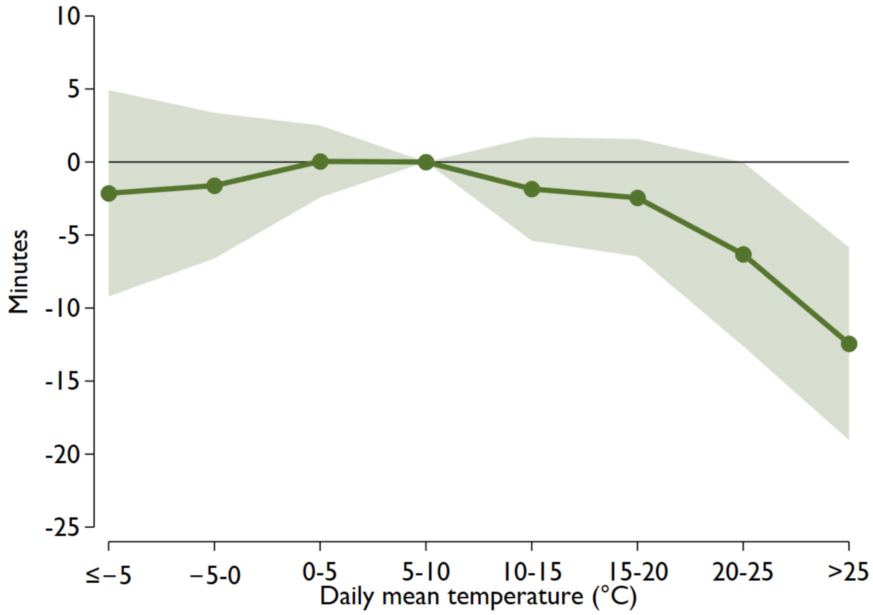

Figure 1. The effect of daily mean temperature on sleep duration

The circles are the β coefficients estimated using Eq. (2). The reference temperature is 5–10 °C. The shaded area represents 95% confidence intervals computed using standard errors clustered at the county and individual levels. The model has controls for precipitation, humidity, the characteristics of the respondent and the interview day (gender, age, education, labor market status, household size, day-of-week, public holiday), and county-by-year-by-month fixed effects. N = 121,670.

Similar patterns are obtained when estimating a restricted cubic spline regression or using narrower (2 °C-wide) temperature categories (Figure 2). Below the reference temperature, no sizeable effects are observed, but at higher temperature levels sleep duration is reduced, Importantly, in both cases, the marginal effect appears to be higher at extremely hot temperatures than just above the reference point. The conclusions remain the same if daily maximum or minimum temperature is used in place of daily mean temperature (Figure A1, Supplementary Materials).

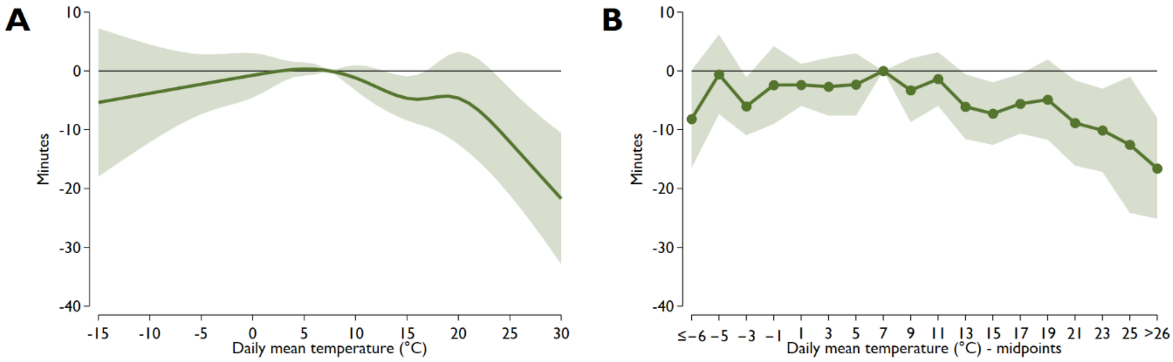

Figure 2. Estimations applying a cubic polynomial spline function and using narrower temperature bins

(A) The estimates come from restricted cubic spline functions with six knots. The reference temperatures are 7.5 °C. (B) 2 °C-wide temperature bins, the lowest category is ≤−6 °C, and the highest category is >26 °C. The reference temperature is 6–8 °C. The models have controls for precipitation, humidity, the characteristics of the respondent and the interview day (gender, age, education, labor market status, household size, day-of-week, public holiday), and county-by-year-by-month fixed effects. The shaded areas represent 95% confidence intervals computed using standard errors clustered at the county and individual levels. N = 121,670.

The sensitivity of the results is explored by a series of robustness tests, including the use of different fixed effects, exclusion of control variables, alternative methods for clustering the standard errors, and excluding extremely short (<4 hours) and long (>12 hours) sleep duration (Table A5, Supplementary Materials). None of these changes alter the conclusions.

There may be a concern that ambient temperatures could influence participation in the time use survey. On cold or hot days different respondents might be available which could bias the estimated effects. This possibility is investigated by using the observable characteristics of the respondents as the outcome variable of interest. The results demonstrate that respondents' characteristics do not change considerably with temperatures (Table A6, Supplementary Materials). Only a few coefficients are statistically significant at the 5 percent level (four out of sixty-three), and no clear temperature patterns are observed. In addition, as shown above, removing individual controls does not affect the conclusions (Table A5, Supplementary Materials). These results suggest that the estimated relationship between sleep and ambient temperature is unlikely to be driven by an endogenous selection of respondents.

Next, a falsification test is performed to rule out that unmeasured seasonal factors drive the results. Specifically, the temperature variables are replaced with temperature measured exactly one year after the completion of the time use diary. Current sleep duration should not be affected by the temperature of the distant future, therefore, zero coefficients are expected in this estimation. Indeed, the estimated temperature coefficients are practically zero and all of them are statistically insignificant at the 5 percent level (Figure 3).

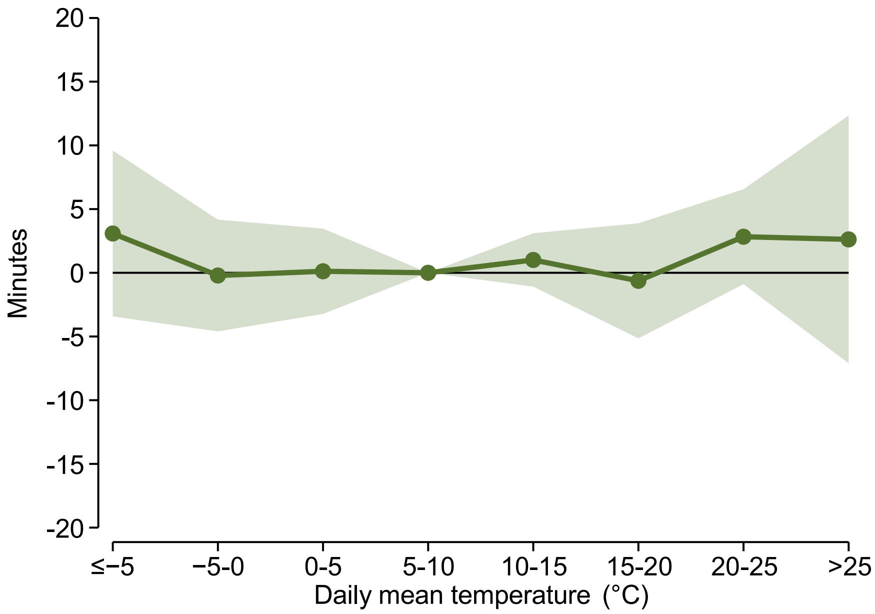

Figure 3. Falsification test with future temperatures

Estimates based on temperature values measured one year after the completion of the time use diary. The circles are the temperature coefficients (β). The reference temperature is 5–10 °C. The shaded area represents 95% confidence intervals computed using standard errors clustered at the county and individual levels. The model has controls for future precipitation, future humidity, the characteristics of the respondent and the interview day (gender, age, education, labor market status, household size, day-of-week, public holiday), and county-by-year-by-month fixed effects. N = 121,670.

In three out of the five waves of the HTUS, each person completed four diaries (one per season), which allows for the inclusion of individual fixed effects. In this way, not only the observed characteristics of the individuals can be controlled for, but all person-specific factors that do not change during the survey year. These fixed effects control for all unobserved individual characteristics except, for example, sudden changes in health status. Although a sizeable portion of the sample is excluded from this estimation, including individual fixed effects does not change the main patterns of the temperature-sleep duration relationship (Figure 4).

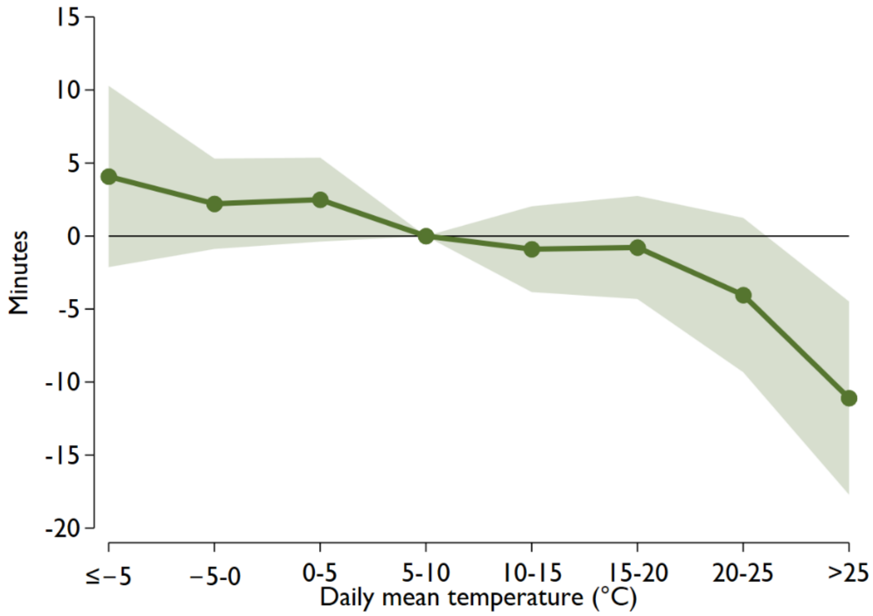

Figure 4. Temperature coefficients from a model with individual fixed effects

The circles are the temperature coefficients (β). The reference temperature is 5–10 °C. The shaded area represents 95% confidence intervals computed using standard errors clustered at the county and individual levels. The model has controls for precipitation, humidity, the characteristics of the respondent and the interview day (gender, age, education, labor market status, household size, day-of-week, public holiday), county-by-year-by-month fixed effects, and individual fixed effects. The wave of 1993 and 2009/2010 are excluded, as only one diary was completed by each respondent. N = 101,623.

As alternative outcome variables, four binary indicators are used showing whether the total sleep time is less than 6 hours, between 6 and 8 hours, between 8 and 9 hours, or at least 9 hours (Figure A2, Supplementary Materials). The results of these estimations suggest that heat increases not only the chance of short sleep duration but also the chance of a healthy length of sleep. At the same time, the chance of long sleep duration (at least 9 hours) is significantly reduced by high temperatures. Cold temperatures do not affect these outcomes.

Finally, the impact of heatwaves is examined. A heatwave is defined in two ways. The first definition is a period of at least three consecutive days where the daily mean temperature exceeds 25°C. Accordingly, heatwave days are those >25 °C days that are preceded by at least two other >25 °C days. The second definition is that a heatwave day is a day above 25 °C preceded by at least four other days above 25 °C. Table A7 in Supplementary Materials summarizes these estimations. Most coefficients are virtually identical to baseline results shown in Figure 1, but >25 °C days are disentangled into two groups: heatwave days and non-heatwave days. Extremely hot (>25 °C) days that are not preceded by two >25 °C days decrease daily sleep by 11.4 minutes, while the effect of a heatwave day (preceded by at least two others) is −14.1. Although this difference seems to be non-negligible, it is not statistically significant at any conventional level ($p = 0.57$). However, when heatwave days are defined as hot days preceded by at least four other hot days, the effect of heatwave days is statistically stronger than the effect of non-heatwave days with >25 °C (−22.7 minutes vs. −10.7 minutes, $p = 0.04$).

As these results suggest that the effects of temperature bins below the reference category are practically identical, in the next sections, more parsimonious models are estimated where the lowest three temperature bins are merged.

4.2. Temporal displacement, heterogeneity, and further results

The results of the previous section show that people suffer sleep loss on hot days, but the heat might affect sleep duration on the subsequent days too. Some may sleep more on the following days to make up for lost sleep. But it is also possible that extreme heat might have a delayed negative impact on sleep duration. To check these possibilities, lagged temperatures are included from the previous two days. The results suggest that previous days' temperatures do not influence sleep duration (Figure A3, Supplementary Materials). While the effects of contemporaneous temperatures (lag 0) replicate the baseline findings, the coefficients of the lagged temperatures are statistically insignificant and much smaller without any meaningful pattern. It is especially apparent for the two highest temperature categories. A similar conclusion is obtained when including lagged temperatures up to six days (Figure A4, Supplementary Materials). The sum of the six lags is not statistically different from for any temperature category, whereas the sum of the contemporaneous and lagged temperatures replicates the baseline pattern (Figure A5, Supplementary Materials).

Next, the heterogeneity in the effects of temperatures is explored. Specifically, a series of equations are estimated that are based on Eq. (2) but in which the interactions between the temperature variables and the categorical variable representing (i) workdays and holidays, (ii) education groups, (iii) age groups, or (iv) females and males are included. Important insights emerge from these results (Figure 5). First, the estimated effects of extreme heat (>25 °C days) are much stronger on weekends and public holidays (−31.0 minutes) than on workdays (−4.2 minutes). As sleep duration is constrained by rigid schedules on workdays due to work, school, or other compulsory duties, there is less room for an external factor to disturb sleep. In contrast, bedtime and wake-up time are less constrained on holidays, so the role of an external disturbance can be more pronounced. Second, individuals with low education seem to be slightly more affected by exposure to hot temperatures than individuals with high education, although the differences do not reach the level of statistical significance. Third, older people seem to suffer larger sleep loss due to exposure to extreme heat than young and middle-aged individuals. The effect of a >25 °C day is −28.4 minutes among 61 years old or older, −9.1 minutes among 41-60 years old, and −5.1 minutes among 18-40 years old. Although this data does not allow to specify the reasons behind the age-related differences, previous research showed that aging is associated with more fragile sleep (Mander, Winer, and Walker 2017). Finally, the negative effects of hot temperatures are stronger among males than among females.

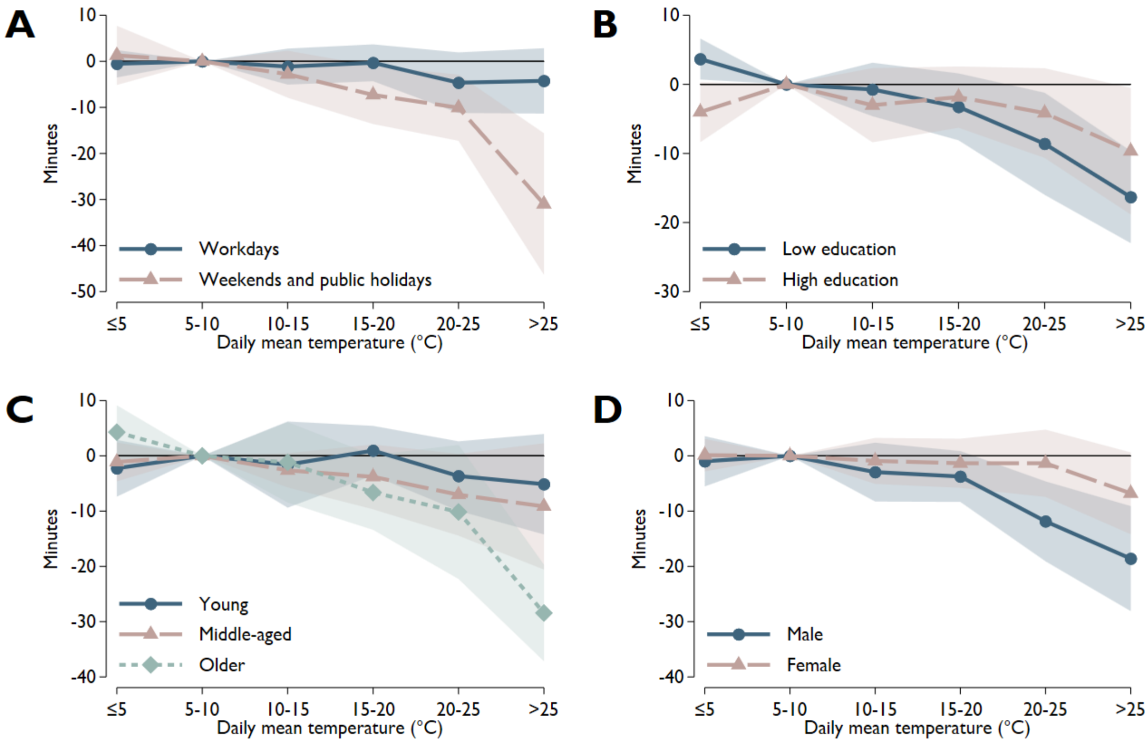

Figure 5. Heterogeneous effects of temperature on sleep duration

The circles are the temperature coefficients (β). The reference temperature is 5–10 °C. The shaded area represents 95% confidence intervals computed using standard errors clustered at the county and individual levels. (B) Low education = primary school, high education = secondary school or college education. (C) Young = 18-40 years old, middle-aged = 41-60 years old, older = 61+ years old. The models have controls for precipitation, humidity, the characteristics of the respondent and the interview day (gender, age, education, labor market status, household size, day-of-week, public holiday), and county-by-year-by-month fixed effects. The formal tests of the differences between the coefficients are shown in Supplementary Materials: Table A8 (panel A), Table A9 (panel B), Table A10 (panel C), and Table A11 (panel D). N = 121,670.

Heterogeneity over time, or in other words, adaptation is also explored (Figure A6, Supplementary Materials). The results of this exercise suggest that the effect of heat has not changed during the thirty-five years of this analysis. The effect of a >25 °C day is −11.8 minutes during the first three waves (1976/1977, 1986/1987, 1993) and −12.3 minutes in the two more recent waves (1999/2000, 2009/2010).

Figure 6 examines how temperatures influence the time of waking up and going to bed. Wake-up is defined as the end of the last sleep period before 11:00, whereas the time of going to bed is the start of the first sleep period after 19:00. Looking at the graph, one can see that the time of waking up is much more influenced by hot temperatures than the time of going to bed. However, it must be noted that the time of going to bed is likely to be different from the time of falling asleep. Respondents of the time use surveys are likely to report the time of going into bed rather than the actual time of falling asleep (even if the corresponding time spell is labeled as a sleep event). Even if heat delays the time it takes to fall asleep, this cannot be observed in time use surveys, only the effect on bedtime. Consequently, Figure 6 provides solid and credible evidence for the effect of temperature on the time of waking up. The time of going to bed seems to be not influenced by temperature.

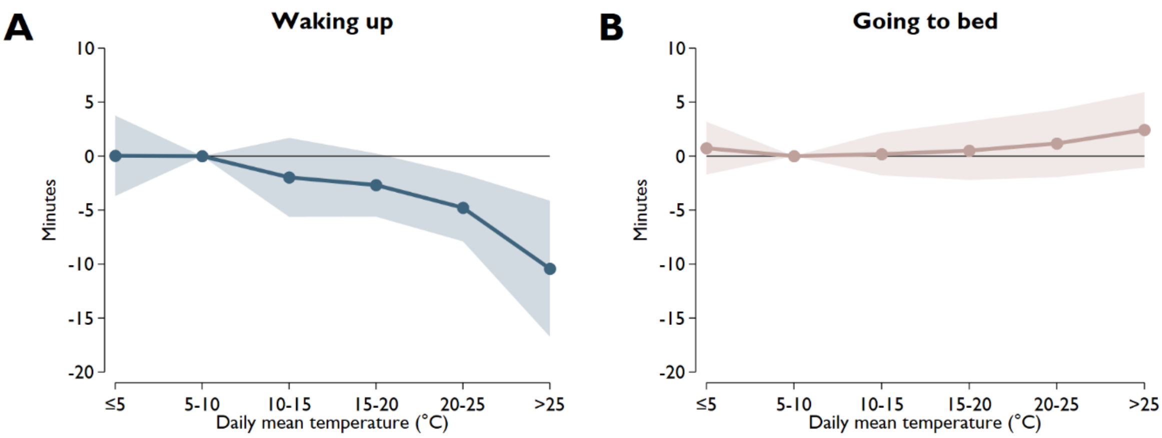

Figure 6. The effects of temperature on the time of waking up and going to bed

The circles are the temperature coefficients (β). The reference temperature is 5–10 °C. The shaded areas represent 95% confidence intervals computed using standard errors clustered at the county and individual levels. Dependent variable: (A) time of waking up, (B) time of going to bed. The model has controls for precipitation, humidity, the characteristics of the respondent and the interview day (gender, age, education, labor market status, household size, day-of-week, public holiday), and county-by-year-by-month fixed effects. The wave of 1976/77 is not included, as the total daily sleep duration is available in the dataset without specifics on the sleep spells. N = 96,213 (A) and 95,081 (B).

Finally, the effects on night and daytime sleep are explored (Figure A7, Supplementary Materials). Night sleep is defined as sleep time between 20:00 and 7:59, while day sleep is defined as the sleep time between 8:00 and 19:59. These results show that the effect of temperature on total sleep time is driven by the effect on night sleep. The temperature coefficients for daytime sleep are close to zero. Importantly, the estimated effect of a 25 °C day on daytime sleep is −1.6 minutes, which means that a night's sleep disrupted by heat cannot be compensated for by a longer daytime nap. On the contrary, if there is an effect, daytime sleep is also reduced because of the heat.

4.3. The impacts of climate change

Under the assumption that future sleep duration will be influenced by temperatures in a similar way as sleep duration has been influenced by them in the past (somewhat justified by the adaptation result), the change in annual sleep duration is projected in response to climate change-induced warming. The projections are made separately for the four SSP scenarios and show estimates for each of the remaining decades of the 21st century. The projections are based on data from twenty-four climate models and the historical relationship between temperature and sleep (the uncertainty of which is captured by 200 bootstrap samples). The baseline period to which the future temperature distributions are compared is 1990-2014.

Figure 7 shows the projections for the 2050s and 2090s, while Figure A8 in Supplementary Materials shows the results for all decades. The median projections suggest considerable sleep loss already for the middle of the century under each SSP scenario, compared to 1990-2014. For the 2050s, the total annual sleep loss per person due to warming is 3.7 hours in the SSP1-2.6 scenario, 4.2 hours in the SSP2-4.5 scenario, 5.3 hours in the SSP3-7.0 scenario, and 6.4 hours in the SSP5-8.5 scenario. By the end of the century, the median projection in SSP1-2.6 does not change considerably: −3.7 hours (the middle 95% of the projections: −0.7–−10.0 hours). In the other three scenarios, the median projections are steadily increasing. Consequently, they are significantly larger by the 2090s: −6.7 hours (middle 95%: −1.7–−13.9 hours) in the SSP2-4.5 scenario, −10.4 hours (middle 95%: −3.9–−20.1 hours) in the SSP3-7.0 scenario, and −14.0 hours (middle 95%: −4.7–−26.0) in the SSP5-8.5 scenario. Although there are differences between the individual projections, which are captured by the wide range of projected impacts, almost all of them predict a nonnegligible average annual sleep loss, especially under the less optimistic scenarios.

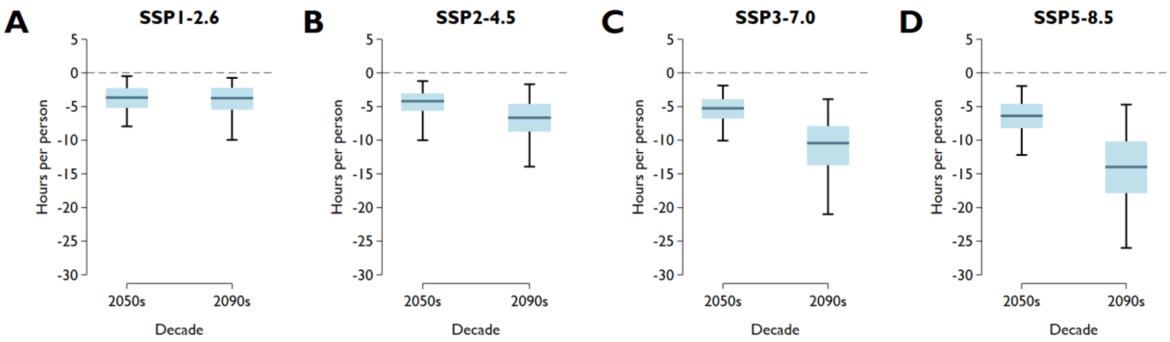

Figure 7. Projected annual sleep loss for the 2050s and 2090s

The changes are calculated using the projected within-model differences in temperature distribution between 1990-2014 and each decade in the 21st century and the estimated effect of temperatures on sleep duration (estimated by 200 bootstrap samples). The boxplots show the distribution of the projections: the medians, the interquartile ranges, and the middle 95% of the projections.

Figure A9 in Supplementary Materials shows the projected impacts for the 2090s by calendar month. Most of the projected annual sleep loss is concentrated in the summer and early autumn. Under all SSP scenarios, the median projections are practically zero for the winter months, whereas around 70-80% of the annual sleep losses occur between June and September. The median projections of the total sleep loss over these four months are −3.2 hours (SSP1-2.6), −5.5 hours (SSP2-4.5), −8.3 hours (SSP3-7.0), and −10.6 hours (SSP5-8.5) per person. In terms of daily sleep loss, these projections represent −1.6 minutes (SSP1-2.6) and −5.2 minutes (SSP5-8.5) per person per day. In relative terms, these correspond to a daily sleep loss of 0.3% and 1.0%, respectively. But the uncertainty of the projections is quite wide. E.g., the middle 95% of projections for SSP5-8.5 are between −1.7 and −10.2 minutes.

These projections fail to take into account the possible heterogeneous impacts of climate change, although different groups in society may be affected in significantly different ways by a warming climate. Figure 8 shows the projected annual sleep loss for the 2090s by age group. As shown earlier, the elderly suffer greater sleep loss due to exposure to high temperatures than young and middle-aged adults, and are therefore projected to be more severely affected by climate change. According to the median projections, the predicted sleep losses for older people is about 4.5 times greater than for the middle-aged and 9 times greater than for young adults. For example, in the worst-case scenario (SSP5-8.5), the annual sleep loss for 18-40 and 41-60 year olds is 4.2 hours and 8.1 hours, respectively, compared to 37.6 hours for older people.

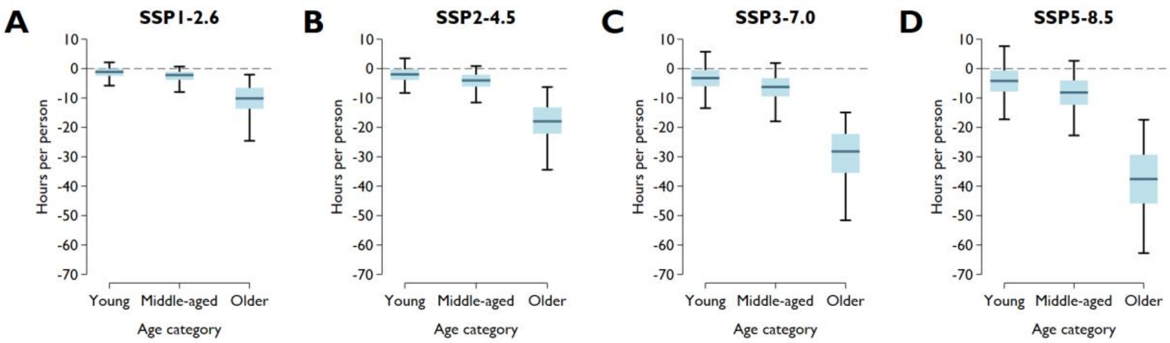

Figure 8. Projected annual sleep loss for the 2090s by age

Young = 18-40 years old, middle-aged = 41-60 years old, older = 61+ years old. The changes are calculated using the projected within-model differences in temperature distribution between 1990-2014 and 2090-2099 and the estimated effect of temperatures on sleep duration (estimated by 200 bootstrap samples). The boxplots show the distribution of the projections: the medians, the interquartile ranges, and the middle 95% of the projections.

During the 21st century, not only the number of hot days but also the number of consecutive hot days (heatwave days) will increase sharply. It has already been shown that the effect of these heatwave days on sleep can be stronger than that of a "normal" hot day. It is perhaps worth pointing out that, taking into account the impact of these days and the future change in their number, the projected impact of climate change for the 2090s is much stronger than the baseline projection (considering the median projections). In the SSP5-8.5 scenario, the median projection is −22.7 hours when heatwave days are taken into account (Figure A10, Supplementary Materials), compared to the −14.0 hours of the baseline model shown in Figure 7. The median projections for SSP1-2.6, SSP2-4.5, and SSP3-7.0 are 1 hours, 2.3 hours, and 5.1 hours stronger than the baseline approach, respectively.

5. Discussion and conclusion

Based on nationally representative time use survey data of a European country with a continental climate, this paper provides evidence that ambient temperature has a considerable effect on sleep duration. The estimated relationship is highly nonlinear. Compared to a mild temperature (5-10 °C), sleep duration is not affected by the cold. However, as daily mean temperatures rise, sleep duration starts to decrease. The impact of an extremely hot (>25 °C) day on daily sleep duration is −12.4 minutes. For the current adult population of Hungary (~8 million), it means that an extremely hot day results in a total of 1.65 million hours of lost sleep, compared to a day with a daily mean temperature of 5-10 °C. Even compared to a non-extremely hot day (20-25 °C), the total sleep loss is 0.8 million hours on >25 °C days. The effect of hot temperatures is especially large on weekends and public holidays, for older individuals, and for males. Importantly, there is no evidence for the short-run recovery from the temperature-induced sleep deficit. Combining the estimated temperature effects with temperature projections of twenty-four climate models, it is found that the warming climate will decrease sleep duration during the 21st century. The median projections for the 2090s range between −3.7 and −14.0 hours per person per year under the four SSP scenarios considered in the analysis, while taking into account heatwave days they range between −4.7 and −22.7 hours. This sleep loss is mostly concentrated in the summer months. This study also shows that older people are projected to be much more affected than average by climate change.

The estimated effects of temperature and climate change are nonnegligible and might lead to further consequences. Previous studies that leverage exogenous variation in sleep provide evidence that even a minor disruption in sleeping patterns or a small amount of sleep deprivation can lead to substantial consequences. Some of these papers analyze the impact of Daylight Saving Time. At the spring transition, clocks are moved forward by one hour, which results in a decrease of 40-60 minutes of sleep (Lahti et al. 2006; Barnes and Wagner 2009). This leads to increases in the number of fatal car accidents, workplace injuries, and the incidence of myocardial infarction (Barnes and Wagner 2009; Toro, Tigre, and Sampaio 2015; Smith 2016; Manfredini et al. 2018; Fritz et al. 2020; Osborne-Christenson 2022), and a drop in general well-being (Kountouris and Remoundou 2014). After the transition in the fall, similar effects with the opposite sign are observed in some studies (Jin and Ziebarth 2020), although others fail to establish any relationship (Fritz et al. 2020; Osborne-Christenson 2022). Other papers examine variation in the timing of natural light across or within time zones that causes small differences in total sleep time. An analysis of U.S. data finds that a regular loss of 19 minutes of sleep per day has negative effects on weight, diabetes, cardiovascular diseases, and income (Giuntella and Mazzonna 2019). Another paper shows that both a short-run and a permanent increase in weekly sleep increase earnings (Gibson and Shrader 2018). Results based on Indian (Jagnani 2022) and Chinese (Giuntella, Han, and Mazzonna 2017) data show that later sunset time and the resulting loss of sleep reduces test scores in the short run and years of education in the long run, decreases cognitive skills and exacerbates depression symptoms. Geographical position within a time zone and disturbance of circadian rhythm also affect cancer risks (Gu et al. 2017; VoPham et al. 2018). In sum, these studies show that a slight but regular loss of sleep (which is alike to the potential effects of climate change) leads to substantial health and labor marker effects, but even an occasional shock to sleep duration can cause non-negligible impacts.

In light of the results of these studies, sleep loss due to exposure to hot days – and especially to heatwave days – and a warming climate may have non-negligible consequences on a wide range of outcomes, including health, cognitive performance, and general well-being. These effects can be particularly significant for older people.

Climate change-induced sleep loss is likely to have sizable macroeconomic consequences. The economic cost of poor sleep is already high. A study in Australia estimate the annual cost of inadequate sleep at 45.2 billion US dollars in 2016-2017 (Hillman et al. 2018). Another study finds that 681.2 billion US dollars are lost each year due to insufficient sleep across five OECD countries (USA, Canada, Japan, Germany, UK) in the early 2010s (Hafner et al. 2017). In addition, a recent study estimates that the costs of insufficient sleep duration in Canada in 2020 were 502 million Canadian dollars (Chaput et al. 2022). The expected sleep loss due to climate change will further increase these economic burdens.

The results of this paper are an important contribution to the vast literature that analyzes the effects of temperature and climate change on human societies (Dell, Jones, and Olken 2014; T. A. Carleton and Hsiang 2016), including the effects on productivity (Burke, Hsiang, and Miguel 2015b; Zhang et al. 2018; Miller et al. 2021; LoPalo 2022; Heyes and Saberian 2022), cognitive performance/learning (Graff Zivin, Hsiang, and Neidell 2018; Cook and Heyes 2020; Garg, Jagnani, and Taraz 2020; Graff Zivin et al. 2020; Park et al. 2020; Park, Behrer, and Goodman 2021; Park 2022), aggression/crime (S. M. Hsiang, Burke, and Miguel 2013; Ranson 2014; Burke, Hsiang, and Miguel 2015a), and health (Deschênes and Moretti 2009; Barreca 2012; Ye et al. 2012; Gasparrini et al. 2015; Mora et al. 2017; White 2017; Karlsson and Ziebarth 2018; Agarwal et al. 2021; Hajdu and Hajdu 2021; T. Carleton et al. 2022; Conte Keivabu 2022; Hajdu and Hajdu 2023). Sleep may be one of the channels through which heat and climate change affect human health, performance, and behavior.

Some important features of this study should be taken into account when assessing the results. First, time use diaries measure sleep duration with some bias. As mentioned before, sleep periods in the diaries are more likely to correspond to the time spent in bed rather than actual sleep. If heat affects (increases) the time it takes to fall asleep, then the effects on sleep duration are underestimated. Second, sleep quality might be as important for many health outcomes as sleep duration. To get complete knowledge about the effect of ambient temperature on sleep, the characteristics of sleep other than duration cannot be ignored. Third, the time use data allow a relationship to be established between temperature and sleep duration, but other data are needed to explore the mechanism. Fourth, the assumptions behind the projection of the impact of climate change must be made clear. Following the literature (Obradovich et al. 2017; Minor et al. 2022) and given the results of the present study on adaptation, the projections assume that the relationship between temperature and sleep duration will be similar in the future as it has been in the past. The projected impacts can be considered as a benchmark. However, the impact of climate change can be influenced by a number of factors. Adaptation may occur in the future, which could mitigate the impact of climate change. Other factors might lead to an amplified impact of climate change. In the future, not only will the number of days with average temperatures above 25 °C increase, but also the average temperature of these days. As the marginal effect of temperature seems to be increasing, the effect of a >25 °C day is likely to be substantially larger in the next decades. In addition, temperature extremes that are beyond human experience are likely to occur during the century. The effects of unprecedented temperature extremes can be especially strong.

The findings of this study imply that policymakers should design strategies to mitigate the sleep-related threats of heat and climate change, particularly among older people. Raising awareness of the effect of heat on sleep may lead to individual actions, but planning at the societal level may also be needed to effectively mitigate the negative effects of future heatwaves and a warmer climate.

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Supplementary Materials for

Temperature exposure and sleep duration: evidence from time use surveys

This PDF file includes:

Figure A1-A10

Table A1-A11

Figures

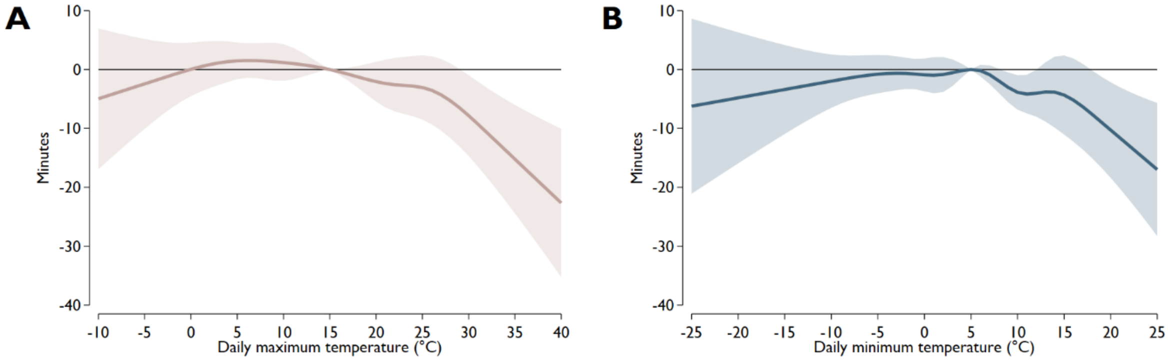

Figure A1. Estimations using daily maximum and minimum temperatures

The estimates come from restricted cubic spline functions with seven knots. The reference temperatures are 15 °C (A) and 5 °C (B). The model has controls for precipitation, humidity, the characteristics of the respondent and the interview day (gender, age, education, labor market status, household size, day-of-week, public holiday), and county-by-year-by-month fixed effects. The shaded area represents 95% confidence intervals computed using standard errors clustered at the county and individual levels. N = 121,670.

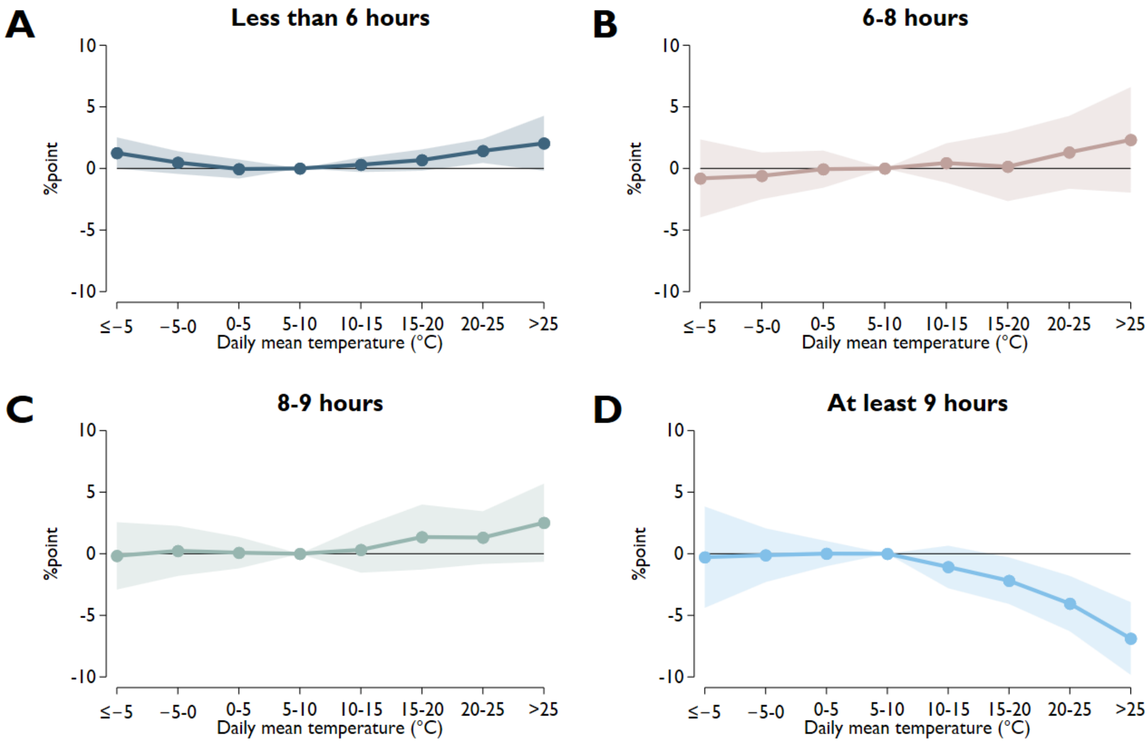

Figure A2. Binary outcomes indicating different sleep durations

The circles are the temperature coefficients (β). The reference temperature is 5–10 °C. The shaded areas represent 95% confidence intervals computed using standard errors clustered at the county and individual levels. The models have controls for precipitations, humidity, the characteristics of the respondent and the interview day (gender, age, education, labor market status, household size, day-of-week, public holiday), and county-by-year-by-month fixed effects. N = 121,670.

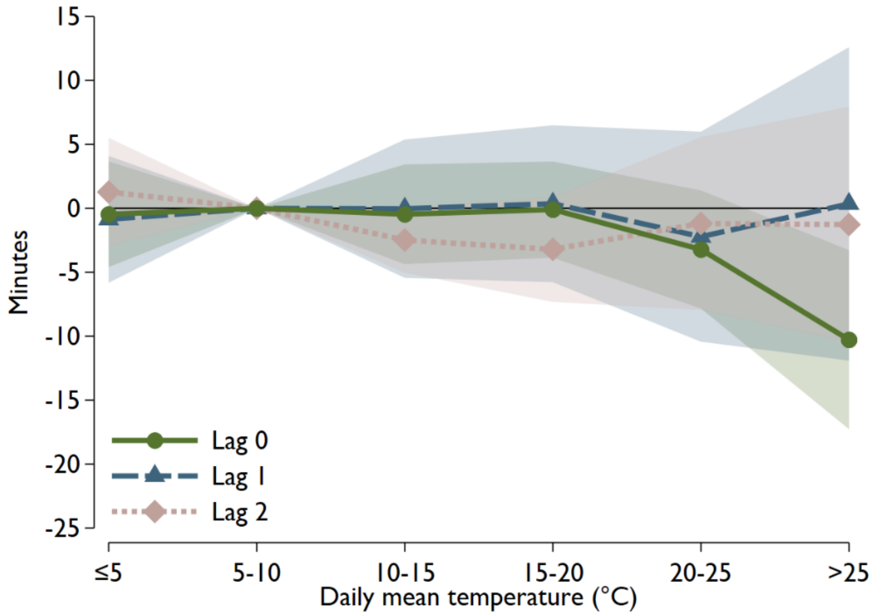

Figure A3. Testing near-term displacement

Estimation including two temperature lags. The circles are the temperature coefficients (β). The reference temperature is 5–10 °C. The shaded areas represent 95% confidence intervals computed using standard errors clustered at the county and individual levels. Lag 0 shows the contemporaneous effects, whereas lag 1 and lag 2 the effects of temperatures of the two previous days. The model has controls for contemporaneous and lagged precipitations, contemporaneous and lagged humidity, the characteristics of the respondent and the interview day (gender, age, education, labor market status, household size, day-of-week, public holiday), and county-by-year-by-month fixed effects. N = 121,670.

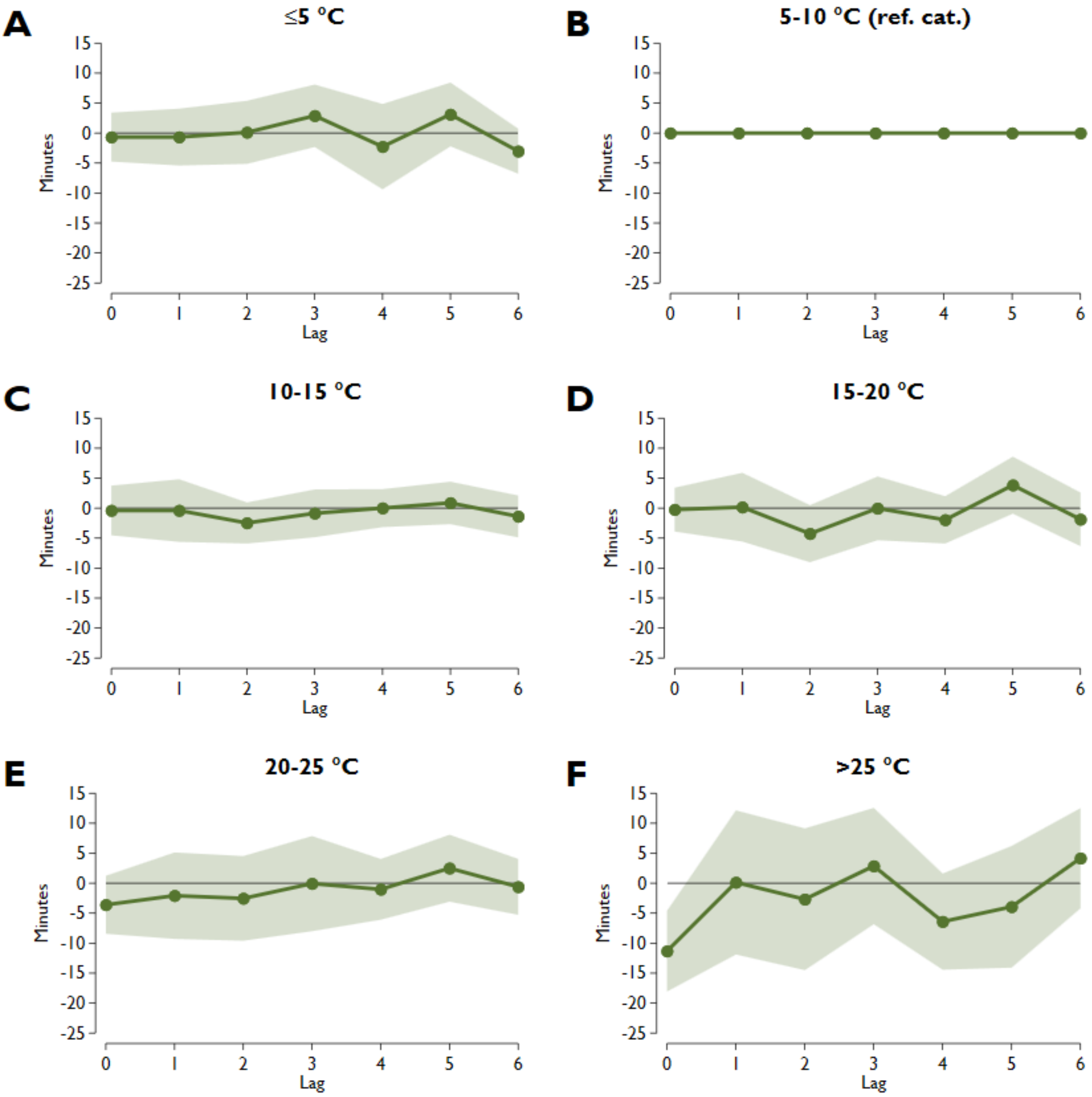

Figure A4. Including lagged temperatures up to six days

Estimation including six temperature lags. The circles are the temperature coefficients (β). The reference temperature is 5–10 °C. The shaded areas represent 95% confidence intervals computed using standard errors clustered at the county and individual levels. The model has controls for contemporaneous and lagged precipitations, contemporaneous and lagged humidity, the characteristics of the respondent and the interview day (gender, age, education, labor market status, household size, day-of-week, public holiday), and county-by-year-by-month fixed effects. N = 121,670.

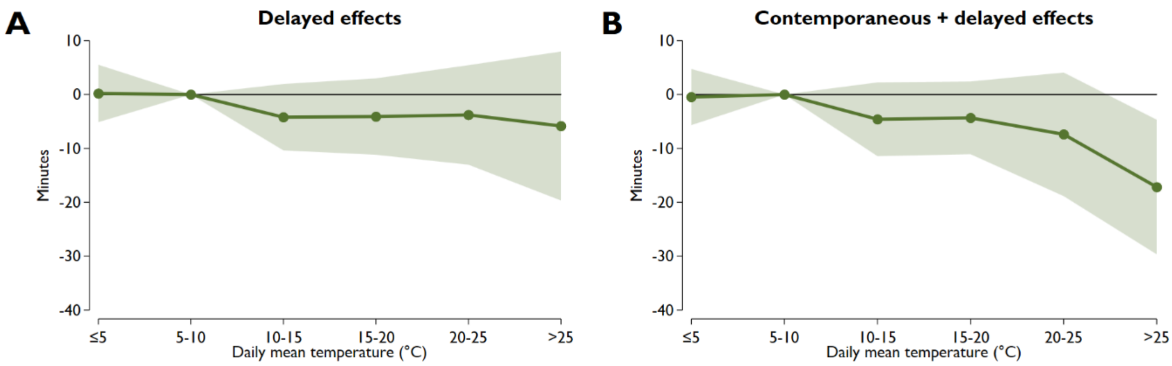

Figure A5. The cumulative effect of exposure to ambient temperature

Estimation including six temperature lags. (A) Sum of the coefficients on the lagged temperature variables. (B) Sum of the coefficients on the contemporaneous and lagged temperature variables. The reference temperature is 5–10 °C. The shaded areas represent 95% confidence intervals computed using standard errors clustered at the county and individual levels. The model has controls for contemporaneous and lagged precipitations, contemporaneous and lagged humidity, the characteristics of the respondent and the interview day (gender, age, education, labor market status, household size, day-of-week, public holiday), and county-by-year-by-month fixed effects. N = 121,670.

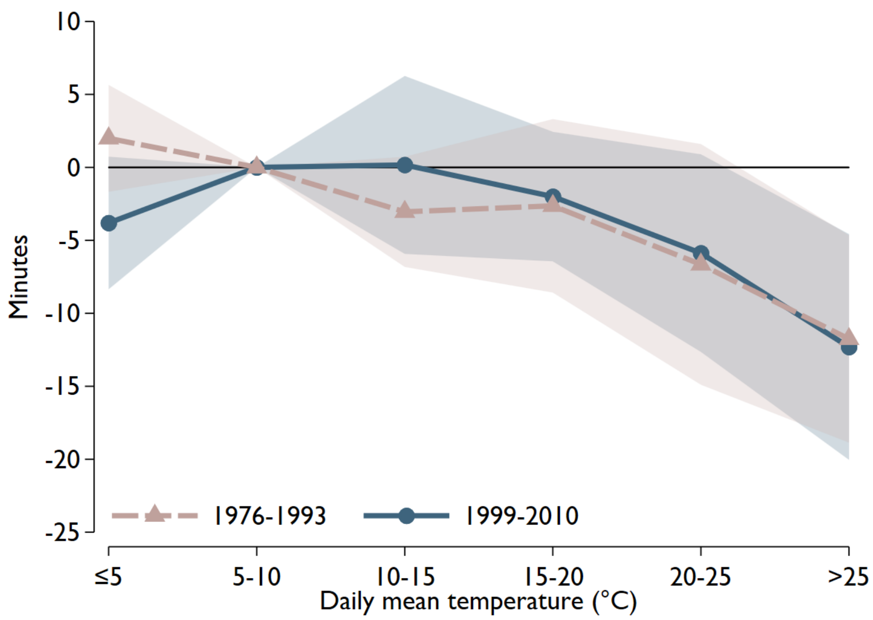

Figure A6. The effect of temperature on sleep duration over time

The circles are the temperature coefficients (β). The reference temperature is 5–10 °C. The shaded area represents 95% confidence intervals computed using standard errors clustered at the county and individual levels. The model has controls for precipitation, humidity, the characteristics of the respondent and the interview day (gender, age, education, labor market status, household size, day-of-week, public holiday), and county-by-year-by-month fixed effects. N = 121,670.

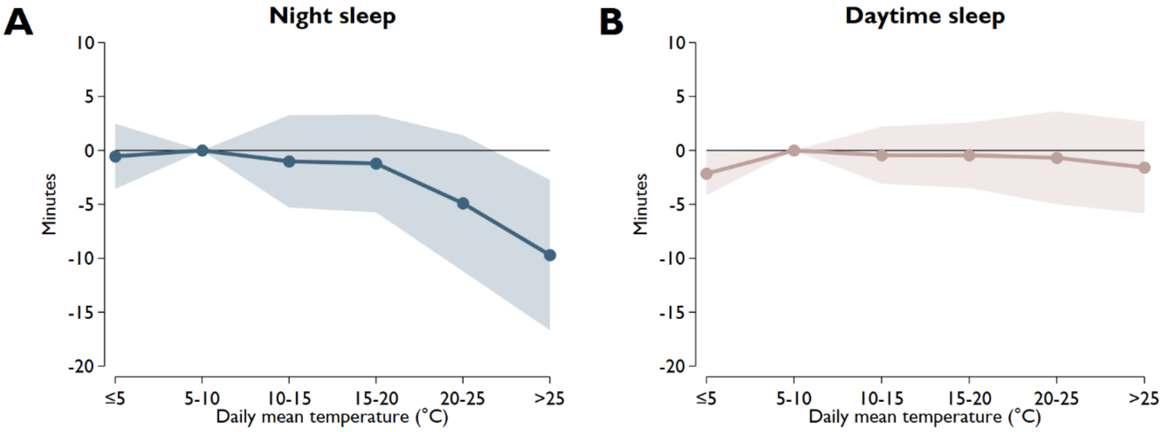

Figure A7. The effects of temperature on night and daytime sleep

The circles are the temperature coefficients (β). The reference temperature is 5–10 °C. The shaded areas represent 95% confidence intervals computed using standard errors clustered at the county and individual levels. Dependent variable: (A) sleep time between 20:00 and 7:59, (B) sleep time between 8:00 and 19:59. The model has controls for precipitation, humidity, the characteristics of the respondent and the interview day (gender, age, education, labor market status, household size, day-of-week, public holiday), and county-by-year-by-month fixed effects. The wave of 1976/77 is not included, as the total daily sleep duration is available in the dataset without specifics on the sleep spells. N = 98,076.

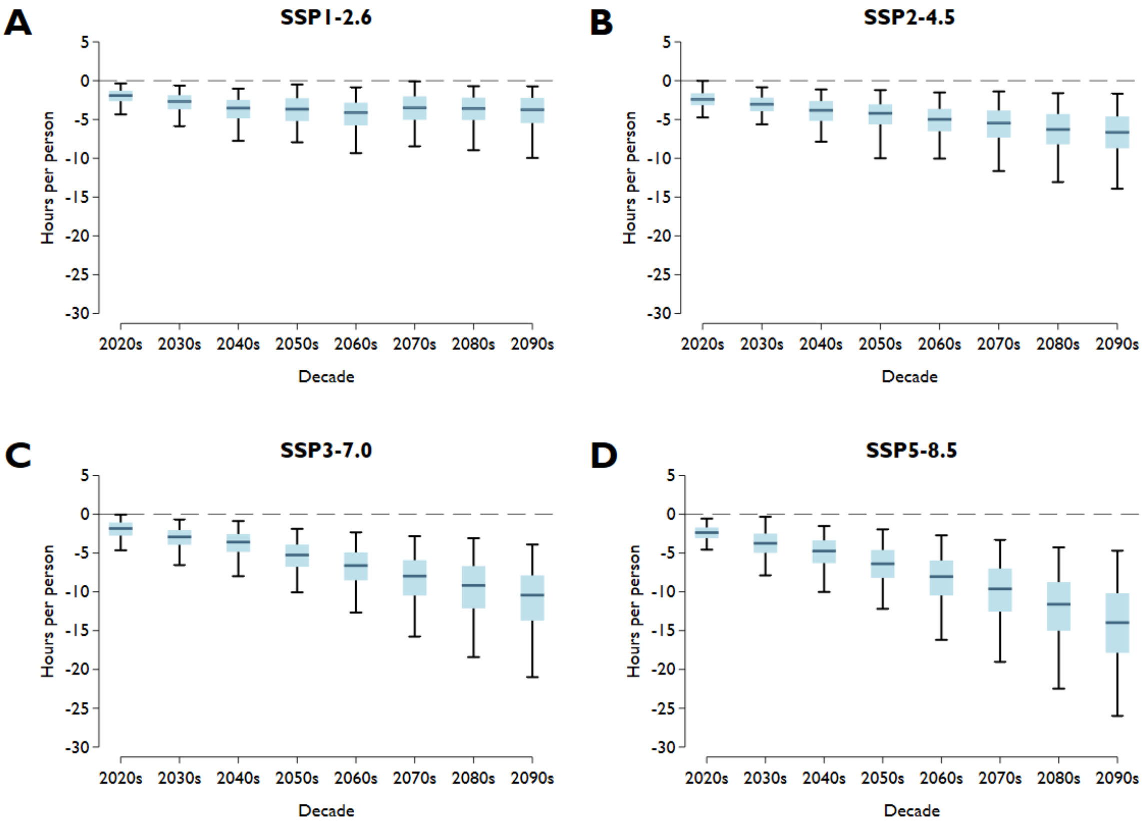

Figure A8. Projected sleep loss during the 21st century for each decade

The changes are calculated using the projected within-model differences in temperature distribution between 1990-2014 and each decade in the 21st century and the estimated effect of temperatures on sleep duration (estimated by 200 bootstrap samples). The boxplots show the distribution of the projections: the medians, the interquartile ranges, and the middle 95% of the projections.

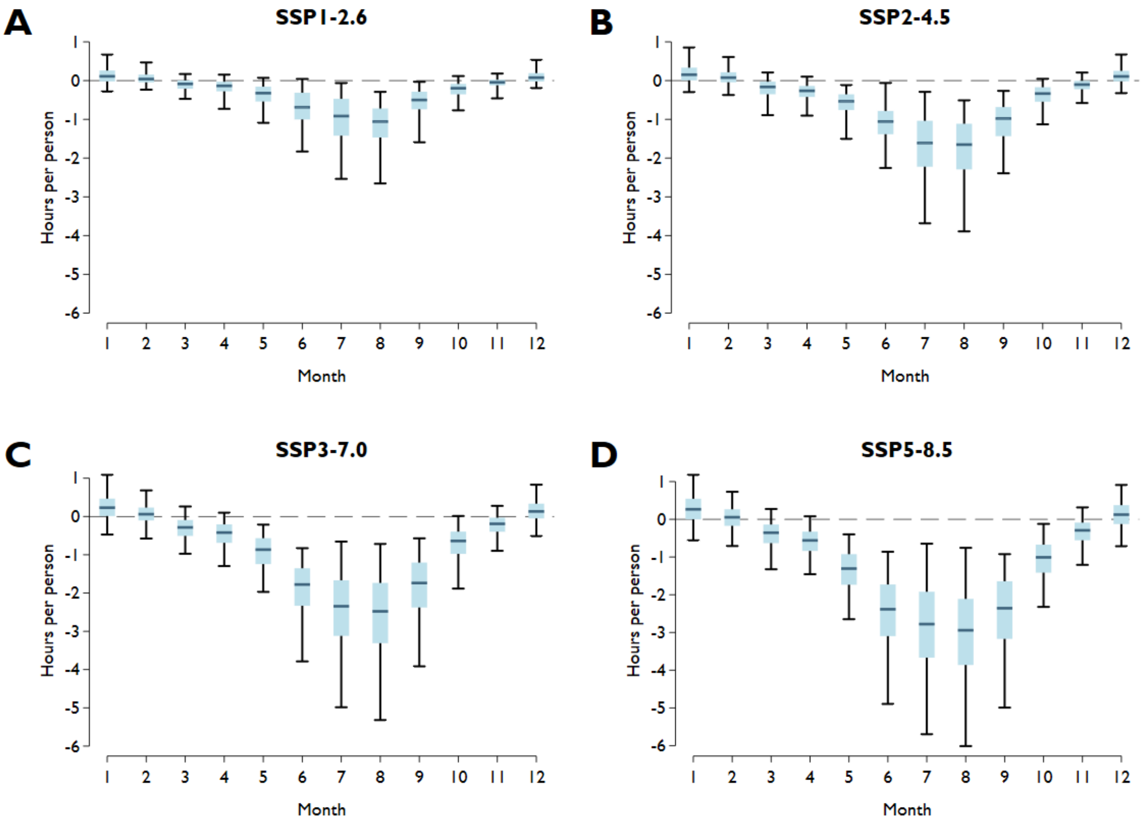

Figure A9. Projected sleep loss by calendar month for the 2090s

The changes are calculated using the projected within-model differences in temperature distribution between 1990-2014 and 2090-2099 and the estimated effect of temperatures on sleep duration (estimated by 200 bootstrap samples). The boxplots show the distribution of the projections: the medians, the interquartile ranges, and the middle 95% of the projections.

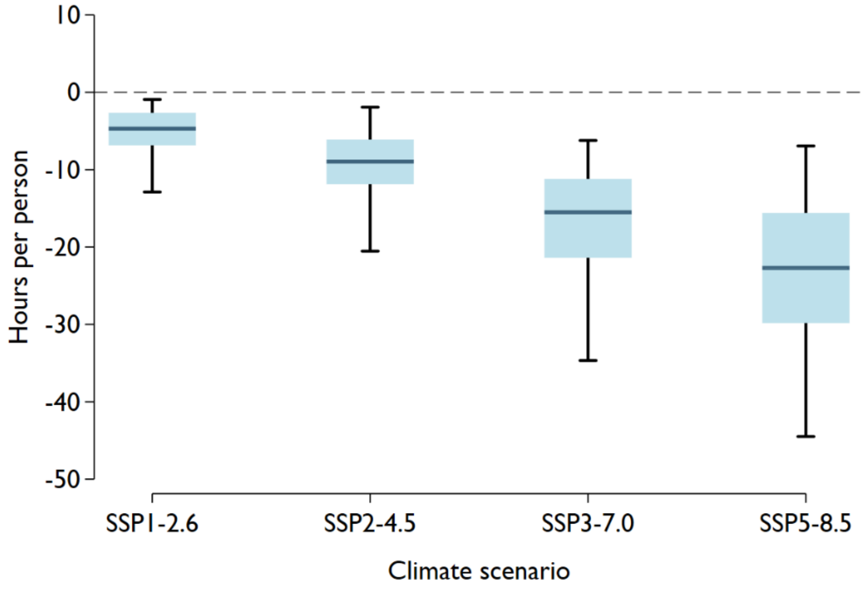

Figure A10. Projected sleep loss for the 2090s considering the effects of heatwave days

Heatwave day is a day above 25 °C preceded by at least four other days above 25 °C. The changes are calculated using the projected within-model differences in temperature distribution between 1990-2014 and 2090-2099 and the estimated effect of temperatures on sleep duration (estimated by 200 bootstrap samples). The boxplots show the distribution of the projections: the medians, the interquartile ranges, and the middle 95% of the projections.

Tables

Table A1. The main characteristics of the time use surveys

	1976/1977	1986/1987	1993	1999/2000	2009/2010
Survey time span	1976/11/01- 1977/10/31	1986/03/01- 1987/03/08	1993/02/01- 1993/05/30	1999/09/01- 2000/09/06	2009/10/01- 2010/10/21
Age range	15-69	15-79	18-79	15-84	10-84
Time diaries start	00:00	00:00	00:00	04:00	04:00
N of diaries	24,507	39,617	11,174	43,172	8,391
N of individuals	6,639	10,732	11,174	11,416	8,391
Type of diary	Open	Open	Open	Open	Open

Table A2. Number of diaries and individuals in the analysis sample

Wave	N of diaries	N of individuals
1976/1977	23,594	6,405
1986/1987	37,149	10,164
1993	11,108	11,108
1999/2000	42,023	11,113
2009/2010	7, 7967	7,796
Total	121,670	46,586

Table A3. Sample selection by steps

	N of diaries
Raw dataset	126,861
Excluding less than 18 years old	122,347
Excluding observation with missing values	121,753
Excluding county-by-year-by-month “cells” with less than 10 diaries	121,670

Table A4. Descriptive statistics

Variable	Mean	SD	Min	Max	N
Sleep durations (minutes)	513.18	104.29	0	1440	121,670
Daily mean temperature (°C)					
≤−5	0.03	0.17	0	1	121,670
−5 to 0	0.12	0.33	0	1	121,670
0 to 5	0.17	0.38	0	1	121,670
5 to 10	0.18	0.38	0	1	121,670
10 to 15	0.16	0.36	0	1	121,670
15 to 20	0.20	0.40	0	1	121,670
20 to 25	0.12	0.32	0	1	121,670
>25	0.02	0.15	0	1	121,670
Daily precipitation (mm)					
0	0.69	0.46	0	1	121,670
0 to 3	0.15	0.36	0	1	121,670
3 to 5	0.06	0.24	0	1	121,670
5 to 10	0.06	0.25	0	1	121,670
10+	0.03	0.17	0	1	121,670
Age					
-20	0.05	0.22	0	1	121,670
21-30	0.17	0.38	0	1	121,670
31-40	0.19	0.39	0	1	121,670
41-50	0.19	0.39	0	1	121,670
51-60	0.18	0.38	0	1	121,670
61-70	0.15	0.35	0	1	121,670
71-	0.07	0.25	0	1	121,670
Education					
Primary	0.47	0.50	0	1	121,670
Vocational	0.19	0.39	0	1	121,670
High school	0.24	0.43	0	1	121,670
College/university	0.10	0.30	0	1	121,670
Labor force status					
Employed	0.55	0.50	0	1	121,670
Unemployed	0.04	0.20	0	1	121,670
Maternity leave	0.03	0.18	0	1	121,670
Student	0.03	0.17	0	1	121,670
Retired	0.29	0.45	0	1	121,670
Other	0.05	0.22	0	1	121,670
N of household members					
1	0.10	0.30	0	1	121,670
2	0.26	0.44	0	1	121,670
3	0.23	0.42	0	1	121,670
4	0.24	0.43	0	1	121,670
5	0.09	0.29	0	1	121,670
6+	0.05	0.22	0	1	121,670
Unknown	0.01	0.11	0	1	121,670
Day-of-week					
Monday	0.14	0.35	0	1	121,670
Tuesday	0.14	0.35	0	1	121,670
Wednesday	0.14	0.35	0	1	121,670
Thursday	0.14	0.35	0	1	121,670
Friday	0.14	0.35	0	1	121,670
Saturday	0.14	0.35	0	1	121,670
Sunday	0.14	0.35	0	1	121,670
Public holiday	0.02	0.15	0	1	121,670

Weighted figures.

Table A5. Sensitivity tests

Daily mean temperature (°C)	(1) Baseline	(2) Excl. controls	(3) Excl. precipitation and humidity	(4) C-Y, C-M FE	(5) C, Y, M FE + time trend	(6) County + Y-M clustering	(7) Sleep duration 4-12 hours
≤−5	−2.1 (3.4)	−3.5 (3.5)	−2.4 (3.4)	−3.0 (3.1)	−2.5 (3.4)	−2.1 (4.8)	−2.6 (3.3)
−5 to 0	−1.6 (2.4)	-3.8^{*} (2.1)	−1.6 (2.4)	−2.6 (2.2)	−2.5 (2.3)	−1.6 (2.8)	−0.5 (2.0)
0 to 5	0.0 (1.2)	−0.5 (1.4)	0.3 (1.2)	−0.5 (1.0)	−0.5 (1.1)	0.0 (1.7)	0.7 (1.3)
5 to 10	ref. cat.	ref. cat.	ref. cat.	ref. cat.	ref. cat.	ref. cat.	ref. cat.
10 to 15	−1.8 (1.7)	−2.0 (1.8)	−2.5 (1.6)	−2.2 (1.7)	−2.3 (1.9)	−1.8 (1.4)	−2.2 (1.4)
15 to 20	−2.4 (1.9)	-4.4^{**} (1.9)	-4.3^{**} (1.6)	−2.7 (1.9)	−2.6 (1.8)	−2.4 (1.5)	-4.3^{**} (1.7)
20 to 25	-6.3^{**} (3.0)	-9.4^{***} (2.8)	-8.7^{***} (2.5)	-6.4^{**} (2.8)	-6.4^{**} (2.9)	-6.3^{**} (2.9)	-7.2^{**} (2.6)
>25	-12.4^{***} (3.2)	-10.4^{**} (3.6)	-15.8^{***} (2.6)	-13.1^{***} (2.8)	-12.2^{***} (3.3)	-12.4^{***} (2.9)	-14.2^{***} (3.2)
Fixed effects	C-Y-M	C-Y-M	C-Y-M	C-Y, C-M	C, Y, M	C-Y-M	C-Y-M
Time trend	No	No	No	No	C-spec. quadratic	No	No
Controls	Yes	No	Yes	Yes	Yes	Yes	Yes
Precipitation and humidity	Yes	Yes	No	Yes	Yes	Yes	Yes
SE clustering	County + individual	County + individual	County + individual	County + individual	County + individual	County + Y-M	County + individual
Weighted	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.16	0.03	0.16	0.15	0.15	0.16	0.17
N	121,670	121,670	121,670	121,670	121,670	121,670	117,358

Controls: gender, age, education, labor market status, household size, day-of-week, public holiday. Standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A6. Temperature and respondent characteristics

Daily mean temperature (°C)	(1) Female	(2) High education	(3) Young	(4) Middle-aged	(5) Older	(6) Employed	(7) Retired	(8) Other	(9) Large household size
≤−5	0.016	0.000	−0.018	−0.001	0.019	−0.000	0.018	−0.017	−0.013
	(0.015)	(0.015)	(0.011)	(0.013)	(0.013)	(0.019)	(0.014)	(0.012)	(0.012)
−5 to 0	0.013	0.008	0.012	−0.005	−0.006	0.006	−0.008	0.002	−0.002
	(0.014)	(0.011)	(0.009)	(0.011)	(0.010)	(0.015)	(0.011)	(0.008)	(0.008)
0 to 5	0.001	−0.002	0.000	0.009	−0.009	0.013	−0.009	−0.004	0.002
	(0.008)	(0.010)	(0.012)	(0.011)	(0.007)	(0.010)	(0.006)	(0.008)	(0.004)
5 to 10	ref. cat.	ref. cat.	ref. cat.	ref. cat.	ref. cat.	ref. cat.	ref. cat.	ref. cat.	ref. cat.
10 to 15	0.003	−0.008	0.006	0.007	−0.013*	0.004	−0.018***	0.014**	0.014**
	(0.007)	(0.005)	(0.009)	(0.011)	(0.007)	(0.009)	(0.006)	(0.006)	(0.006)
15 to 20	0.017**	0.001	0.000	0.005	−0.006	0.008	−0.014*	0.005	0.010
	(0.006)	(0.008)	(0.012)	(0.010)	(0.008)	(0.011)	(0.007)	(0.010)	(0.008)
20 to 25	0.009	0.005	0.003	−0.009	0.006	0.003	−0.008	0.005	0.010
	(0.007)	(0.011)	(0.012)	(0.012)	(0.009)	(0.010)	(0.008)	(0.009)	(0.008)
>25	0.001	−0.008	−0.014	0.001	0.013	−0.009	0.003	0.006	0.004
	(0.013)	(0.014)	(0.011)	(0.015)	(0.012)	(0.016)	(0.016)	(0.012)	(0.012)
R-squared	0.01	0.17	0.02	0.02	0.03	0.06	0.04	0.03	0.04
N	121,670	121,670	121,670	121,670	121,670	121,670	121,670	121,670	119,424

The dependent variables are indicated in the titles of the columns. Precipitation, humidity, and county-by-year-by-month fixed effects are included. Standard errors clustered at the county and individual levels are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A7. The effects of heatwave days

Daily mean temperature (°C)	(1) Heatwave: at least 3 days	(2) Heatwave: at least 5 days
≤−5	−2.1 (3.4)	−2.1 (3.4)
−5 to 0	−1.6 (2.4)	−1.6 (2.4)
0 to 5	0.0 (1.2)	0.0 (1.2)
5 to 10	ref. cat.	ref. cat.
10 to 15	−1.8 (1.7)	−1.9 (1.7)
15 to 20	−2.5 (1.9)	−2.5 (1.9)
20 to 25	-6.3^{**} (3.0)	-6.4^{**} (3.0)
>25 (non-heatwave day)	-11.4^{***} (4.0)	-10.7^{***} (3.4)
>25 (heatwave day)	-14.1^{***} (3.7)	-22.7^{***} (5.1)
R-squared	0.16	0.16
N	121,670	121,670
p-value (non-heatwave day vs. heatwave day)	0.57	0.04

The models have controls for precipitation, humidity, the characteristics of the respondent and the interview day (gender, age, education, labor market status, household size, day-of-week, public holiday), and county-by-year-by-month fixed effects. Standard errors clustered at the county and individual levels are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A8. The effects of temperatures on workdays and non-workdays

Daily mean temperature (°C)	Workday (1)	Weekend and public holidays (2)	p (1) vs. (2) (3)
≤5	-0.5 (1.4)	1.3 (3.1)	0.58
5 to 10	ref. cat.	ref. cat.	
10 to 15	-1.1 (1.9)	-2.8 (2.4)	0.52
15 to 20	-0.3 (1.9)	-7.3^{**} (3.0)	0.01
20 to 25	-4.6 (3.1)	-10.1^{***} (3.4)	0.05
>25	-4.2 (3.4)	-31.0^{***} (7.3)	0.00
R-squared	0.16		
N	121,670		

The model has controls for precipitation, humidity, the characteristics of the respondent and the interview day (gender, age, education, labor market status, household size, day-of-week, public holiday), and county-by-year-by-month fixed effects. Standard errors clustered at the county and individual levels are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A9. The effects of temperatures by education

	Low education	High education	p (1) vs. (2)
Daily mean temperature (°C)	(1)	(2)	(3)
≤5	3.7** (1.4)	-4.0* (2.1)	0.00
5 to 10	ref. cat.	ref. cat.	
10 to 15	-0.7 (1.8)	-3.0 (2.6)	0.45
15 to 20	-3.3 (2.3)	-1.8 (2.1)	0.52
20 to 25	-8.6** (3.5)	-4.2 (3.1)	0.18
>25	-16.3*** (3.2)	-9.7** (4.4)	0.20
R-squared	0.16		
N	121,670		

The model has controls for precipitation, humidity, the characteristics of the respondent and the interview day (gender, age, education, labor market status, household size, day-of-week, public holiday), and county-by-year-by-month fixed effects. Standard errors clustered at the county and individual levels are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A10. The effects of temperatures by age

	Young	Middle-aged	Older	p (1) vs. (2)	p (1) vs. (3)	p (2) vs. (3)
Daily mean temperature (°C)	(1)	(2)	(3)	(4)	(5)	(6)
≤5	-2.2 (2.4)	-1.1 (1.7)	4.3* (2.3)	0.67	0.08	0.09
5 to 10	ref. cat.	ref. cat.	ref. cat.			
10 to 15	-1.6 (3.7)	-2.6* (1.5)	-1.2 (3.5)	0.80	0.94	0.67
15 to 20	0.9 (2.1)	-3.8 (2.8)	-6.6* (3.2)	0.05	0.04	0.50
20 to 25	-3.6 (3.0)	-7.0* (3.5)	-10.2* (5.8)	0.34	0.27	0.46
>25	-5.1 (4.3)	-9.1 (5.5)	-28.4*** (4.2)	0.53	0.00	0.01
R-squared		0.16				
N		121,670				

The model has controls for precipitation, humidity, the characteristics of the respondent and the interview day (gender, age, education, labor market status, household size, day-of-week, public holiday), and county-by-year-by-month fixed effects. Standard errors clustered at the county and individual levels are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A11. The effects of temperatures by gender

Daily mean temperature (°C)	Male (1)	Female (2)	p (1) vs. (2) (3)
≤5	-1.0 (2.2)	0.1 (1.4)	0.66
5 to 10	ref. cat.	ref. cat.	
10 to 15	-2.9 (2.5)	-0.9 (2.0)	0.51
15 to 20	-3.7 (2.2)	-1.3 (2.1)	0.24
20 to 25	-11.8*** (3.5)	-1.3 (2.9)	0.00
>25	-18.6*** (4.5)	-6.8* (3.5)	0.03
R-squared	0.16		
N	121,670		

The model has controls for precipitation, humidity, the characteristics of the respondent and the interview day (gender, age, education, labor market status, household size, day-of-week, public holiday), and county-by-year-by-month fixed effects. Standard errors clustered at the county and individual levels are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$