The effects of temperature on mental health: Evidence from China

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Abstract: In this paper, we examine the effects of ambient temperatures on individual mental health using a nationally representative longitudinal survey of Chinese individuals. We find that temperatures over 30℃ significantly increase the likelihood of depression. High temperatures have larger detrimental effects on the mental health of middle-aged and elderly residents, females, residents with lower education, and agricultural workers. High temperatures significantly raise the incidence of physical illness and reduce sleeping time, which may lead to worsened mental health status. We find suggestive evidence of air conditioners moderating the adverse impacts of high temperatures and adaptation to high temperatures in the long term. Our results imply that governments in developing countries can encourage the use of air conditioners to reduce the harm of high temperatures on people's mental health.

Keywords: mental health, depression, high temperature, climate change, adaptation

JEL Codes: I12, I18, Q51, Q54

Declarations

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The data set used in this analysis can be made open access after anonymization. The code used in this analysis can be made open access.

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1. Introduction

Identifying the influencing factors of mental disorders is essential to the treatment of mental diseases and the improvement of people's overall health status. Mental disorders constitute 13% of the global burden of disease, and depression alone is the largest single factor of nonfatal health losses (Collins et al. 2011). Affecting 0.32 billion people around the world, depression causes the afflicted person to "suffer greatly and function poorly at work, at school and in the family" (World Health Organization 2017). Mental disorders have placed significant health burdens on developing countries. Depression is estimated to generate losses of over 50 million years lived with disability (YLD) in 2015, 80% of which occurred in low- and middle-income countries (World Health Organization 2017). At the same time, under the scenario of climate change, extreme temperatures are becoming more frequent, intense, and widespread, which can further deteriorate individual mental health. Extreme high temperatures can increase physical illness; arouse negative emotions such as anxiety and psychological pressure; increase economic pressure and social instability; and alter people's living habits, such as sleeping patterns, thereby leading to poorer mental health (Dell et al. 2009; Hsiang et al. 2013; Ranson 2014; Carleton 2017; Obradovich et al. 2017; White 2017; Karlsson and Ziebarth 2018). Despite the increasing number of studies that focus on the health and productivity impacts of temperature (Barreca et al. 2016; Yu et al. 2019; Adhvaryu et al. 2020; Somanathan et al. 2021), studies that explore the distributional impacts of extreme high temperatures on mental health and the influencing channels remain scarce.

In this study, we estimate the effects of ambient temperatures on depression. Data on depression and other individual characteristics are collected from the China Family Panel Studies (CFPS) — a nationally representative, longitudinal survey of Chinese communities, families, and individuals. Two waves of CFPS data (2010 and 2014) are used in this study. Based on six questions that elicit the degree of depression during the past month at the individual level, we construct the Center for Epidemiologic Studies Depression Scale (CES-D) in a six-item scale, which is also known as the Kessler Psychological Distress Scale (K6) instrument (Kessler et al. 2002). Temperature and other weather conditions at the station-by-day level are collected from the China Meteorological Data Sharing Service System (CMDSSS). Combining the CES-D score with the number of days with mean temperature in 5℃ bins over the previous month based on city and interview date, we estimate the nonlinear effects of temperatures on mental health. The identification relies on the plausibly exogenous variations in temperatures within an individual over years after controlling for other meteorological variables, city fixed effects (FE), rich common time trends, and time-varying individual demographic characteristics. We find that temperatures over 30℃ significantly increase the likelihood of depression for Chinese individuals. Our estimates are robust across alternative temperature measures and specifications. The effects of high temperatures on depression are larger for middle-aged and elderly residents, females, residents with lower education, and agricultural workers. Suggestive evidence indicates that owning air conditioners reduces the negative impacts of high temperatures on mental health. In addition, we find evidence of adaptation that increased experience of hot days during the previous 10 years significantly reduces the adverse impact of the current month's heat. Finally, under the Representative Concentration Pathway (RCP) 8.5 policy scenario, our estimates imply a 3.1% (5.3%) increase in the CES-D score in the medium (long) term.

This paper contributes to the literature in three aspects. First, this analysis is among the first to examine the causal effects of ambient temperatures on individual mental health using a nationally representative, longitudinal survey of a large developing economy that includes mental health measures with strong psychometric properties. Existing research on the mental-health effects of high temperatures rely mostly on data from developed countries. Some studies that explore the self-reported mental health measure from the Centers for Disease Control and Prevention's (CDC's) Behavioral Risk Factor Surveillance System (BRFSS) find that exposure to extreme weather conditions such as high temperatures is associated with worsened mental health in the United States (Obradovich et al., 2018; Mullins and White 2019; Li et al. 2020). Regarding the measure of self-reported mental health across studies, Obradovich et al. (2018) and Li et al. (2020) use a dependent variable that is 1 if respondents indicate mental health difficulties over the previous 30-day period, and 0 otherwise. Mullins and White (2019) uses the number of days with self-reported poor mental health over the prior 30 days as the dependent variable.[1] Mullins and White (2019) also examines the effects of high temperatures on emergency department (ED) visits for mental illness and suicide. In comparison, the mental health measure used in this study (K6 instrument) captures multidimensional emotional experiences, has strong psychometric properties for detecting depressive disorders that may not be strong enough to cause ED visits or suicides, and is widely used in general-

[1] The three studies all use the mental health data from BRFSS as their dependent variables. In BRFSS, respondents answered the following question: "Now thinking about your mental health, which includes stress, depression, and problems with emotions, for how many days during the past 30 days was your mental health not good?"

purpose government health surveys (Kessler et al. 2002; Chen et al. 2018). In addition, whereas the BRFSS is not a longitudinal survey at the individual level, the CFPS includes repeated observations of the same individual over multiple years. This allows us to include individual FE in the model, which helps absorb time invariant unobservable confounders and gives a cleaner identification than studies that rely on the mental health measure of BRFSS. Using a dataset of expressed sentiment for the United States and six other English-speaking countries, Baylis (2020) also finds declines in expressed sentiments from both hot and cold temperatures. Nevertheless, estimates obtained in the context of developed countries may not be simply extrapolated to developing countries for three reasons. First, a nonlinear dose-response function between temperature and mental health outcomes may exist, which is unknown to researchers *ex ante*. Second, institutional and socioeconomic backgrounds, such as the level of health care, may moderate the impacts of temperatures on mental health but differ markedly between developed and developing countries (Arceo et al. 2016). Third, avoidance behavior against high temperatures also varies across countries. Compared with those in developed countries, the mental health of the residents in developing countries is likely more vulnerable to extreme temperatures because facilities and public awareness of climate adaptation tend to be much more limited.[2] This study also adds to the scant empirical evidence on the influencing mechanisms of temperatures on mental health. Based on the rich information on people's living habits in CFPS, we also find that high temperatures increase the incidence of physical illness and reduce sleeping time, which could further worsen individual mental health.

Second, broadly speaking, this analysis contributes to the literature on the health impacts of climate change. Existing studies have found that high temperatures lead to higher mortality rates, increased morbidity costs, and deteriorated infant health outcomes (Deschênes and Moretti 2009; Barreca et al. 2016; White 2017; Karlsson and Ziebarth 2018; Yu et al. 2019; Chen et al. 2020; Heutel et al. 2020; Agarwal et al. 2021). By estimating the impacts of temperature on mental health, our paper adds to the findings on the morbidity effects of extreme temperatures, which are relatively scant compared with the studies on the mortality effects of extreme temperatures. This study also contributes to the examination of the effectiveness of external adaptation measures (e.g., technological strategies) on the impacts of temperatures on health outcomes and long-term adaptation

[2] Two scientific studies examine the impacts of environmental factors on emotion or mental health of Chinese individuals. Wang et al. (2020) finds that extreme weather worsens emotional expressions on social media in China. Xue et al. (2019) estimates the impacts of long-term temperature level and temperature variability on mental health using the CFPS. We compare our results with Xue et al. (2019) in Section 3.2.

effects (Barreca et al. 2016; Mullins and White 2020). We find suggestive evidence that owning air conditioners reduces the adverse effects of high temperatures on mental health for Chinese individuals, which differs from the finding of no adaptation to high temperatures in mental health for Americans (Mullins and White 2019).

Third, this paper highlights the importance of climatic condition as an influencing factor of mental health. Previous studies have shown that certain socioeconomic factors including income, labor-market fluctuation, migration, adult child emigration, social networks, early-life experience, and air pollution may influence people's mental health status (Gardner and Oswald 2007; Charles and DeCicca 2008; Stillman et al. 2009; Mosca and Barrett 2016; Zhang et al. 2017; Chen et al. 2018; Adhvaryu et al. 2019; Scheffel and Zhang 2019; Singhal 2019; Meng and Xue 2020). Our work reveals that high temperatures also increase the likelihood of depression and lead to poorer mental health, and heterogeneous effects exist across individuals of different age groups, gender, education levels, and job sectors.

This study provides direct policy implications on ways to improve people's mental health under the threat of climate change. China had over 95 million patients living with depression by 2019. In addition, under the high emissions (RCP 8.5) scenario, the average temperature during June – August is predicted to exceed 32.2°C in some areas in China, South Asia, the Arabian Peninsula, North Africa, and the USA in 2080–2099 (Climate Impact Lab 2021). For our sample area, the Hadley Centre Global Environment Model version 2 (Hadley GEM2-ES) predicts that the number of days with daily mean temperature over $30^{o}C$ will increase by 38 days in 2040–2069 and 73 days in 2070–2099. Because China is the most populous middle-income developing country, the estimated impact of extreme temperature on mental health in this study is salient for understanding the impacts of climate change on mental health in developing countries globally. In addition, our results reveal the populations whose mental health is more vulnerable under climate change and indicate that although long-term acclimatization is limited, promoting pleasant sleeping environments and appropriate heat adaptation measures such as air conditioners can moderate the harm from heat on the mental health of residents in developing countries.

The rest of the paper is organized as follows. Section 2 describes the dataset and the empirical strategy. Section 3 presents the average and heterogeneous effects of temperatures on mental health. Section 4 explains the estimation results related to the influencing mechanisms, effectiveness of adaptation and acclimatization, the willingness to pay to avoid extreme high temperatures, and projected impacts of climate change on mental health. Section 5 concludes the paper.

2. Data and Empirical Strategy

In this section, we first describe the dataset and present relevant summary statistics. We next introduce the empirical approach used to identify the mental health impacts of extreme temperatures.

2.1. Data

Data on depression and demographic characteristics at the individual level are collected from the CFPS. Initiated in 2010, CFPS is conducted by the Institute of Social Science Survey at Peking University. The sample of CFPS is drawn from 25 provincial administrative units (provinces, municipalities, and autonomous regions) in China, excluding Hong Kong, Macao, Taiwan, Xinjiang, Tibet, Qinghai, Inner Mongolia, Ningxia, and Hainan (Figure 1). The population of these 25 administrative areas accounts for 95% of the total population of mainland China.[3] Overall, CFPS is a nearly nationwide, comprehensive, longitudinal social survey that is intended to serve research needs on a large variety of social phenomena in contemporary China (Xie and Lu 2015). CFPS collects individual demographic characteristics, such as age, gender, educational attainment, and self-reported health condition, and household characteristics, such as per capita income in the last year.

[Insert Figure 1 about here]

We use data from the 2010 and 2014 waves of CFPS in this study. The two waves of survey include six questions that allow for the construction of the CES-D in a six-item scale, which is also recognized as the K6 instrument (Kessler et al. 2002). The K6 instrument is an abbreviated version of the K10 instrument, which is a 10-question screening scale of psychological distress. The brevity and strong psychometric properties make the K6 instrument attractive for wide use in screening people's depressive symptomatology. Proven to be as effective as the K10 instrument, the K6 instrument is

[3] According to Xie and Lu (2015) and Xie et al. (2017), the original target sample size was 16,000 households. 8,000 households were generated by oversampling with five independent sampling frames (called "large provinces") of Shanghai, Liaoning, Henan, Gansu, and Guangdong. The "large provinces" were self-representative at the regional level, which could contribute to provincial population inferences and cross-region comparisons. Another 8,000 households were from an independent sampling frame composed of 20 provinces (called "small provinces"). With second-stage sampling, the five "large provinces" together with the "small provinces" made up the overall sampling frame to be representative of the national population.

already being used in annual government health surveys in countries such as the US and Canada, and in worldwide programs such as the WHO World Mental Health Surveys (Kessler et al. 2002; Prochaska et al. 2012; Chen et al. 2018).

The six questions in CFPS that measure the degree of depression for each individual are as follows: during the past *month*, how often did you feel (a) so frustrated/depressed that nothing could cheer you up, (b) nervous, (c) so restless that you could not stay calm, (d) hopeless about the future, (e) that everything was an effort, and (f) that life is meaningless. In each question, the respondent is asked to choose what best represents the frequency of the stated feeling from the following categories: most or all of the time (4 points), a considerable amount of the time (3 points), half of the time (2 points), a little of the time (1 point), or never (0 points). Based on the respondents' answers, we construct the CES-D score as the sum of the answers to the six questions. The CES-D score ranges from 0 to 24, with a higher score indicating a higher degree of depression for an individual.

In CFPS, individuals aged 16 and above are defined as adults, and those under 16 are defined as children. Adults and children between 10 and 16 complete the survey themselves (adults answer the adult questionnaire and children answer the child questionnaire), whereas the child questionnaire for those under 10 years old is completed by the main custodian (i.e., the child's parent or the primary caregiver who knows the child best). Thus, the self-reported depression measures are missing for children under 10 years old. The measure of depression is missing for 61.7% and 70.2% of respondents in the child sample of the 2010 and 2014 wave, respectively. In addition, children's mental status tends to be relatively immature, making their depression measures less reliable compared with adults. Thus, we focus on the adult sample (16 years old and above) for our analysis.

Meteorological characteristics including daily average, maximum and minimum temperatures, total precipitation amount, average relative humidity, average wind speed, sunshine duration, and atmospheric pressure for 699 weather stations in China are attained from the China Meteorological Data Sharing Service System (CMDSSS). To merge weather characteristics with variables from CFPS, we first calculate daily weather variables for each prefecture-level city from 2010 to 2015 based on station-level weather records following the inverse-distance weighting method.[4] Specifically, for each city, we draw a circle of 150 km from the city's centroid and calculate the weighted average daily weather variables using stations within the 150 km circle, with the weights being the

[4] Prefecture-level city (*Dijishi*) is the second-level administrative division in China that ranks below province-level division and above county-level division.

inverse of the distance between the city's centroid and each station. In this way, stations that are closer to the centroid of each city are assigned more weight.

Since the survey questions that measure the degree of depression set a time frame for recalling "during the past *month*," we calculate the daily weather characteristics for each of the previous 30 days before the date of interview for each observation. We next calculate the number of days with daily mean temperature falling into each of the eight $5℃$ bins ($> 30℃$, $25-30℃$, $20-25℃$, $15-20℃$, $10-15℃$, $5-10℃$, $0-5℃$, $< 0℃$), which allows us to examine the nonlinear effects of temperatures on mental health (Deschênes and Greenstone 2011; Barreca et al. 2016). Since temperature can be correlated with other meteorological characteristics that might influence mental health as well, we calculate the average value over the 30 days before the interview date for other meteorological characteristics, which are included as control variables in the empirical model. Finally, we match the weather variables to mental health and individual characteristics based on city and interview date.[5]

The 2010 (2014) wave of CFPS lasts from April 2010 (July 2014) to September 2011 (June 2015). After omitting observations with missing CES-D scores, individual characteristics or weather information, we obtain a panel data set that includes 53,557 observations of 36,400 residents in 127 prefecture-level cities. Two waves of CFPS for 17,157 longitudinally-surveyed respondents are used for our analyses. The other 19,243 respondents that appeared only once are omitted. Table 1 presents the summary statistics of the sample used for our main regression analyses. The average CES-D score is 3.1. The daily average temperature has a mean of 22.6℃. The average number of days with daily mean temperature in the bins of $\{> 30℃,\ 25-30℃,\ 20-25℃,\ 15-20℃,\ 10-15℃,\ 5-10℃,\ 0-5℃,\ < 0℃\}$ in the past 30-day period prior to interview is 1.6, 10.3, 10.5, 4.4, 1.7, 0.7, 0.4, and 0.3, respectively (Figure 2).

[Insert Table 1 and Figure 2 about here]

2.2. Model

Following the existing literature on the health impacts of temperature on health outcomes (Barreca et al. 2016; Mullins and White 2019; Chen et al. 2020), we use the following model to examine the nonlinear effects of temperatures on mental health:

[5] For instance, if a person was surveyed on May 1st, 2010, then the temperature variables and weather characteristics during April 1st –April 30th of 2010 of the city he/she lived are merged with his/her mental health variables.

$$Y_{ict} = \beta_0 + \sum_k \beta_k \times Temp_{ctk} + \boldsymbol{W}_{ct}\boldsymbol{\lambda} + \boldsymbol{X}_{it}\boldsymbol{\theta}$$
$$+\mu_i + \delta_c + \pi_{ym} + f(t) + \varepsilon_{ict} \quad (1)$$

Y_{ict} refers to the degree of depression for individual i that was interviewed in city *c* on date *t*. Logarithm of the CES-D score is not used since around 34% of observations are zero. For each observation, $Temp_{ctk}$ represents the number of days with daily mean temperature falling into the k^{th} bin of $\{> 30℃,\ 25{-}30℃,\ 15{-}20℃,\ 10{-}15℃,\ 5{-}10℃,\ 0{-}5℃,\ < 0℃\}$ in the 30-day period before interview date *t*. These temperature measures impose a functional form assumption that the impact of the daily average temperature on individual mental health is constant within each $5℃$ interval. Since existing research shows that people feel no thermal stress under the physiological equivalent temperature range of $18 - 23^oC$ (Matzarakis and Mayer, 1996), we use $20{-}25℃$ ($68{-}77$°F) as the baseline group. The coefficients on the other temperature-bin day variables are hence interpreted as the depression effect of replacing a reference day with a day in another temperature bin. β_k $(k = 1, 2, \ldots, 7)$ are of central interests in this study, especially β_1 that captures the depression effect of over $30℃$. Regarding other confounding weather characteristics, i.e., total <u>precipitation amount, average relative humidity, average wind speed, sunshine duration, and atmospheric pressure</u>, <u>we calculate their averages in the 30-day period before interview date *t* for each interviewee (vector $\boldsymbol{W}_{ct}$) and directly control for them</u>. Since recalling of the respondent is likely biased towards the very recent experience, we also construct the meteorological variables in shorter periods (1 week, 2 weeks, 3 weeks, and 4 weeks before the interview date) as robustness checks (Mullins and White 2019).

We further control for time-varying individual/household characteristics including household per capita income, self-reported relative income level, and self-reported social status (vector $\boldsymbol{X}_{it}$). Individual FE (μ_i), city FE (δ_c), and year-by-month FE (π_{ym}) are also included. The individual FE absorb time invariant individual characteristics. The city FE control for city-level characteristics that do not change during our sample period (e.g., geographic environment). The year-by-month FE control for changes in mental health that are common across all the regions in our sample. $f(t)$ refers to linear and quadratic trends in the month that the interview date falls, which allows for smooth changes in mental health over time. We also try adding the interview date FE as a robustness check. Results are displayed in column (4) of Table 5. The estimates are similar to our main estimates. β_k

are identified from the plausibly exogenous variations in temperatures within an individual across dates after adjusting for covariates, time-invariant city characteristics, and nonparametric controls for nationwide shocks to mental health at the year-by-month level. We cluster standard errors at the city level to allow for serial correlation across respondents that live in the same city. We also try two-way clustering the standard errors at the city and interview month levels as robustness checks (Table A2).

3. Impact of Temperature on Depression

In this section, we first report the average effects of temperatures on the CES-D score and the value of each component of the CES-D score. We next show that our results are consistent across a battery of robustness checks. Finally, we study the heterogeneous effects of high temperatures on CES-D scores across various demographic characteristics to identify vulnerable populations.

3.1. Main Results

Table 2 presents the estimated effects of temperatures on the CES-D score. In a parsimonious model that controls for the temperature-bin day variables, individual FE, city FE, month FE, and year FE (column [1]), replacing a day with mean temperature in the baseline bin of $20-25^{o}C$ in the previous month by a day with mean temperature over $30^{o}C$ significantly increases the CES-D score by 0.15 (4.78% of sample mean). Column (2) additionally controls for time-varying individual/household demographic characteristics, including household per capita income (in log), self-reported relative income level, and self-perceived social status. Column (3) controls for additional meteorological characteristics, including average precipitation amount, relative humidity, sunshine duration, wind speed, and atmospheric pressure in the previous month; column (4) further controls for the linear and quadratic monthly trends. Column (5) replaces the month FE and year FE in column (4) by the year-by-month FE. Experiencing one additional day with mean temperature over $30^{o}C$ in the previous month significantly increases the CES-D score by 0.15, 0.21, 0.20, and 0.21 in columns (2) to (5), respectively. Overall, the estimated impacts of extreme high temperatures over $30^{o}C$ in the previous month are similar across the five specifications although more stringent controls in the model lead to larger estimated coefficients on the high temperature bins.

Table 2 also indicates that most other temperature-bin day variables are insignificant across the five specifications. To visualize the nonlinear effects of exposure to different temperature bins, we plot the estimated coefficients and 95% confidence intervals of the temperature-bin day variables in Figure 3. Because column (5) includes the strictest set of controls, we use this specification for Figure 3 and the interpretation of the remaining results. Overall, there exists a U-shaped relationship between temperature and the CES-D score, with a turning point at the $5-10^{o}C$ range.[6] This implies if we replace a day with mean temperature in the bin of $5-10^{o}C$ by an over $30^{o}C$ day, the CES-D score will increase by 0.354 (11.3% of sample mean). The relatively low frequency of low temperatures in the data may contribute to the insignificance of the low temperature bins. In addition, public infrastructure and household appliances for winter heating are widely available in China, which could have contributed to the insignificant coefficients on the low temperature bins as well. Overall, compared with the coefficients on the lower temperature bins, temperatures over $30^{o}C$ have larger adverse effects on mental health.

[Insert Table 2 and Figure 3 about here]

Other meteorological variables may affect mental health (Connolly 2013; Baylis et al. 2018). We find that the coefficients on sunshine duration, precipitation, wind speed, and atmospheric pressure are negative, whereas the coefficient on relative humidity is positive. Nevertheless, all these estimates are insignificant. This could be ascribed to the small variation in the monthly average value of each meteorological characteristic within the same respondent across the waves of the survey. Lastly, the impacts of demographic characteristics on mental health have intuitive signs. Higher household per capita income, relative income level, and social status result in lower CES-D scores and lower propensities of depression.

Because the CES-D score is constructed from the responses to six survey questions, each of which asks for the frequency of having a specific depressive symptom, we next explore the nonlinear effects of temperatures on the degree of each of the depressive symptoms separately. Table 3 presents these results. A larger coefficient indicates an increasing effect on the likelihood of depression. Figure 4 plots the coefficients as well as the associated 95% confidence intervals for each depressive symptom. We find that extreme high temperatures significantly increase the occurrence of four depressive symptoms. Replacing a day in the $20-25^{o}C$ bin with a day over $30^{o}C$ significantly increases the score of feeling frustrated, nervous, that life is difficult, and that life is

[6] The estimates in columns (1)–(4) suggest a consistent turning point range.

meaningless by 0.065 points (8.7% of sample mean), 0.034 points (5.9% of sample mean), 0.039 points (6.6% of sample mean), and 0.030 points (8.8% of sample mean), respectively. As a comparison, the effects of an additional day with mean temperature over $30^{o}C$ on the propensity of feeling restless or hopeless are also positive but insignificant. Overall, Figure 4 implies a U-shaped relationship between temperature and the score of each of the depressive symptoms.

[Insert Table 3 and Figure 4 about here]

3.2. Robustness Checks

We next perform a series of robustness checks to show that our main estimates are insensitive to alternative definitions of the dependent variable, unobserved confounders, or various model specifications. First, following the common practice (Kessler et al. 2002; Prochaska et al. 2012; Chen et al. 2018), we define a dummy variable of *severe mental illness*, which is 1 if the CES-D score is higher than 13, and 0 otherwise. We next estimate the effects of temperatures on this dummy variable using the linear probability model. Results in column (1) of Table 4 show that replacing a day in the $20-25^{o}C$ bin by a day over $30^{o}C$ significantly increases the probability of depression by 2.0%. Second, as a placebo test, we estimate the effects of the number of days with mean temperature in different bins in the month after the interview. Column (2) of Table 4 shows that the estimated coefficients of these temperature-bin day variables are mostly insignificant and suggest a dramatically different relationship between temperature and mental health. This implies that our main results are not driven by spurious variations in the temperature variables.

Second, we rerun a regression that adds the temperature-bin number-of-days variables in lead one-three weeks as a placebo test. Results are displayed in Appendix Table A2. Most of the variables since the lead two week are insignificant and do not represent a U relationship between temperature and mental health. Temperature variables in the lead one week exhibit a U relationship between temperature and mental health, but the number of days over $30^{o}C$ in the lead one week is not significantly different from any other number-of-days variable in the lead one week. Thus, we do not find a significant effect of high temperature in the lead one week on current mental health as well.

Third, we calculate the average temperature in the month before the interview, construct a series of dummy variables of monthly mean temperature in the bins of $\{>$

30℃, 25– 30℃, 20– 25℃, 15– 20℃, 10– 15℃, 5– 10℃, 0– 5℃, < 0℃}, and estimate their effects on mental health. Column (3) of Table 4 suggests a similar U-shaped relationship between temperature and mental health and a significantly positive coefficient on the dummy of monthly mean temperature over 30℃.

[Insert Table 4 about here]

Table 5 includes results for four more robustness checks using alternative specifications. Column (1) shows that the significance levels of the estimates from two-way clustering standard errors by city and interview month are very close to the main estimates. Based on the CFPS, Xue et al. (2019) estimates the impacts of long-term temperature level (annual mean) and temperature variability (SD of daily temperature within a calendar year) on mental health. Xue et al. (2019) finds that only increased temperature variability is significantly associated with worsened mental health status. In comparison, in column (2), we control for the city-by-month FE so that the estimated coefficients on the high temperature variables are purged of long-term climate effects in each city and can be interpreted as the effects of positive deviations from long-term climate. The result shows that an additional day with mean temperature over 30℃ increases the CES-D score by 0.159 (significant at the 5% level), suggesting a causal effect that large positive deviations from long-term climate significantly deteriorate mental health.

In column (3), we include city-by-year FE as a robustness check. Because data collection in the same prefecture-level city was usually completed in a short period of time in each wave of survey, including this FE will eliminate excessive variations in temperature and other weather variables. Nevertheless, we find that an additional day with mean temperature over 30℃ significantly increases the CES-D score by 0.178, and the pattern of the relationship between temperatures and mental health are similar to our main estimates. In column (4), we try adding the interview date FE as a robustness check. The estimates are similar to our main estimates.

[Insert Table 5 about here]

Daily average temperature may not capture extreme temperature exposure as well as daily maximum or minimum temperature. Thus, we construct the temperature-bin day variables using daily maximum temperature and minimum temperature and estimate their effects on mental health using Equation (1). The coefficients are presented in Appendix Table A3 and plotted in Appendix Figure A1. Replacing a day with maximum temperature in the 20– 25℃ bin in the previous month with a day over 30℃ significantly increases the CES-D score, whereas the other temperature bins are insignificant. We find a similar pattern of results by using the temperature-bin day variables constructed from daily minimum temperature. Interestingly, the coefficient on the number of days with daily minimum temperature over 30℃ is much larger than those on the over-30℃-bin day variables that are constructed from daily maximum or average temperatures. Daily minimum temperature usually appears at night, so daily minimum temperature over 30℃ implies even higher daily average and maximum temperatures, rendering a larger adverse effect on mental health. The minimum temperature results suggest that our main estimates from focusing on daily average temperature do not overestimate the temperature effects on mental health.

As another robustness check, we re-estimate model (1) using 3℃ and 6℃ temperature bins (instead of 5℃ bins). Appendix Table A4 and Figure A2 present these results. In the 3℃ temperature-bin model, an additional day with mean temperature over $30^{o}C$ relative to a 21– 24℃ day significantly increases the CES-D score by 0.23 points; in the 6℃ temperature-bin model, an additional day with mean temperature over $30^{o}C$ relative to a 18– 24℃ day significantly increases the CES-D score by 0.23 points. These estimates are highly similar to the main estimate in column (5) of Appendix Table A2. Both panels of Appendix Figure A2 suggest that the relationship between temperature and mental health is approximately U-shaped.[7]

3.3. Heterogeneity Analyses

To identify populations whose mental health is more susceptible to extreme high temperatures, we investigate the heterogeneous effects of temperatures on depression across individuals with different innate attributes (age, gender, and *Hukou* status) and acquired characteristics (educational level, job sector).[8]

First, we divide the sample into five groups based on the respondent's age (aged 16–29, 30–39, 40–49, 50–59, and over 60) and estimate the impacts of temperature for each

[7] Appendix Table A2 includes results for three more robustness checks. Column (1) shows that the significance levels of the estimates from two-way clustering standard errors by city and interview month are very close to the main estimates. To compare our main estimates with Xue et al. (2019), we control for city-by-month FE in column (2) so that the estimated coefficients on the high temperature variables can be interpreted as the effects of positive deviations from long-term climate. The result shows that an additional day with mean temperature over 30℃ increases the CES-D score by 0.159 (significant at the 5% level). Column (3) shows that if we control for city-by-year FE, an additional day with mean temperature over 30℃ significantly increases the CES-D score by 0.178. Columns (2) and (3) both show that the estimated impact of an additional day with mean temperature in the $25-30$℃ bin is significant.

[8] *Hukou* is a system of household registration used in mainland China. A household registration record officially identifies a person as a permanent resident of an area and includes identifying information such as one's name, parents, spouse, and date of birth.

age group separately. Results in Table 6 show that extreme high temperatures do not have significant effects on the CES-D scores of those under 40. However, replacing a day with mean temperature $20-25$℃ in the previous month by a day over $30^{o}C$ significantly increases the CES-D scores of those aged 40–49, 50–59, and over 60 by 0.41, 0.20, and 0.38, respectively. The coefficients for each age group are plotted in Figure 5. For the youngest group, high temperatures and low temperatures both have no effect on mental health. For the oldest group, both high temperatures and low temperatures significantly increase the CES-D score. Existing literature has found that the elderly are the most vulnerable to weather shocks among all age groups (Deschenes and Moretti 2009; Karlsson and Ziebarth 2018; Yu et al. 2019). Our results are consistent with the hypothesis that extreme temperatures may deteriorate the mental health of the elderly. That longer exposure to extreme high temperatures also damages the mental health of the middle-aged respondents (aged 40–59) indicates that attention and resources are also needed to protect the mental health of those of working age from extreme temperatures.

[Insert Table 6 and Figure 5 about here]

Next, to examine the differential impacts of temperature on mental health across different populations, we enhance Equation (1) by adding a dummy variable of individual characteristics (gender, lower education group, agricultural worker, *Hukou* status) and its interaction with the number of days with daily mean temperature falling into the bin of over 30^{o}C ($Temp_{ct1}$) one by one:

$$Y_{ict} = \beta_0' + \sum_k \beta_k' \times Temp_{ctk} + \alpha I_{ict} + \gamma Temp_{ct1} \times I_{ict}$$
$$+\boldsymbol{W}_{ct}\boldsymbol{\lambda}' + \boldsymbol{X}_{it}\boldsymbol{\theta}' + \mu_i' + \delta_c' + \pi_{ym}' + f(t) + \varepsilon_{ict} \quad (2)$$

I_{ict} refers to the individual characteristics. In our sample, gender and *Hukou* status do not vary across time and are absorbed by the individual FE (μ_i'), whereas the dummy variables of lower education group and agricultural worker do vary across time.

Existing literature finds that females are more prone to mental illness induced by extreme temperatures than males (Obradovich et al. 2018). Consistent with the literature, we find that <u>mental health of females is damaged by 3.6 percentage points more than the mental health of males</u> by an additional day over $30^{o}C$ in the previous month relative to a $20-25$℃ day (column [1], Table 7).[9] Since mental health is critical for the

[9] This percentage change is calculated by dividing the coefficient on Number of Days (AT >=30℃) × Female (1/0) (0.114) by the mean of the dependent variable (3.139).

development of human capital, our finding suggests that climate change may aggravate gender inequality in human capital accumulation.

Education may equip people with more knowledge on how to cope with extreme temperatures. It is also likely that people with lower education levels are more engaged in outdoor work compared with people with higher education levels and that exposure to extreme temperatures is more intense for outdoor workers. We next define a dummy variable of low educational attainment based on the median number of education years in the sample (9 years). Individuals who completed at least (less than) 9 years of education are classified into the higher education (lower education) group.[10] Results in column (2) of Table 7 reveal that mental health of the lower education group is damaged by 5.4 percentage points more than the mental health of the higher education group by an additional day with mean temperature over $30^{o}C$ in the previous month relative to a $20-25$℃ day.[11]

Agricultural work usually involves intensive outdoor tasks. Existing literature has found that extreme high temperatures can decrease the output of crops including rice, wheat, corn, and soybeans in developing countries, which can worsen the mental health status of agricultural workers (Chen et al. 2016; Zhang et al. 2017). Carleton (2017) finds that a $1^{o}C$ increase in a single day's temperature (above $20^{o}C$) causes approximately 70 suicides during India's agricultural growing season, when heat lowers crop yields. Therefore, we proceed to examine the heterogeneous impacts of temperature on mental health between workers inside and outside the agricultural sector. As shown in column (3) of Table 7, mental health of agricultural workers is damaged by 4.0 percentage points more than the mental health of nonagricultural workers by an additional day with mean temperature over $30^{o}C$ in the previous month relative to a $20-25$℃ day.[12] Finally, column (4) of Table 7 shows that the impact of temperature on mental health is homogenous across individuals with rural *Hukou* and those with urban *Hukou*.[13]

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[10] China's compulsory education law was enacted in 1986, which requires that all children should receive at least nine years of education (six years in primary school plus three years in junior high school). Some respondents in our data set completed their school education before 1986, for whom the years of schooling could be lower than nine years.

[11] This percentage change is calculated by dividing the coefficient on Number of Days (AT >=30℃) × Lower education (1/0) (0.170) by the mean of the dependent variable (3.139).

[12] This percentage change is calculated by dividing the coefficient on Number of Days (AT >=30℃) × Working in the agricultural sector (1/0) (0.127) by the mean of the dependent variable (3.139). Note that the number of observations used for this regression is smaller than the whole sample because some respondents did not report their job types. Appendix Table A5 shows the effects of temperature on CES-D score using the subsample of respondents whose job sectors are unknown, in which we do not find significant effects of exposure to high temperatures on mental health.

[13] In China, whether an area is urban or rural is defined at the county level, which means a prefecture-level city (synonym for prefecture-level administrative unit) can have both rural and urban area. Table 1 suggests that 53.7% of the respondents hold a rural *Hukou*, whereas a Google search suggests that the urbanization rate based on permanent residency is over 50%. This is because a large number of rural-to-urban migrant workers (280 million in 2020) live in

[Insert Table 7 about here]

4. Discussion

In this section, we first discuss the temperature effects when varying the time span of calculating the temperature-bin day variables. We next discuss the potential mechanisms of the effects of high temperatures on depression, after which we examine how adaptation to extreme high temperatures could influence mental health, including the moderating effects of owning air conditioners and experience of extreme heat in the past. Finally, we calculate the predicted impacts of climate change on mental health.

4.1. Varying the Time Span of Calculating the Temperature-Bin Day Variables

The CFPS sets a month's time frame for respondents to recall their degree of depression. We examine the effects of the temperature-bin day variables constructed from different time spans, which facilitates better understanding on the timing of relevant policy interventions. First, we estimate the nonlinear effects of temperature on the interview day. Specifically, we construct a series of dummy variables with daily average temperature falling into each of the $5°C$ bins $\{> 30°C,\ 25-30°C,\ 20-25°C,\ 15-20°C,\ 10-15°C,\ 5-10°C,\ 0-5°C,\ < 0°C\}$. Results are displayed in Table 8. Column (1) shows that the dummy of daily temperature over $30°C$ is positive but insignificant. Column (2) further presents the results when the dummy variables of the interview-day temperature and the temperature-bin day variables during the previous 30 days are controlled for. We find insignificant effects of the interview-day average temperature, whereas additional exposure to temperature over 30℃ during the previous 30 days significantly increases the CES-D score. There are two reasons for the insignificant coefficients on the temperature variables of the interview day. First, the survey team of CFPS usually books the interview at least one day in advance, which means adaptation behavior may have been adopted one day in advance, making the indicators of temperature over $30°C$ on the interview day and the day before interview insignificant. Second, the interview usually takes place indoors; for instance, in rural areas, the interview is often conducted in village committee's offices, which usually have air conditioners or electronic fans.[14]

urban areas but are not officially registered as urban residents.

[14] We also estimate the impacts of the interview-day minimum temperature. Results are in Appendix Table A6. Compared with a 20–25℃ day, daily minimum temperature over 30℃ increases the CES-D score by 1.69 (53.8% of sample mean). A possible reason is that daily minimum temperature over 30℃ indicates a larger daily average or maximum temperature. Most of the other temperature-bin variables are insignificant no matter which temperature

[Insert Table 8 about here]

Second, we examine whether temperature-bin day variables constructed from a time span shorter than a month before interview may influence mental health and how those effects differ from our main estimates. Specifically, we focus on the 1-week, 2-week, 3-week, and 4-week periods before interview, which allow for enough variations in the temperature-bin day variables but are closer to the interview than the previous 30-day period. Results are presented in columns (2)–(5) of Table 9. We place the main estimates in column (1) for the purpose of comparison. Estimates of extreme high temperatures remain significant across shorter time spans. Replacing a day over 30℃ by a $20-25$℃ day in the previous 1, 2, 3, and 4 weeks significantly increases the CES-D score by 0.38 (12.1% of sample mean), 0.29 (9.1% of sample mean), 0.24 (7.6% of sample mean), or 0.23 (7.2% of sample mean).

Third, we rerun a series of regressions that gradually add the dummy variables of daily average temperature in the bins of $\{> 30$℃, $25-30$℃, $15-20$℃, $10-15$℃, $5-10$℃, $0-5$℃, < 0℃$\}$ ($20-25$℃ used as the reference bin) over the previous 1–7 days, respectively. Results are displayed in columns (2) – (8) of Appendix Table A7. For comparison purposes, column (1) displays the results from a regression that only adds the daily temperature variables of the interview day (column [1], Table 9). Across all regressions, the dummy variable of temperature over 30℃ on the interview date is insignificant; the indicator of temperature over 30℃ on the day before interview is insignificant but has a much larger magnitude. Indicators of daily temperature over 30℃ over the previous 2–7 days are all significant and have much larger magnitudes than the dummy variable of temperature over 30℃ on the interview date (column [8], Appendix Table A7) and the coefficient on the number of days over 30℃ three weeks ago (columns [4]–[5], Table 9).

Fourth, we examine how extending the time span to two months and three months before interview may influence the coefficients on temperature-bin day variables. Results in columns (6)–(7) of Table 9 show that replacing a day with mean temperature in the $20-25$℃ bin by a day over 30℃ in the previous two months significantly increases the CES-D score by 0.13 (4.2% of sample mean). This effect is smaller than our main estimate (0.21, 6.7% of sample mean). When the time span is extended to three months before interview, the coefficient on the number of days over 30℃ becomes insignificant. These

variable is used.

results imply that exposure to extreme high temperatures over the previous two months significantly impairs mental health. We plot the coefficients on the temperature-bin number-of-day variables in columns (2)–(7) of Table 9 in Figure 7.

[Insert Table 9 and Figure 6 about here]

Overall, psychological counseling or other policy interventions within two months of extreme high temperatures may help counteract the negative effects of high temperatures on people's mental health. As the extreme high temperature exposure within a week's time has the largest effects, those interventions implemented soon after the extreme high temperatures occur may work the best.

4.2. Mechanisms

Existing literature has suggested that high temperatures impair physical health (Barreca et al. 2016; White 2017; Karlsson and Ziebarth 2018), which can lead to deteriorated mental health conditions (补文献). In addition, high temperatures may also change people's living habits such as reducing physical activities and decreasing sleeping time, which further worsens mental health status.

The CFPS asks each individual whether he/she experienced any physical injury or illness during the past two weeks, based on which we define a dummy variable of physical illness. We next estimate the effects of temperatures on this dummy variable using a linear probability model. Results are displayed in column (1) of Table 10. The number of days with mean temperature over $30^{o}C$ is significantly positive, suggesting that extreme high temperatures hurt physical health of the respondents, which could contribute to deteriorated mental health status.

The CFPS also collects information on the frequency of taking physical exercise during the past week. We next estimate whether high temperatures affect the status of individual physical exercise because the existing literature suggests that more frequent physical exercise alleviates depression (Schuch et al. 2016; Kanamori et al. 2018). Columns (2) and (3) of Table 10 show that the effects of extreme high temperatures on physical exercise are insignificant at both the intensive and extensive margins, indicating that variations in participation and frequency of physical exercise do not contribute to our estimated impact of high temperatures on mental health.

We further examine whether high temperatures affect individuals' sleeping time, which is shown to be strongly correlated with mental health (Lõhmus 2018; Jin and

Ziebarth 2020). The question in CFPS that collects a respondent's sleeping time is as follows: "Under normal circumstances, how many hours do you spend sleeping every day?" The answer represents the daily average sleeping time a respondent recalled for her recent sleep. Therefore, we estimate the effects of temperature on daily average sleeping time (in hour) and a dummy variable of whether an individual receives inadequate sleep, which equals 1 if the daily average sleeping time falls below six hours, and 0 otherwise. Results presented in columns (4) and (5) of Table 10 show that replacing a day with mean temperature in the $20-25℃$ bin with a day over $30^{o}C$ significantly reduces sleeping time by 0.19 hours and increases the probability of insufficient sleep by 2.2%. Thus, disturbance of sleep is another possible mechanism behind high temperatures' influence on depression.

Since it is relatively easy to influence one's sleeping and exercise behavior, as a robustness check of the mechanisms, we undertake a mediation analysis by including the temperature-bin day variables, the mechanism indicator (for sleeping time and exercise, respectively), and the interactions of the temperature-bin day variables and the mechanism indicator in the main regression. Note that this set of results (in Appendix Table A8) are more association because mental health and the mechanism indicator may influence each other. The frequency of physical exercise, the dummy variable of taking physical exercise, sleeping time, and the dummy variable of inadequate sleep are all insignificant. Meanwhile, more sleeping hours significantly decrease the impacts of extreme high temperatures on the CES-D score, and the incidence of inadequate sleep increases the high temperature effect, suggesting the effect on sleeping time as a mechanism of the depression effect of high temperature is robust. Participation in physical exercise remains irrelevant since the interactions with the high-temperature-bin day variables are insignificant. To further strengthen the influencing mechanism of sleep, we run a regression that simultaneously estimates the impacts of the average maximum and minimum temperatures over the 30-day period before interview, which capture the temperature exposure during daytime and nighttime, respectively (Mullins and White 2019). Results in Appendix Table A9 corroborate the sleep mechanism since the average maximum temperature is significantly positive and much larger than the average minimum temperature, which is insignificant.

[Insert Table 10 about here]

4.3. Adaptation

We next examine how the extent of adaptation to extreme high temperatures could influence mental health. First, we estimate the moderating effect of owning air conditioners on the impact of temperatures on mental health. In the two waves of CFPS data, only the 2014 wave asks the respondent whether their household possesses an air conditioner or not. Based on the subsample of the 2014 survey wave, we estimate a model that adds a dummy variable of the possession of air conditioners and its interactions with the temperature-bin day variables. Individual FE are omitted due to the cross-sectional feature of the dataset, but the other control variables are the same as Equation (1). Compared with respondents without air conditioners, the mental health of the respondents in households with air conditioners is 5.0% less impaired by temperatures over 30^oC and 4.3% less impaired by temperatures between 25^oC and 30^oC. Although we acknowledge that these effects are only associational due to data limitations, our findings differ from those of Mullins and White (2019), who find no significant moderating effect of owning air conditioners on the mental health effect of high temperatures in the United States.

[Insert Table 11 about here]

Second, we investigate the existence of medium-term and long-term adaptation to extreme heat since people that experience hotter temperatures more regularly are less sensitive to exposures to extreme heat. Adaptation can be represented by routine exposure to heat in the past. We measure medium-term and long-term high temperature exposure by the number of days with an average temperature over 30^oC that a respondent experienced during the pre-interview 31^{st}–395^{th} day period and the average number of days over 30^oC per year during the 10-year period before the interview, respectively. We enhance Equation (1) by including the high-temperature-day variable and its interaction with the corresponding temperature bin day variable in the previous 30 days. The interaction term captures the adaptation effect. Columns (1) and (3) of Table 12 examine the medium- and long-term adaptation effects, respectively. Columns (2) and (4) restrict the data to local residents whose household registration (*Hukou*) city is the same as the current living city, to reduce the measurement error in the number of days over 30^oC during the pre-interview 31^{st}–395^{th} day and 10-year periods, respectively. We find significant medium- and long-term adaptation effects for high temperature exposure. The results from the restricted sample suggest that the long-term adaptation effect is more robust.

Local residents might be more capable of adapting to extreme temperatures and less mentally disturbed by local weather conditions compared to their non-local counterparts in the long term. We examine this hypothesis by interacting a dummy variable of local residency with the number of days with an average temperature over 30^oC during the previous 30-day period. Column (5) of Table 12 suggests that local residency has no effect on the capability to adapt to high temperatures. One possible reason could be that residents who are less capable of adapting to high temperatures migrate to areas with milder climates.

[Insert Table 12 about here]

4.4 Predicted Impact of Climate Change on Mental Health

We obtain the predicted daily mean temperatures at a spatial resolution of 0.8° × 0.5° in the medium term (2041–2060) and long term (2061–2080) from the Hadley GEM2-ES.[15] We focus on the predictions from the RCP 8.5 policy scenario, which provides simulation results under the "business-as-usual" emissions growth rates (Agarwal et al. 2021). Climate change shifts the distribution of temperature. As shown in Figure 7, Hadley GEM2-ES predicts that the number of days with daily mean temperature over 30^oC will increase by 38 days in the medium term and 73 days in the long term.

We calculate the projected impacts for each temperature bin for each city and sum across all the cities and temperature bins to get the impacts of climate change on mental health using the following formula (Yu et al. 2019; Agarwal et al. 2021):

$$Impact = \sum_j \widehat{\beta}_j' \times \sum_c \Delta Temp_c^j \times \frac{population_c}{\sum_c population_c} \tag{3}$$

where c denotes city, j refers to temperature bin, $\widehat{\beta}_j$ represent the estimated percentage change in the CES-D score for each temperature bin from our main regression (column (5) of Table 2) and $population_c$ represent the population of city c. First, we assign the predicted temperature of the grid that is closest to the city's centroid and calculate the average number of days in each temperature bin per year for each city. Second, we calculate $\Delta Temp_c^j$, which represents the differences in the average temperature-bin-day variables between our sample period (2010-2014) and each time horizon for each city. Third, we calculate a population-weighted average of the change of the number-of-days variables using data from all the sample cities and multiply it by the estimated percentage change in the CES-D score in the corresponding temperature bin. Finally, we sum across all cities and temperature bins to get the overall estimated impacts of climate change. Because the total effect is a linear function of our estimated coefficients, the calculation of

[15] Data source: https://cera-www.dkrz.de/WDCC/ui/cerasearch/q?query=CMIP5&page=0&rows=15

standard errors is straightforward. Since city-level population projections in China are unavailable, Equation (3) implicitly assumes that the proportions of population of each city are unchanged.

Table 13 presents the prediction results. In the medium term, mental health will deteriorate by 3.1%, whereas the long-term mental-health impact is 5.3%. In both time horizons, most of the impacts come from the highest temperature bin.

[Insert Figure 7 and Table 13 about here]

5. Conclusion

Mental disorders have become a severe threat to public health in both developing and developed countries and are now the second-greatest contributor to the global disease burden. In addition to the traditional socioeconomic factors, climate change and the associated extreme weather events may also worsen people's mental health conditions. In this paper, we examine the impacts of high temperatures on depression by matching a nationally representative survey of Chinese individuals to meteorological characteristics at the monitoring-station level. Our identification comes from the exogenous variation in temperatures within an individual across time after controlling for other meteorological variables, city FE, rich common time trends, and time-varying individual demographic characteristics. We find that exposure to high temperatures over $30^{o}C$ in the month preceding the data of survey significantly increases the CES-D score and damages the mental health of Chinese individuals.

Heterogeneous analyses on the depression effects of high temperature help to uncover vulnerable populations in terms of mental health. Females suffer a larger impact from high temperatures than males, suggesting aggravated gender inequality in human capital resulting from climate change. Both middle-aged and elderly individuals are affected more than the younger individuals, which complements the findings in the extant literature that high temperatures impose the largest impacts on mortality and health-related costs for the elderly. The mental health of less educated individuals and agricultural workers are more impaired by high temperatures, possibly due to longer outdoor exposure during working hours. Regarding the influencing channels, high temperatures are found to significantly increase the incidence of physical illness and reduce the number of sleeping hours. Furthermore, we find evidence that ownership of air conditioners can moderate the depression effects of high temperatures, and adaptation to high temperatures seems to exist.

The identified effects of high temperatures on mental health enrich the studies on the socioeconomic costs of extreme temperatures. Our findings suggest that the elderly, females, and certain working populations are more vulnerable to the adverse effects of high temperatures on mental health. Measures to encourage adequate sleep, improve access to medical services, and develop climate adaptation strategies such as increasing the penetration rate of air conditioners may be introduced as the prediction shows that without proper intervention, the depression effect of climate change is likely to last and increase in China.

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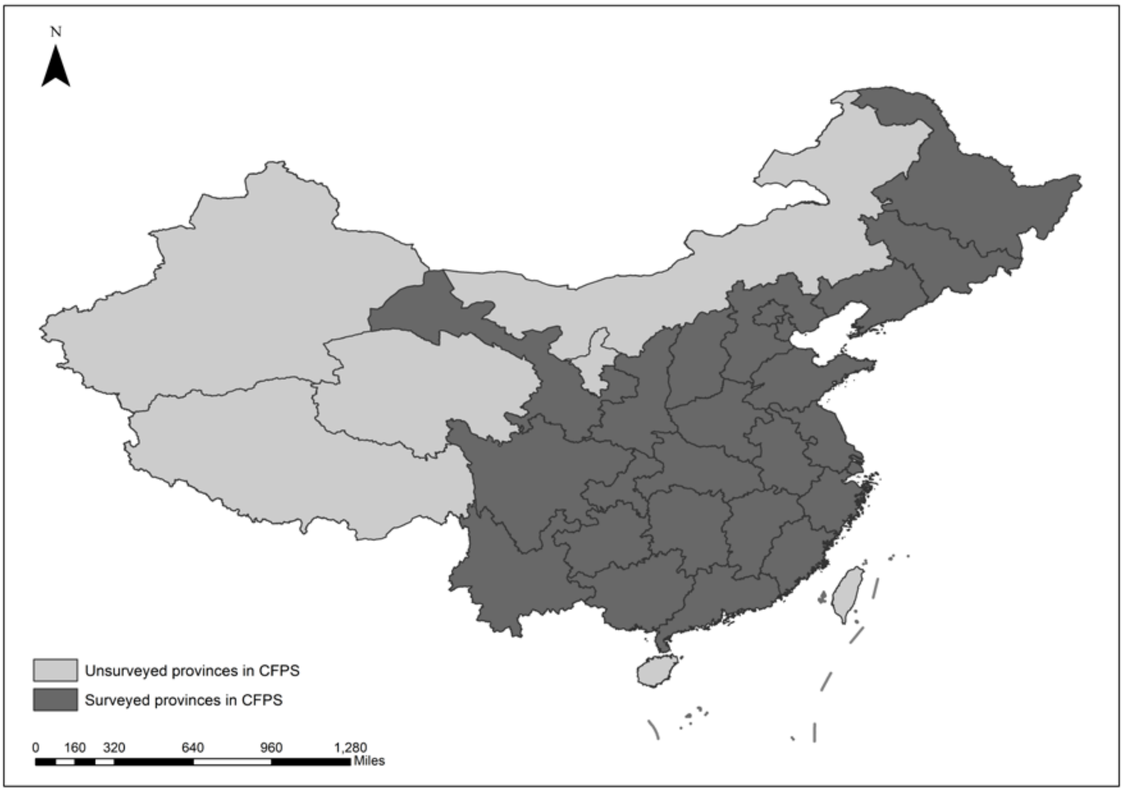

Figure 1: Provinces surveyed by the China Family Panel Studies

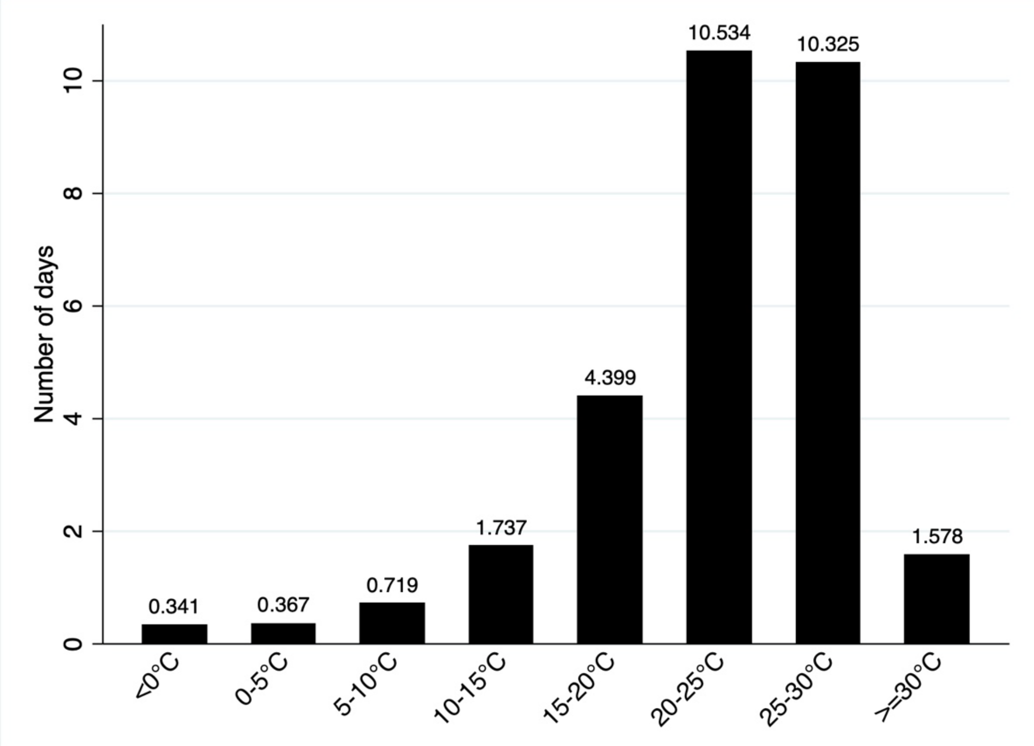

Figure 2: Distribution of average temperatures in the previous month in the estimation sample. The figure shows the average distribution of daily mean temperatures across 8 temperature-day bins. Each bar represents the average number of days in each temperature category in the 30-day period prior to the interview date.

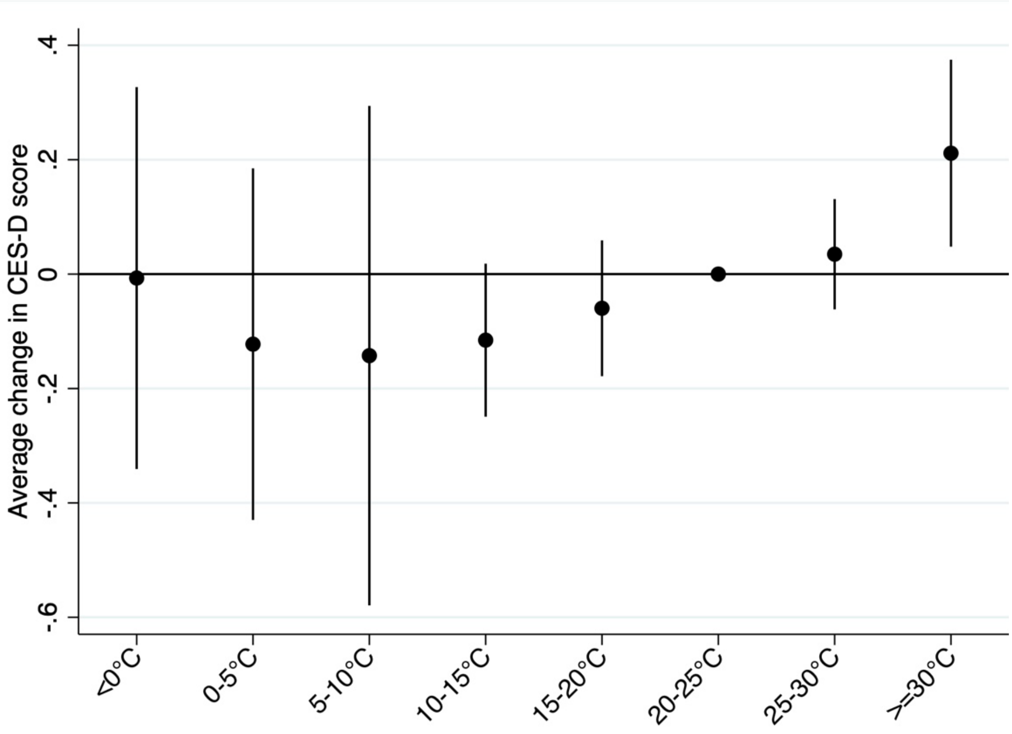

Figure 3: Estimated temperature-mental health relationship. The figure plots the response function between CES-D score and average daily temperatures, obtained by fitting Equation (1). In the response function, the 20–25℃ category is set as the baseline group so that each estimate represents the estimated impact of an additional day in bin *j* on the CES-D score relative to the CES-D score associated with a day on which the temperature is between 20℃ and 25℃. The temperature exposure window is defined as 30 days before the interview date, and seven temperature-day bin variables are included in the model. The estimation controls the average precipitation amount, relative humidity, wind speed, sunshine duration, atmospheric pressure, individual FE, self-perceived relative income status, self-perceived social status, city FE, year-by-month FE, quadratic trends in the month that the interview date falls. Standard errors are clustered at the city level.

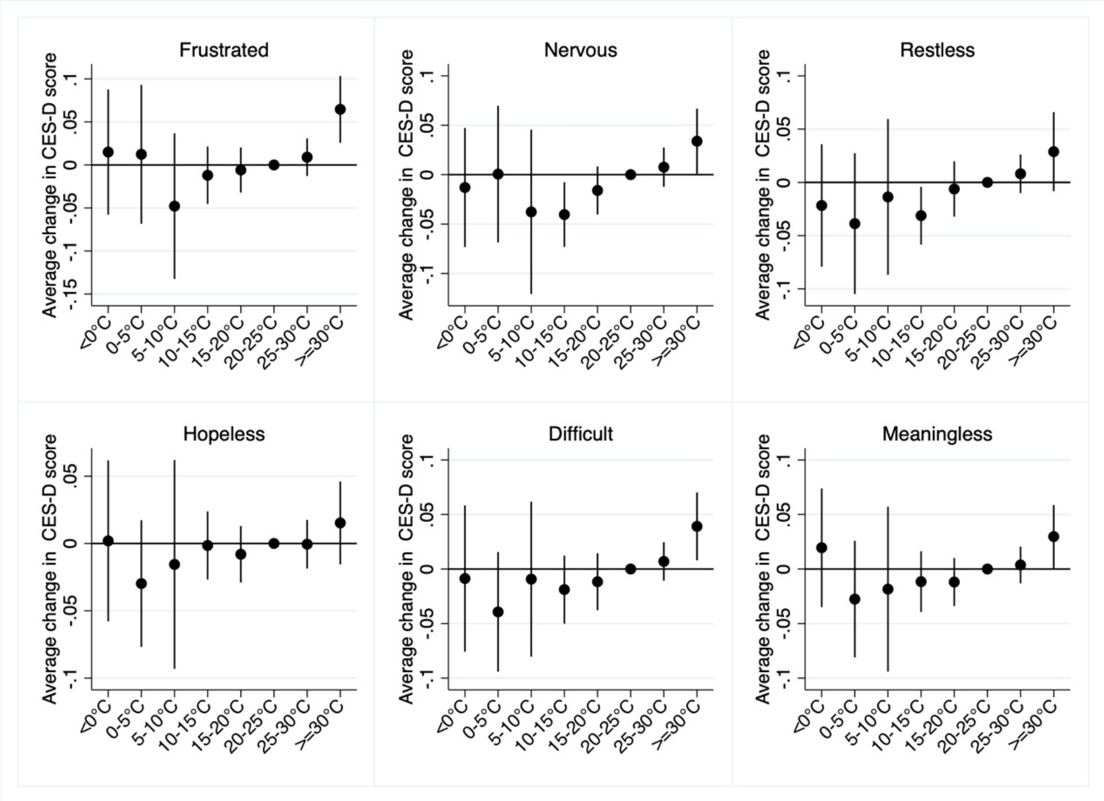

Figure 4: Estimated temperature-mental health relationship by symptoms. The figure plots the response function between each component of the CES-D score and average daily temperatures, obtained by fitting Equation (1). In the response function, the 20–25°C category is set as the baseline group so that each estimate represents the estimated impact of an additional day in bin *j* on the CES-D score component relative to the CES-D score component associated with a day on which the temperature is between 20°C and 25°C. The temperature exposure window is defined as 30 days before the interview date, and seven temperature-day bin variables are included in the model. The estimation controls the average precipitation amount, relative humidity, wind speed, sunshine duration, atmospheric pressure, individual FE, self-perceived relative income status, self-perceived social status, city FE, year-by-month FE, quadratic trends in the month that the interview date falls. Standard errors are clustered at the city level.

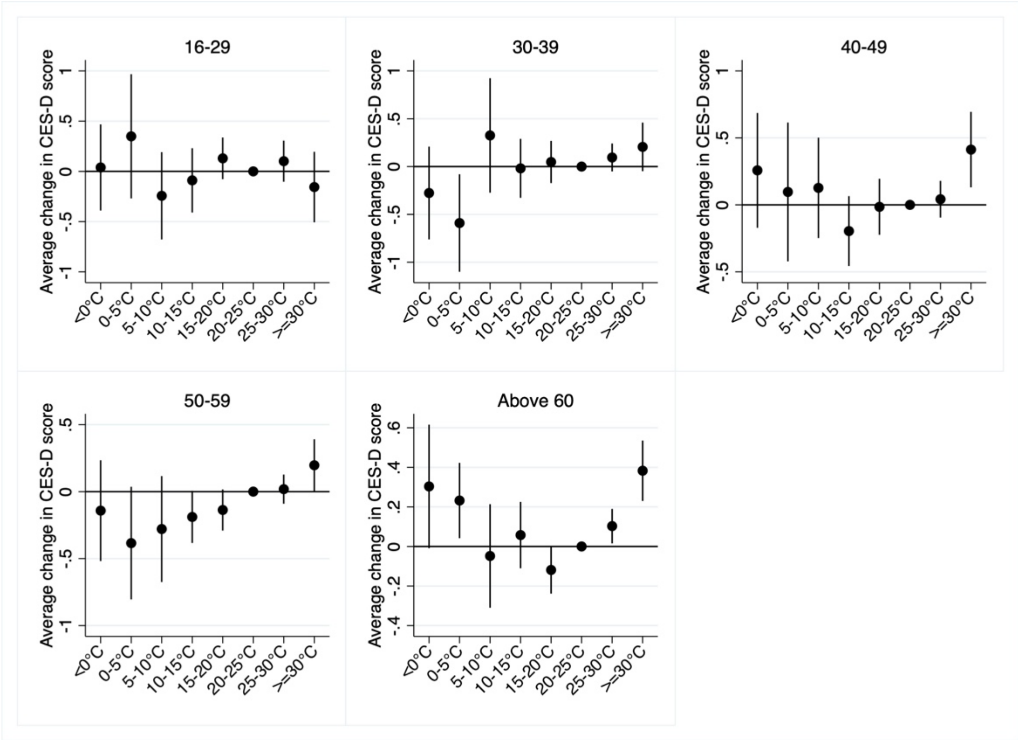

Figure 5: Estimated temperature-mental health relationship by age groups. In the response function, the 20–25℃ category is set as the baseline group so that each estimate represents the estimated impact of an additional day in bin *j* on the CES-D score component relative to the CES-D score component associated with a day on which the temperature is between 20℃ and 25℃. The temperature exposure window is defined as 30 days before the interview date, and seven temperature-day bin variables are included in the model. The estimation controls the average precipitation amount, relative humidity, wind speed, sunshine duration, atmospheric pressure, individual FE, self-perceived relative income status, self-perceived social status, city FE, year-by-month FE, quadratic trends in the month that the interview date falls. Standard errors are clustered at the city level.

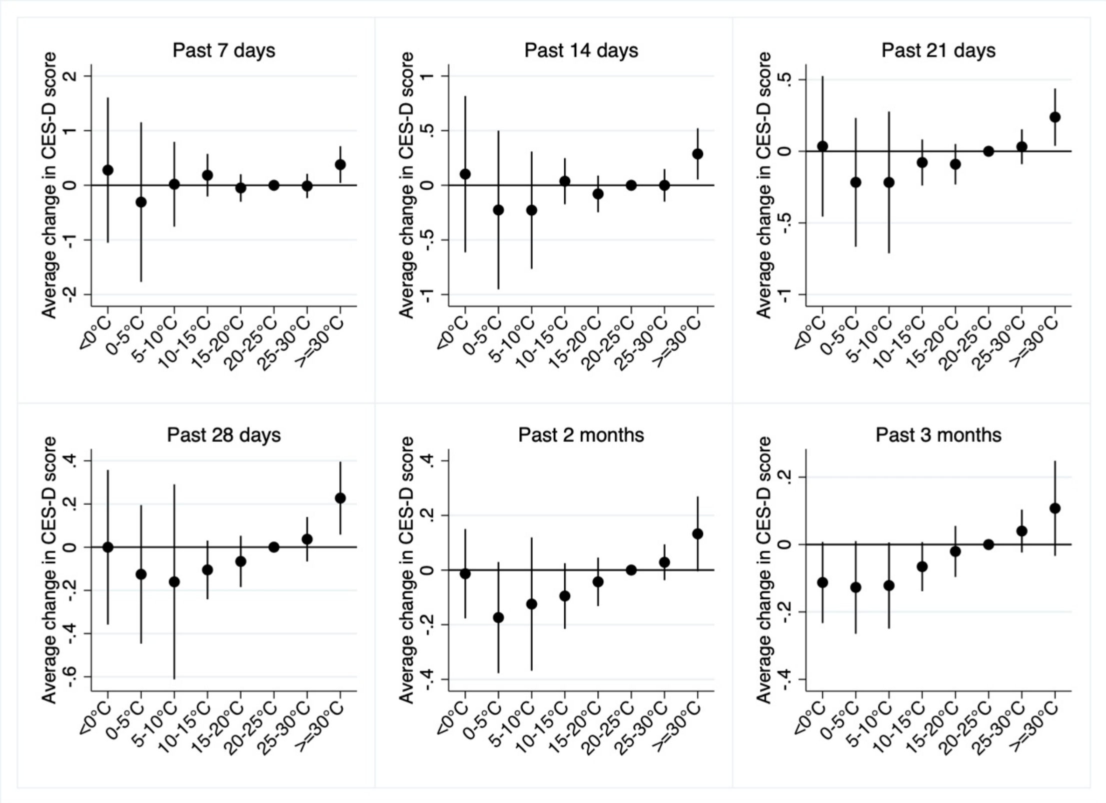

Figure 6: Coefficients on the temperature-bin number-of-day variables in different time spans. This figure displays the coefficients in columns (2)–(7) of Table 9. In the response function, the 20–25°C category is set as the baseline group so that each estimate represents the estimated impact of an additional day in bin *j* on the CES-D score relative to the CES-D score associated with a day on which the temperature is between 20°C and 25°C. The temperature exposure window is defined as 7, 14, 21, 28, 60, 90 days before the interview date across the six panels in the figure, respectively, and seven temperature-day bin variables are included in the model. The estimation controls the average precipitation amount, relative humidity, wind speed, sunshine duration, atmospheric pressure, individual FE, self-perceived relative income status, self-perceived social status, city FE, year-by-month FE, quadratic trends in the month that the interview date falls. Standard errors are clustered at the city level.

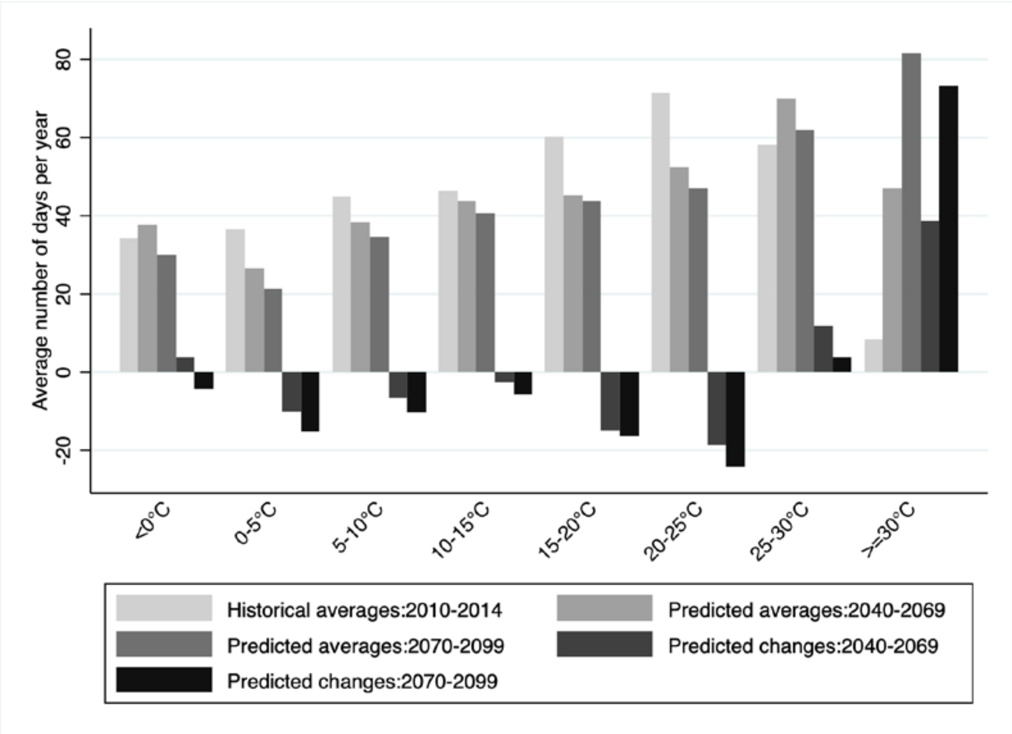

Figure 7: Distribution of annual daily mean temperature and predicted distribution in 2040-2069 and 2070-2099 according to Hadley GEM2-ES. The "Historical averages: 2010-2015" bars represent the average number of days per year in each temperature bin for the 124 cities in our sample. The "Predicted averages: 2040-2069" bars represent the average number of days per year of these 124 cities in 2040-2069 projected by Hadley GEM2-ES. The "Predicted averages: 2070-2099" bars represent the average number of days per year of these 124 cities in 2070-2099 projected by Hadley GEM2-ES. The "Predicted changes: 2040-2069" bars represent change in the average number of days per year of the 124 cities in 2040-2069 projected by Hadley GEM2-ES relative to that of 2010-2014. The "Predicted changes: 2070-2099" bars represent change in the average number of days per year of the 124 cities in 2070–2099 projected by Hadley GEM2-ES relative to that of 2010-2014. All bars are weighted by the population in each city during 2010-2014.

Table 1: Summary statistics

Variable	Obs.	Mean	Std. Dev.	Min.	Max.
***Panel A: depression variables**, individual-by-date level*					
CES-D Score	34,314	3.139	3.935	0.000	24.000
Frustrated	34,314	0.750	0.953	0.000	4.000
Nervous	34,314	0.580	0.873	0.000	4.000
Restless	34,314	0.523	0.859	0.000	4.000
Hopeless	34,314	0.354	0.771	0.000	4.000
Difficult	34,314	0.592	0.923	0.000	4.000
Meaningless	34,314	0.341	0.758	0.000	4.000
***Panel B: temperature variables for the 30-day period before interview date**, city-by-date level*					
Avg mean temperature (℃)	9,513	22.553	5.898	-20.678	31.048
Number of days (AT >=30℃)	9,513	1.578	3.191	0.000	22.000
Number of days (AT 25–30℃)	9,513	10.325	9.436	0.000	30.000
Number of days (AT 20–25℃)	9,513	10.534	8.533	0.000	30.000
Number of days (AT 15–20℃)	9,513	4.399	6.283	0.000	30.000
Number of days (AT 10–15℃)	9,513	1.737	4.421	0.000	29.000
Number of days (AT 5–10℃)	9,513	0.719	2.610	0.000	27.000
Number of days (AT 0–5℃)	9,513	0.367	2.136	0.000	27.000
Number of days (AT<0℃)	9,513	0.341	2.640	0.000	30.000
***Panel C: other meteorological variables averaged in the 30-day period before interview date**, city-by-date level*					
Total precipitation (mm)	9,513	4.407	3.190	0.000	19.041
Avg relative humidity (%)	9,513	72.834	8.906	29.827	89.253
Avg wind speed (m/s)	9,513	2.050	0.437	0.943	3.685
Sunshine duration (hour)	9,513	5.904	1.719	0.415	10.833
Air pressure (0.1hPa)	9,513	9622.229	583.146	6866.059	10292.320
***Panel D: demographic characteristics**, household-by-date or individual-by-date level*					
Household per capita income (log)	34,314	8.798	1.158	-1.386	13.610
Relative income	34,314	2.383	0.989	1.000	5.000
Social status	34,314	2.871	0.982	1.000	5.000
Age	34,314	48.404	14.043	16.000	95.000
Gender (0/1)	34,314	0.494	0.500	0.000	1.000
Education	34,314	7.013	4.617	0.000	22.000
Lower Education (0/1)	34,314	0.492	0.500	0.000	1.000
Agricultural worker (0/1)	23,334	0.528	0.499	0.000	1.000
Rural *Hukou* (0/1)	34,090	0.537	0.499	0.000	1.000
Physical illness (0/1)	34,314	0.706	0.456	0.000	1.000
Weekly physical exercise sessions	34,314	1.643	2.845	0.000	50.000
Physical exercise (0/1)	34,314	0.310	0.462	0.000	1.000
Sleep time (hour)	34,314	4.999	4.125	0.000	22.000
Inadequate sleep (0/1)	34,314	0.410	0.492	0.000	1.000
***Panel E: air conditioner variables**, household level*					
Air conditioner (0/1)	9,542	0.353	0.478	0.000	1.000

Note: This table presents the summary statistics for the sample used for our main regression analyses. Observations in Panels A and D are at the individual-by-date level. Observations in Panels B and C are at the city-by-date level. Observations in Panel E are at the household level. In Panel A, "Frustrated" represents self-reported frequency of feeling frustrated/depressed that nothing could cheer you during the previous month: most or all of the time (4), considerable amount of the time (3), half of the time (2), moderate amount of the time (1), never (0). "Difficult" represents self-reported frequency of feeling that everything was an effort during the previous month: most or all of the time (4), considerable amount of the time (3), half of the time (2), moderate amount of the time (1), never (0). The meanings of the other four variables are defined in similar ways. The CES-D Score is the sum of "Frustrated", "Nervous", "Restless", "Hopeless", "Difficult", and "Meaningless". In Panel B, "AT" is an abbreviation for "average temperature". In Panel D, respondents in CFPS reported their "relative local income level" and "local social status" by choosing from the following five categories: 1 – "very low", 2 – "low", 3 – "average", 4 – "high", and 5 – "very high". Larger numbers represent higher self-perceived income levels or social status. Household per capita income is calculated as household income divided by household size.

Table 2: Average effects of temperature exposure on CES-D score

	(1)	(2)	(3)	(4)	(5)
Number of days (AT >=30℃)	0.150**	0.151**	0.208**	0.200**	0.211**
	(0.065)	(0.066)	(0.080)	(0.081)	(0.083)
Number of days (AT 25–30℃)	0.010	0.010	0.028	0.026	0.035
	(0.046)	(0.045)	(0.047)	(0.048)	(0.049)
Number of days (AT 15–20℃)	-0.058	-0.056	-0.043	-0.049	-0.060
	(0.055)	(0.055)	(0.058)	(0.059)	(0.060)
Number of days (AT 10–15℃)	-0.118**	-0.118**	-0.098	-0.080	-0.116*
	(0.058)	(0.057)	(0.064)	(0.064)	(0.068)
Number of days (AT 5–10℃)	-0.176	-0.160	-0.115	-0.140	-0.143
	(0.177)	(0.175)	(0.194)	(0.204)	(0.221)
Number of days (AT 0–5℃)	-0.143	-0.141	-0.105	-0.141	-0.123
	(0.128)	(0.125)	(0.133)	(0.144)	(0.155)
Number of days (AT<0℃)	0.008	0.018	0.037	0.005	-0.007
	(0.145)	(0.142)	(0.151)	(0.160)	(0.169)
Household per capita income (log)		-0.990*	-0.992**	-0.996**	-0.998**
		(0.513)	(0.487)	(0.499)	(0.494)
Relative income		-0.759***	-0.758***	-0.760***	-0.758***
		(0.190)	(0.189)	(0.189)	(0.189)
Social status		-0.585***	-0.587***	-0.586***	-0.587***
		(0.151)	(0.151)	(0.152)	(0.152)
Precipitation			-0.077	-0.073	-0.063
			(0.099)	(0.099)	(0.101)
Relative humidity			0.054	0.055	0.062
			(0.063)	(0.063)	(0.064)
Wind speed			-0.566	-0.661	-0.506
			(0.881)	(0.876)	(0.877)
Sunshine duration			-0.113	-0.085	-0.117
			(0.251)	(0.259)	(0.260)
Atmospheric pressure			-0.008	-0.009	-0.006
			(0.015)	(0.015)	(0.015)
Mean of dependent variable	3.139	3.139	3.139	3.139	3.139
Individual FE	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	No
Year FE	Yes	Yes	Yes	Yes	No
Year-by-month FE	No	No	No	No	Yes
Linear and quadratic monthly trends	No	No	No	Yes	Yes
Observation	34,314	34,314	34,314	34,314	34,314
R^2	0.102	0.160	0.169	0.170	0.179

Note: The baseline temperature bin is 20–25℃. Robust standard errors clustered at the city level are in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 3: Effects of temperature on each component of CES-D score: by symptom

Dependent Variable	(1) Frustrated	(2) Nervous	(3) Restless	(4) Hopeless	(5) Difficult	(6) Meaningless
Number of Days (AT >=30°C)	0.065***	0.034**	0.029	0.015	0.039**	0.030**
	(0.020)	(0.017)	(0.019)	(0.016)	(0.016)	(0.015)
Number of Days (AT 25–30°C)	0.009	0.008	0.008	-0.001	0.007	0.004
	(0.011)	(0.010)	(0.009)	(0.009)	(0.009)	(0.008)
Number of Days (AT 15–20°C)	-0.006	-0.016	-0.006	-0.008	-0.012	-0.012
	(0.013)	(0.012)	(0.013)	(0.011)	(0.013)	(0.011)
Number of Days (AT 10–15°C)	-0.012	-0.040**	-0.031**	-0.001	-0.019	-0.012
	(0.017)	(0.017)	(0.014)	(0.013)	(0.016)	(0.014)
Number of Days (AT 5–10°C)	-0.048	-0.038	-0.014	-0.016	-0.009	-0.018
	(0.043)	(0.042)	(0.037)	(0.039)	(0.036)	(0.038)
Number of Days (AT 0–5°C)	0.012	0.001	-0.039	-0.030	-0.039	-0.028
	(0.041)	(0.035)	(0.033)	(0.024)	(0.028)	(0.027)
Number of Days (AT<0°C)	0.015	-0.013	-0.022	0.002	-0.009	0.020
	(0.037)	(0.030)	(0.029)	(0.030)	(0.034)	(0.027)
Mean of dependent variable	0.750	0.580	0.523	0.354	0.592	0.341
Demographic characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Other meteorological variables	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-by-month FE	Yes	Yes	Yes	Yes	Yes	Yes
Linear and quadratic monthly trends	Yes	Yes	Yes	Yes	Yes	Yes
Observation	34,314	34,314	34,314	34,314	34,314	34,314
R^2	0.155	0.118	0.093	0.091	0.118	0.092

Note: The baseline temperature bin is 20–25°C. Demographic characteristics include household per capita income, self-reported relative income level and social status. Other meteorological variables include precipitation, relative humidity, wind speed, sunshine duration, and atmospheric pressure. Robust standard errors clustered at the city level are in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 4: Robustness checks: alternative specifications

	(1)	(2)		(3)
	Dependent Variable: Severe mental illness	Placebo test		Binary independent variable
Number of Days (AT >=30℃)	0.002***	-0.018	AT >=30℃	1.572**
	(0.000)	(0.093)		(0.798)
Number of Days (AT 25–30℃)	-0.000	-0.072	AT 25–30℃	0.211
	(0.000)	(0.044)		(0.163)
Number of Days (AT 15–20℃)	-0.001	-0.017	AT 15–20℃	-0.528**
	(0.000)	(0.072)		(0.225)
Number of Days (AT 10–15℃)	-0.000	0.037	AT 10–15℃	0.432
	(0.000)	(0.081)		(0.295)
Number of Days (AT 5–10℃)	0.000	0.211**	AT 5–10℃	1.446**
	(0.001)	(0.100)		(0.678)
Number of Days (AT 0–5℃)	0.000	-0.038	AT 0–5℃	0.854
	(0.000)	(0.159)		(0.729)
Number of Days (AT<0℃)	0.000	0.134	AT<0℃	1.543*
	(0.000)	(0.165)		(0.818)
Mean of dependent variable	0.038	3.139	Mean of dependent variable	3.139
Demographic characteristics	Yes	Yes	Demographic characteristics	Yes
Other meteorological variables	Yes	Yes	Other meteorological variables	Yes
Individual FE	Yes	Yes	Individual FE	Yes
City FE	Yes	Yes	City FE	Yes
Year-by-month FE	Yes	Yes	Year-by-month FE	Yes
Linear and quadratic monthly trends	Yes	Yes	Linear and quadratic monthly trends	Yes
Observation	34,314	34,314	Observation	34,314
R^2	0.248	0.177	R^2	0.063

Note: The baseline temperature bin is 20–25℃. Demographic characteristics include household per capita income, self-reported relative income level and social status. Other meteorological characteristics include precipitation, relative humidity, wind speed, sunshine duration, and atmospheric pressure. Robust standard errors clustered at the city level are in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 5: Robustness checks: alternative specifications

	(1)	(2)	(3)	(4)
	Two-way cluster	Add city-month FE	Add city-year FE	Add interview date FE
Number of Days (AT >=30°C)	0.211**	0.159**	0.178*	0.163*
	(0.088)	(0.080)	(0.103)	(0.090)
Number of Days (AT 25–30°C)	0.035	0.073*	0.098**	0.017
	(0.048)	(0.040)	(0.048)	(0.055)
Number of Days (AT 15–20°C)	-0.060	-0.114*	0.036	-0.018
	(0.060)	(0.059)	(0.058)	(0.065)
Number of Days (AT 10–15°C)	-0.116*	-0.221**	-0.047	-0.063
	(0.068)	(0.099)	(0.093)	(0.074)
Number of Days (AT 5–10°C)	-0.143	-0.373**	-0.001	-0.069
	(0.177)	(0.151)	(0.172)	(0.212)
Number of Days (AT 0–5°C)	-0.123	-0.171	-0.154	-0.147
	(0.150)	(0.236)	(0.165)	(0.167)
Number of Days (AT<0°C)	-0.007	0.486	0.182	0.013
	(0.154)	(0.371)	(0.178)	(0.163)
Mean of dependent variable	3.139	3.139	3.139	3.139
Demographic characteristics	Yes	Yes	Yes	Yes
Other meteorological variables	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes
City FE	Yes	No	No	Yes
Year-by-month FE	Yes	Yes	Yes	Yes
City-by-year FE	No	No	Yes	No
City-by-month FE	No	Yes	No	No
Linear and Quadratic monthly trend	Yes	Yes	Yes	Yes
Interview date FE	No	No	No	Yes
Observation	34,314	34,314	34,314	34,314
R^2	0.179	0.102	0.064	0.502

Note: The baseline temperature bin is 20–25°C. Demographic characteristics include household per capita income, self-reported income level and social status. Other meteorological variables include precipitation, relative humidity, wind speed, sunshine duration, and air pressure. Robust standard errors clustered at the city level (columns [1] and [2]) or at both the city and the interview month level (column [3]) are in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 6: Heterogeneous effects across different age subsamples

	(1)	(2)	(3)	(4)	(5)
Age groups	16-29	30-39	40-49	50-59	Above 60
Number of Days (AT >=30°C)	-0.156	0.205	0.413^{***}	0.198^{**}	0.383^{***}
	(0.177)	(0.128)	(0.142)	(0.099)	(0.078)
Number of Days (AT 25–30°C)	0.101	0.095	0.042	0.019	0.103^{**}
	(0.103)	(0.074)	(0.069)	(0.056)	(0.045)
Number of Days (AT 15–20°C)	0.130	0.048	-0.015	-0.138^{*}	-0.119^{*}
	(0.105)	(0.111)	(0.106)	(0.078)	(0.061)
Number of Days (AT 10–15°C)	-0.090	-0.018	-0.196	-0.189^{*}	0.058
	(0.162)	(0.156)	(0.132)	(0.099)	(0.086)
Number of Days (AT 5–10°C)	-0.243	0.325	0.127	-0.275	-0.048
	(0.220)	(0.302)	(0.189)	(0.201)	(0.134)
Number of Days (AT 0–5°C)	0.349	-0.590^{**}	0.096	-0.394^{*}	0.232^{**}
	(0.312)	(0.258)	(0.262)	(0.215)	(0.097)
Number of Days (AT<0°C)	0.039	-0.276	0.258	-0.143	0.304^{*}
	(0.217)	(0.245)	(0.217)	(0.192)	(0.159)
Mean of dependent variable	2.804	2.907	3.171	3.218	3.418
Demographic characteristics	Yes	Yes	Yes	Yes	Yes
Other meteorological variables	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes
Year-by-month FE	Yes	Yes	Yes	Yes	Yes
Linear and quadratic monthly trend	Yes	Yes	Yes	Yes	Yes
Observation	2,610	3,206	5,846	4,408	6,332
R^2	0.049	0.034	0.031	0.031	0.031

Note: The baseline temperature bin is 20–25°C. Demographic characteristics include household per capita income, self-reported relative income level and social status. Other meteorological variables include precipitation, relative humidity, wind speed, sunshine duration, and atmospheric pressure. Robust standard errors clustered at the city level are in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 7: Heterogeneous effects across gender, education level, job sector, and *Hukou* status

	Gender (Dummy: Female=1)	Education (Dummy: Lower Education=1)	Job Sector (Dummy: Agricultural worker=1)	*Hukou* (Dummy: Rural *Hukou* =1)
Number of Days (AT >=30°C)×Dummy	0.114***	0.169***	0.127**	0.005
	(0.040)	(0.058)	(0.058)	(0.133)
Number of Days (AT 25–30°C)×Dummy	-0.002	-0.010	-0.076***	-0.097
	(0.022)	(0.034)	(0.026)	(0.074)
Number of Days (AT 15–20°C)×Dummy	0.031	-0.049	-0.118***	-0.107
	(0.032)	(0.050)	(0.037)	(0.101)
Number of Days (AT 10–15°C)×Dummy	0.015	0.060	0.012	-0.017
	(0.041)	(0.040)	(0.043)	(0.133)
Number of Days (AT 5–10°C)×Dummy	0.011	0.014	0.155*	-0.038
	(0.075)	(0.092)	(0.087)	(0.275)
Number of Days (AT 0–5°C)×Dummy	0.197***	0.008	0.081	0.190
	(0.072)	(0.106)	(0.110)	(0.178)
Number of Days (AT<0°C)×Dummy	-0.080	-0.017	0.015	-0.279
	(0.069)	(0.075)	(0.073)	(0.192)
Dummy		-3.109***	-0.968**	
		(0.621)	(0.453)	
Number of days (AT >=30°C)	0.111*	0.092	0.219***	0.193**
	(0.066)	(0.061)	(0.039)	(0.095)
Number of days (AT 25–30°C)	0.017	0.019	-0.033*	0.090*
	(0.034)	(0.030)	(0.019)	(0.054)
Number of days (AT 15–20°C)	-0.111**	-0.064	0.007	0.009
	(0.051)	(0.041)	(0.028)	(0.077)
Number of days (AT 10–15°C)	-0.103**	-0.125**	-0.016	-0.108
	(0.052)	(0.058)	(0.028)	(0.123)
Number of days (AT 5–10°C)	-0.091	-0.077	-0.025	-0.102
	(0.139)	(0.146)	(0.055)	(0.313)
Number of days (AT 0–5°C)	-0.176*	-0.083	-0.036	-0.225
	(0.098)	(0.097)	(0.061)	(0.183)
Number of days (AT<0°C)	-0.058	-0.076	0.024	0.114
	(0.104)	(0.100)	(0.048)	(0.224)
Mean of dependent variable	3.139	3.139	3.028	3.129
Demographic characteristics	Yes	Yes	Yes	Yes
Other meteorological variables	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes
Year-by-month FE	Yes	Yes	Yes	Yes
Linear and quadratic monthly trend	Yes	Yes	Yes	Yes
Observation	34,314	34,314	17,890	33,866
R^2	0.182	0.181	0.214	0.185

Note: The baseline temperature bin is 20–25°C. Demographic characteristics include household per capita income, self-reported relative income level and social status. Other meteorological variables include precipitation, relative humidity, wind speed, sunshine duration, and atmospheric pressure. "High Edu" and "Low Edu" refer to respondents whose number of education years are above or below the median number, respectively. "Farm" and "Non-farm" represent respondents that work in the agriculture/non-agriculture sector, respectively. "Rural" and "Urban" refer to respondents with a rural/urban *Hukou*. Each dummy variable does not change across time in the sample and has been absorbed by the individual fixed effects in the regression. Robust standard errors clustered at the city level are in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 8: Effects of temperature exposure of the interview day on CES-D score

Temperature measure	(1) Interview day average temperature	(2) Interview day average temperature + past 30 days temperature bin days
AT >=30°C (0/1)	0.449	-0.132
	(0.698)	(0.670)
AT 25–30°C (0/1)	-0.052	-0.414
	(0.422)	(0.403)
AT 15–20°C (0/1)	-0.919*	-0.479
	(0.508)	(0.536)
AT 10–15°C (0/1)	0.357	1.546
	(1.122)	(1.360)
AT 5–10°C (0/1)	-0.252	1.407
	(1.667)	(1.588)
AT 0–5°C (0/1)	-1.575	0.173
	(3.656)	(2.542)
AT<0°C (0/1)	1.964	2.295
	(3.172)	(2.714)
Number of Days (AT >=30°C)		0.208**
		(0.080)
Number of Days (AT 25–30°C)		0.037
		(0.048)
Number of Days (AT 15–20°C)		-0.066
		(0.062)
Number of Days (AT 10–15°C)		-0.147*
		(0.074)
Number of Days (AT 5–10°C)		-0.164
		(0.206)
Number of Days (AT 0–5°C)		-0.125
		(0.146)
Number of Days (AT<0°C)		-0.077
		(0.197)
Mean of dependent variable	3.139	3.139
Demographic characteristics	Yes	Yes
Other meteorological variables	Yes	Yes
Individual FE	Yes	Yes
City FE	Yes	Yes
Year-by-month FE	Yes	Yes
Linear and quadratic monthly trends	Yes	Yes
Observation	34,314	34,314
R^2	0.164	0.187

Note: The baseline temperature bin is 20–25°C. Demographic characteristics include household per capita income, self-reported relative income level and social status. Other meteorological variables include precipitation, relative humidity, wind speed, sunshine duration, and atmospheric pressure. Robust standard errors clustered at the city level in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 9: Effects of temperature exposure in different time spans

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Examined time span	past 30 days	past 7 days	past 14 days	past 21 days	past 28 days	past 2 months	past 3 months
Number of Days (AT >=30℃)	0.211**	0.379**	0.287**	0.238**	0.227***	0.133*	0.107
	(0.083)	(0.170)	(0.118)	(0.101)	(0.085)	(0.069)	(0.071)
Number of Days (AT 25–30℃)	0.035	-0.013	-0.000	0.032	0.037	0.028	0.040
	(0.049)	(0.112)	(0.075)	(0.062)	(0.052)	(0.033)	(0.032)
Number of Days (AT 15–20℃)	-0.060	-0.049	-0.079	-0.090	-0.066	-0.043	-0.020
	(0.060)	(0.127)	(0.085)	(0.071)	(0.060)	(0.045)	(0.038)
Number of Days (AT 10–15℃)	-0.116*	0.184	0.037	-0.078	-0.105	-0.095	-0.066*
	(0.068)	(0.197)	(0.107)	(0.081)	(0.069)	(0.061)	(0.037)
Number of Days (AT 5–10℃)	-0.143	0.019	-0.228	-0.217	-0.160	-0.125	-0.122*
	(0.221)	(0.392)	(0.271)	(0.250)	(0.228)	(0.123)	(0.065)
Number of Days (AT 0–5℃)	-0.123	-0.308	-0.226	-0.217	-0.126	-0.174*	-0.127*
	(0.155)	(0.738)	(0.367)	(0.227)	(0.162)	(0.103)	(0.069)
Number of Days (AT<0℃)	-0.007	0.277	0.102	0.035	-0.000	-0.013	-0.113*
	(0.169)	(0.672)	(0.361)	(0.248)	(0.181)	(0.083)	(0.061)
Mean of dependent variable	3.139	3.139	3.139	3.139	3.139	3.139	3.139
Demographic characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Other meteorological variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-by-month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Linear and quadratic monthly trends	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observation	34,314	34,314	34,314	34,314	34,314	34,314	34,314
R^2	0.179	0.168	0.173	0.173	0.178	0.194	0.206

Note: The baseline temperature bin is 20–25℃. Demographic characteristics include household per capita income, self-reported relative income level and social status. Other meteorological variables include precipitation, relative humidity, wind speed, sunshine duration, and atmospheric pressure. Robust standard errors clustered at the city level in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 10: Mechanisms of the depression effects of high temperature exposure

Dependent Variable	(1) Physical Illness (0/1)	(2) Weekly Exercise Sessions	(3) Physical Exercise (0/1)	(4) Sleep Time (hour)	(5) Inadequate Sleep (0/1)
Number of Days (AT >=30℃)	0.006**	-0.019	-0.003	-0.189***	0.022***
	(0.002)	(0.014)	(0.003)	(0.036)	(0.004)
Number of Days (AT 25–30℃)	-0.001	-0.012	-0.002	-0.082***	0.010***
	(0.001)	(0.007)	(0.001)	(0.017)	(0.002)
Number of Days (AT 15–20℃)	0.001	-0.023*	-0.003	-0.016	0.001
	(0.002)	(0.012)	(0.002)	(0.024)	(0.003)
Number of Days (AT 10–15℃)	0.004*	0.005	-0.000	-0.028	0.003
	(0.002)	(0.018)	(0.003)	(0.037)	(0.005)
Number of Days (AT 5–10℃)	0.001	-0.017	-0.003	0.121**	-0.015**
	(0.003)	(0.025)	(0.004)	(0.059)	(0.007)
Number of Days (AT 0–5℃)	0.008**	-0.028	-0.005	0.137**	-0.016**
	(0.004)	(0.038)	(0.006)	(0.060)	(0.007)
Number of Days (AT<0℃)	0.006*	-0.002	-0.004	0.139***	-0.016***
	(0.003)	(0.026)	(0.005)	(0.022)	(0.003)
Demographic characteristics	Yes	Yes	Yes	Yes	Yes
Other meteorological variables	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes
Year-by-month FE	Yes	Yes	Yes	Yes	Yes
Linear and quadratic monthly trends	Yes	Yes	Yes	Yes	Yes
Observation	34,314	34,314	34,314	34,314	34,314
R^2	0.199	0.040	0.046	0.764	0.745

Note: The baseline temperature bin is 20–25℃. Demographic characteristics include household per capita income, self-reported relative income level, and social status. Other meteorological variables include precipitation, relative humidity, wind speed, sunshine duration, and atmospheric pressure. Robust standard errors clustered at the city level in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 11: Effectiveness of external adaptation: Air conditioning

	(1)
Number of Days (AT >=30℃)×AC	-0.161*
	(0.091)
Number of Days (AT 25–30℃)×AC	-0.139***
	(0.037)
Number of Days (AT 15–20℃)×AC	-0.142**
	(0.061)
Number of Days (AT 10–15℃)×AC	0.012
	(0.085)
Number of Days (AT 5–10℃)×AC	-0.171
	(0.108)
Number of Days (AT 0–5℃)×AC	0.024
	(0.125)
Number of Days (AT<0℃)×AC	0.025
	(0.143)
AC	0.225
	(0.690)
Number of Days (AT >=30℃)	0.532***
	(0.073)
Number of Days (AT 25–30℃)	-0.169***
	(0.020)
Number of Days (AT 15–20℃)	-0.131***
	(0.027)
Number of Days (AT 10–15℃)	-0.006
	(0.037)
Number of Days (AT 5–10℃)	0.105
	(0.067)
Number of Days (AT 0–5℃)	0.059
	(0.069)
Number of Days (AT<0℃)	0.074*
	(0.042)
Mean of dependent variable	3.249
Demographic characteristics	Yes
Other meteorological variables	Yes
City FE	Yes
Year-by-month FE	Yes
Linear and quadratic monthly trends	Yes
Observation	17,157
R^2	0.099

Note: AC represents a dummy variable of whether a household has air conditioners or not. The dummy variable does not change across time in the sample and has been absorbed by the individual fixed effects in the regression. The baseline temperature bin is 20–25℃. Demographic characteristics include household per capita income, self-reported relative income level and social status. Other meteorological variables include precipitation, relative humidity, wind speed, sunshine duration, and atmospheric pressure. Robust standard errors clustered at the city level are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 12: Examination of adaptation

	(1) Full sample	(2) Local residents	(3) Full sample	(4) Local residents	(5) Local vs. Non-local residents
(Number of days AT>=30°C) * (Number of days AT>=30°C in past 31-395 days)	-0.008*	-0.007			
	(0.004)	(0.004)			
Number of days AT>=30°C in past 31-395 days	0.069**	0.069**			
	(0.031)	(0.032)			
(Number of days AT>=30°C) * (Number of days AT>=30°C in past 31-3680 days)			-0.011***	-0.013***	
			(0.003)	(0.004)	
Number of days AT>=30°C in past 31-3680 days			0.056**	0.059**	
			(0.022)	(0.027)	
(Number of days AT>=30°C) * Local					0.011
					(0.104)
Local					-1.076***
					(0.370)
Number of Days (AT >=30°C)	0.234**	0.313***	0.334***	0.310***	0.108
	(0.099)	(0.109)	(0.065)	(0.073)	(0.110)
Number of Days (AT 25–30°C)	0.016	0.025	0.035	0.031	0.017
	(0.051)	(0.051)	(0.049)	(0.051)	(0.053)
Number of Days (AT 15–20°C)	-0.066	-0.068	-0.061	-0.067	-0.055
	(0.060)	(0.061)	(0.060)	(0.062)	(0.061)
Number of Days (AT 10–15°C)	-0.118*	-0.114*	-0.118*	-0.122*	-0.097
	(0.068)	(0.068)	(0.068)	(0.069)	(0.071)
Number of Days (AT 5–10°C)	-0.149	-0.142	-0.147	-0.144	-0.103
	(0.222)	(0.187)	(0.225)	(0.188)	(0.189)
Number of Days (AT 0–5°C)	-0.127	-0.067	-0.128	-0.060	-0.047
	(0.155)	(0.158)	(0.160)	(0.163)	(0.159)
Number of Days (AT<0°C)	-0.013	0.042	-0.018	0.065	0.068
	(0.169)	(0.161)	(0.185)	(0.179)	(0.167)
Mean of dependent variable	3.139	3.157	3.139	3.157	3.133
Demographic characteristics	Yes	Yes	Yes	Yes	Yes
Other meteorological variables	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes
Year-by-month FE	Yes	Yes	Yes	Yes	Yes
Linear and quadratic monthly trends	Yes	Yes	Yes	Yes	Yes
Observation	34,314	30,187	34,314	30,187	34,096
R^2	0.186	0.194	0.179	0.213	0.196

Note: The baseline temperature bin is 20–25°C. Demographic characteristics include household per capita income, self-reported relative income level and social status. Other meteorological variables include precipitation, relative humidity, wind speed, sunshine duration, and atmospheric pressure. Robust standard errors clustered at the city level are in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 13: Predicted average impact of climate change on percentage of CES-D score

		Impact of change in days with temperature							Total temperature impact
		<0°C	0–5°C	5–10°C	10–15°C	15–20°C	25–30°C	>=30°C	
Medium-term (2040-2069)	RCP 8.5	-0.000	0.003	0.002	0.001	0.002	0.001	0.021**	0.031***
		(0.001)	(0.004)	(0.004)	(0.000)	(0.002)	(0.001)	(0.008)	(0.011)
Long-term (2070-2099)	RCP 8.5	0.000	0.005	0.004	0.002**	0.003	0.000	0.040**	0.053**
		(0.002)	(0.006)	(0.006)	(0.001)	(0.003)	(0.000)	(0.016)	(0.021)

Note: The estimates are based on the regression reported in column (5) in Table 2. Robust standard errors clustered at the city level are in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Online Appendix

Appendix A: additional tables

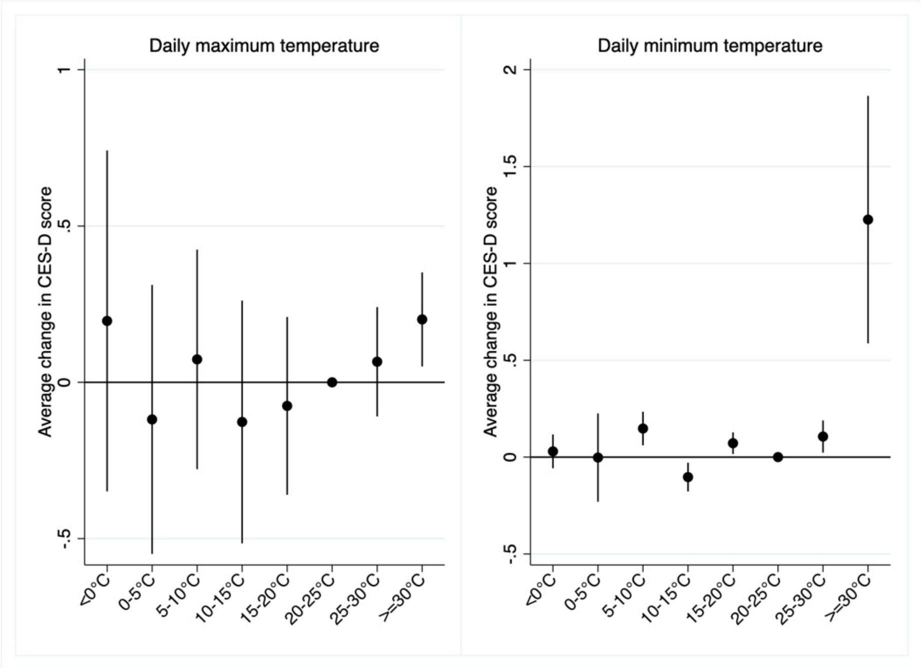

Figure A1: Estimated temperature-mental health relationship using alternative temperature measures. Left: daily maximum temperatures; right: daily minimum temperatures. In the response function, the 20–25℃ category is set as the baseline group so that each estimate represents the estimated impact of an additional day in bin *j* on the CES-D score relative to the CES-D score associated with a day on which the temperature is between 20℃ and 25℃. The temperature exposure window is defined as 30 days before the interview date, and seven temperature-day bin variables are included in the model. The estimation controls the average precipitation amount, relative humidity, wind speed, sunshine duration, atmospheric pressure, individual FE, self-perceived relative income status, self-perceived social status, city FE, year-by-month FE, quadratic trends in the month that the interview date falls. Standard errors are clustered at the city level.

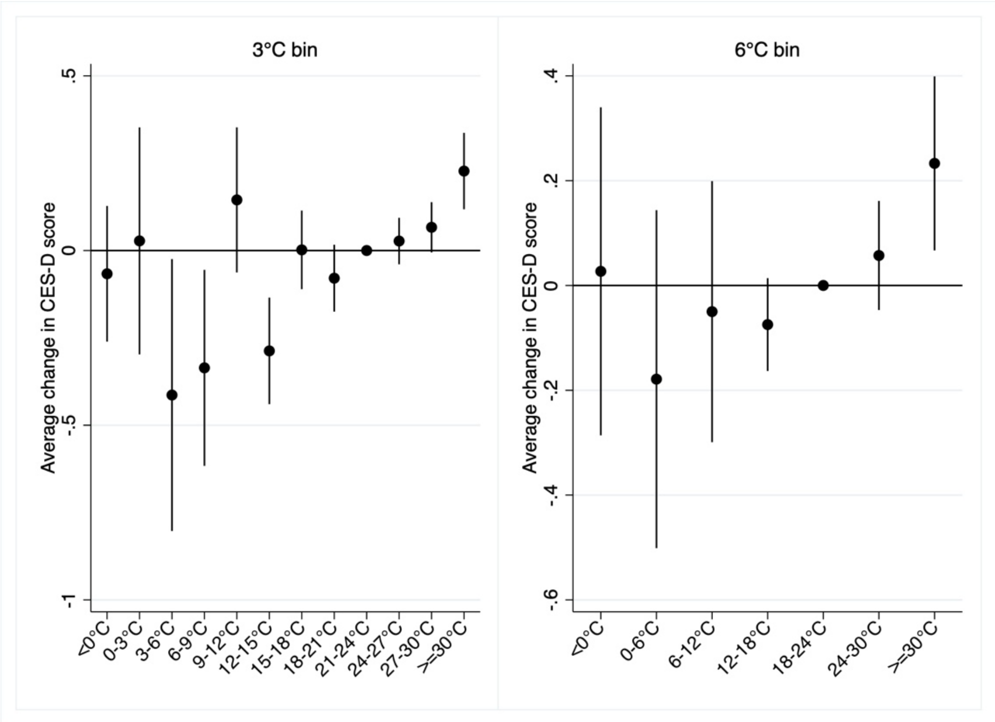

Figure A2: Estimated temperature-mental health relationship using alternative temperature bins. a: 3℃ bins, the 21–24℃ category is set as the baseline group; b: 6℃ bins, the 18–24℃ category is set as the baseline group. In the response function, each estimate represents the estimated impact of an additional day in bin *j* on the CES-D score relative to the CES-D score associated with a day on which the temperature falls in the baseline group. The temperature exposure window is defined as 30 days before the interview date. The estimation controls the average precipitation amount, relative humidity, wind speed, sunshine duration, atmospheric pressure, individual FE, self-perceived relative income status, self-perceived social status, city FE, year-by-month FE, quadratic trends in the month that the interview date falls. Standard errors are clustered at the city level.

Table A1: Additional summary statistics

Variable	Obs.	Mean	Std. Dev.	Min.	Max.
***temperature variables**, city-by-date level*					
Avg Temperature (AT, °C)	9,513	22.553	5.898	-20.678	31.048
Number of days (AT >=35°C)	9,513	0.000	0.000	0.000	0.000
Number of days (AT >=33°C)	9,513	0.043	0.384	0.000	6.000
Number of days (AT 30–35°C)	9,513	1.578	3.191	0.000	22.000
Number of days (AT 30–33°C)	9,513	1.536	3.058	0.000	19.000
Number of days (AT >=30°C)	9,513	1.578	3.191	0.000	22.000
Number of days (AT 27–30°C)	9,513	5.578	7.323	0.000	29.000
Number of days (AT 24–27°C)	9,513	7.299	6.357	0.000	26.000
Number of days (AT 21–24°C)	9,513	6.523	5.982	0.000	26.000
Number of days (AT 18–21°C)	9,513	3.696	4.812	0.000	26.000
Number of days (AT 15–18°C)	9,513	2.163	3.822	0.000	22.000
Number of days (AT 12–15°C)	9,513	1.249	3.131	0.000	25.000
Number of days (AT 9–12°C)	9,513	0.668	2.197	0.000	24.000
Number of days (AT 6–9°C)	9,513	0.436	1.681	0.000	20.000
Number of days (AT 3–6°C)	9,513	0.252	1.271	0.000	19.000
Number of days (AT 0–3°C)	9,513	0.218	1.452	0.000	22.000
Number of days (AT<0°C)	9,513	0.341	2.640	0.000	30.000
Number of days (AT >=30°C)	9,513	1.578	3.191	0.000	22.000
Number of days (AT 24–30°C)	9,513	12.877	9.987	0.000	30.000
Number of days (AT 18–24°C)	9,513	10.219	8.869	0.000	30.000
Number of days (AT 12–18°C)	9,513	3.411	6.219	0.000	30.000
Number of days (AT 6–12°C)	9,513	1.104	3.530	0.000	28.000
Number of days (AT 0–6°C)	9,513	0.470	2.441	0.000	29.000
Number of days (AT<0°C)	9,513	0.341	2.640	0.000	30.000
Max Temperature (MAT, °C)	9,513	27.654	5.632	-15.358	36.296
Number of days (MAT >=30°C)	9,513	12.134	10.026	0.000	30.000
Number of days (MAT 25–30°C)	9,513	10.272	6.934	0.000	30.000
Number of days (MAT 20–25°C)	9,513	4.364	4.974	0.000	22.000
Number of days (MAT 15–20°C)	9,513	1.750	3.517	0.000	22.000
Number of days (MAT 10–15°C)	9,513	0.759	2.454	0.000	25.000
Number of days (MAT 5–10°C)	9,513	0.418	1.926	0.000	21.000
Number of days (MAT 0–5°C)	9,513	0.199	1.518	0.000	22.000
Number of days (MAT<0°C)	9,513	0.094	1.190	0.000	30.000
Min Temperature (MIT, °C)	9,513	18.511	6.324	-25.422	27.333
Number of days (MIT >=30°C)	9,513	0.009	0.144	0.000	3.000
Number of days (MIT 25–30°C)	9,513	4.072	7.675	0.000	30.000
Number of days (MIT 20–25°C)	9,513	10.602	9.587	0.000	30.000
Number of days (MIT 15–20°C)	9,513	8.536	8.522	0.000	30.000
Number of days (MIT 10–15°C)	9,513	3.779	5.917	0.000	28.000
Number of days (MIT 5–10°C)	9,513	1.671	4.169	0.000	28.000
Number of days (MIT 0–5°C)	9,513	0.631	2.183	0.000	23.000
Number of days (MIT<0°C)	9,513	0.699	3.895	0.000	30.000

Table A2: Robustness check: Add temperature-bin number-of-day variables in lead one-three weeks

	(1)
Number of Days (AT >=30°C)	0.138**
	(0.066)
Number of Days (AT 25–30°C)	0.005
	(0.045)
Number of Days (AT 15–20°C)	-0.079
	(0.060)
Number of Days (AT 10–15°C)	-0.175**
	(0.080)
Number of Days (AT 5–10°C)	-0.061
	(0.163)
Number of Days (AT 0–5°C)	-0.004
	(0.174)
Number of Days (AT<0°C)	0.072
	(0.222)
Number of Days (AT >=30°C) (Lead 7 days)	0.187
	(0.190)
Number of Days (AT 25–30°C) (Lead 7 days)	0.122
	(0.118)
Number of Days (AT 15–20°C) (Lead 7 days)	-0.212*
	(0.109)
Number of Days (AT 10–15°C) (Lead 7 days)	-0.652**
	(0.270)
Number of Days (AT 5–10°C) (Lead 7 days)	-0.421
	(0.405)
Number of Days (AT 0–5°C) (Lead 7 days)	-0.706
	(0.571)
Number of Days (AT<0°C) (Lead 7 days)	0.775
	(0.837)
Number of Days (AT >=30°C) (Lead 8-14 days)	0.148
	(0.221)
Number of Days (AT 25–30°C) (Lead 8-14 days)	-0.113
	(0.128)
Number of Days (AT 15–20°C) (Lead 8-14 days)	-0.082
	(0.133)
Number of Days (AT 10–15°C) (Lead 8-14 days)	0.508*
	(0.263)
Number of Days (AT 5–10°C) (Lead 8-14 days)	0.516
	(0.317)
Number of Days (AT 0–5°C) (Lead 8-14 days)	0.487
	(0.642)
Number of Days (AT<0°C) (Lead 8-14 days)	0.386
	(0.518)
Number of Days (AT >=30°C) (Lead 15-21 days)	-0.048
	(0.233)
Number of Days (AT 25–30°C) (Lead 15-21 days)	0.030
	(0.124)
Number of Days (AT 15–20°C) (Lead 15-21 days)	-0.071
	(0.161)
Number of Days (AT 10–15°C) (Lead 15-21 days)	-0.108
	(0.334)
Number of Days (AT 5–10°C) (Lead 15-21 days)	0.271
	(0.408)
Number of Days (AT 0–5°C) (Lead 15-21 days)	-0.509
	(0.591)
Number of Days (AT<0°C) (Lead 15-21 days)	-1.070

	(0.782)
Mean of dependent variable	3.139
Demographic characteristics	Yes
Other meteorological variables	Yes
City FE	Yes
Year-by-month FE	Yes
Linear and quadratic monthly trends	Yes
Observation	34,314
R^2	0.188

Table A3: Robustness check: alternative temperature exposure

	(1)	(2)
Temperature exposure measure	Daily maximum temperature	Daily minimum temperature
Number of Days (MT >=30℃)	0.201***	1.226***
	(0.076)	(0.326)
Number of Days (MT 25–30℃)	0.066	0.106**
	(0.088)	(0.042)
Number of Days (MT 15–20℃)	-0.075	0.072**
	(0.144)	(0.028)
Number of Days (MT 10–15℃)	-0.127	-0.103***
	(0.196)	(0.038)
Number of Days (MT 5–10℃)	0.073	0.148***
	(0.177)	(0.044)
Number of Days (MT 0–5℃)	-0.119	-0.002
	(0.217)	(0.116)
Number of Days (MT<0℃)	0.196	0.030
	(0.276)	(0.045)
Mean of dependent variable	3.139	3.139
Demographic characteristics	Yes	Yes
Other meteorological variables	Yes	Yes
Individual FE	Yes	Yes
City FE	Yes	Yes
Year-by-month FE	Yes	Yes
Linear and quadratic monthly trends	Yes	Yes
Observation	34,314	34,314
R^2	0.188	0.064

Note: The baseline temperature bin is 20–25℃. Demographic characteristics include household per capita income, self-reported relative income level and social status. Other meteorological characteristics include precipitation, relative humidity, wind speed, sunshine duration, and atmospheric pressure. Robust standard errors clustered at the city level are in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A4: Robustness check: alternative temperature bins

Temperature bin	(1) 3℃ bin		(2) 6℃ bin
Number of Days (AT >=30℃)	0.228***	Number of Days (AT >=30℃)	0.233***
	(0.056)		(0.084)
Number of Days (AT 27–30℃)	0.066*	Number of Days (AT 24–30℃)	0.057
	(0.037)		(0.053)
Number of Days (AT 24–27℃)	0.027	Number of Days (AT 12–18℃)	-0.075*
	(0.034)		(0.045)
Number of Days (AT 18–21℃)	-0.079	Number of Days (AT 6–12℃)	-0.050
	(0.049)		(0.126)
Number of Days (AT 15–18℃)	0.002	Number of Days (AT 0–6℃)	-0.179
	(0.057)		(0.163)
Number of Days (AT 12–15℃)	-0.287***	Number of Days (AT <0℃)	0.027
	(0.078)		(0.158)
Number of Days (AT 9–12℃)	0.145		
	(0.106)		
Number of Days (AT 6–9℃)	-0.336**		
	(0.143)		
Number of Days (AT 3–6℃)	-0.414**		
	(0.199)		
Number of Days (AT 0–3℃)	0.028		
	(0.166)		
Number of Days (AT <0℃)	-0.067		
	(0.099)		
Mean of dependent variable	3.139		3.139
Demographic characteristics	Yes		Yes
Other meteorological variables	Yes		Yes
Individual FE	Yes		Yes
City FE	Yes		Yes
Year-by-month FE	Yes		Yes
Linear and quadratic monthly trends	Yes		Yes
Observation	34,314		34,314
R^2	0.190		0.180

Note: The baseline temperature bin is 21–24℃, and 18–24℃ for columns (1) and (2), respectively. Demographic characteristics include household per capita income, self-reported relative income level and social status. Other meteorological characteristics include precipitation, relative humidity, wind speed, sunshine duration and atmospheric pressure. Robust standard errors clustered at the city level are in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A5: Additional results from subsamples related to job types

	(1) Subsample that do not report job types
Number of Days (AT >=30℃)	0.009
	(0.169)
Number of Days (AT 25–30℃)	0.056
	(0.091)
Number of Days (AT 15–20℃)	0.051
	(0.129)
Number of Days (AT 10–15℃)	-0.196
	(0.168)
Number of Days (AT 5–10℃)	-0.108
	(0.431)
Number of Days (AT 0–5℃)	0.458*
	(0.250)
Number of Days (AT<0℃)	-0.272
	(0.322)
Mean of dependent variable	3.256
Demographic characteristics	Yes
Other meteorological variables	Yes
Individual FE	Yes
City FE	Yes
Year-by-month FE	Yes
Linear and quadratic monthly trends	Yes
Observation	5536
R^2	0.0425

Note: The baseline temperature bin is 20–25℃. Demographic characteristics include household per capita income, self-reported relative income level and social status. Other meteorological characteristics include precipitation, relative humidity, wind speed, sunshine duration, and atmospheric pressure. Robust standard errors clustered at the city level in parentheses.

* p < 0.10, ** p < 0.05, *** p < 0.01.

Table A6: Effects of temperature exposure of the interview day on CES-D score

Temperature measure	(1) Interview day maximum temperature	(2) Interview day minimum temperature
AT >=30°C (0/1)	0.503	1.688*
	(0.619)	(0.978)
AT 25–30°C (0/1)	0.465	0.203
	(0.439)	(0.133)
AT 15–20°C (0/1)	-0.861	-0.033
	(0.733)	(0.114)
AT 10–15°C (0/1)	-1.014	-0.184
	(1.669)	(0.192)
AT 5–10°C (0/1)	-0.696	0.012
	(2.547)	(0.271)
AT 0–5°C (0/1)	0.703	-0.124
	(3.978)	(0.415)
AT<0°C (0/1)	4.188	-0.297
	(3.974)	(0.839)
Number of Days (AT >=30°C)		
Number of Days (AT 25–30°C)		
Number of Days (AT 15–20°C)		
Number of Days (AT 10–15°C)		
Number of Days (AT 5–10°C)		
Number of Days (AT 0–5°C)		
Number of Days (AT<0°C)		
Mean of dependent variable	3.139	3.139
Demographic characteristics	Yes	Yes
Other meteorological variables	Yes	Yes
Individual FE	Yes	Yes
City FE	Yes	Yes
Year-by-month FE	Yes	Yes
Linear and quadratic monthly trends	Yes	Yes
Observation	34,314	34,314
R^2	0.161	0.161

Note: The baseline temperature bin is 20–25°C. Demographic characteristics include household per capita income, self-reported relative income level and social status. Other meteorological variables include precipitation, relative humidity, wind speed, sunshine duration, and atmospheric pressure. Robust standard errors clustered at the city level in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A7: Effects of daily temperature variables over the last few days on mental health

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
AT >=30℃ (Interview day)	0.449	0.614	0.508	0.283	0.171	0.113	0.109	0.099
	(0.698)	(0.767)	(0.760)	(0.748)	(0.761)	(0.762)	(0.769)	(0.769)
AT 25–30℃ (Interview day)	-0.052	0.249	0.199	0.080	0.031	0.013	-0.007	-0.029
	(0.422)	(0.448)	(0.445)	(0.430)	(0.427)	(0.431)	(0.430)	(0.429)
AT 15–20℃ (Interview day)	-0.919*	-1.099*	-1.009*	-0.924	-1.009*	-1.011*	-1.006*	-0.991*
	(0.508)	(0.599)	(0.591)	(0.582)	(0.591)	(0.593)	(0.590)	(0.588)
AT 10–15℃ (Interview day)	0.357	-0.137	-0.100	-0.179	-0.309	-0.204	-0.147	0.098
	(1.122)	(1.330)	(1.370)	(1.300)	(1.301)	(1.324)	(1.287)	(1.308)
AT 5–10℃ (Interview day)	-0.252	-0.123	-0.139	-0.075	-0.416	-0.386	0.029	0.290
	(1.667)	(1.876)	(1.801)	(1.797)	(1.784)	(1.691)	(1.727)	(1.671)
AT 0–5℃ (Interview day)	-1.575	0.043	0.211	0.945	0.503	-0.340	0.453	0.722
	(3.656)	(2.579)	(2.330)	(2.107)	(2.099)	(1.904)	(1.951)	(1.934)
AT<0℃ (Interview day)	1.964	5.433**	4.333	5.321*	4.710	3.900	4.455	4.439
	(3.172)	(2.678)	(2.658)	(2.938)	(3.184)	(3.165)	(3.187)	(3.290)
AT >=30℃ (Lag 1 day)		0.884	0.899	0.857	0.812	0.800	0.832	0.969
		(0.663)	(0.779)	(0.794)	(0.795)	(0.792)	(0.797)	(0.798)
AT 25–30℃ (Lag 1 day)		-0.441	-0.335	-0.400	-0.456	-0.448	-0.460	-0.471
		(0.466)	(0.529)	(0.529)	(0.527)	(0.524)	(0.528)	(0.526)
AT 15–20℃ (Lag 1 day)		0.169	0.228	0.244	0.370	0.357	0.353	0.357
		(0.485)	(0.540)	(0.547)	(0.562)	(0.555)	(0.563)	(0.569)
AT 10–15℃ (Lag 1 day)		0.776	0.587	0.514	0.561	0.537	0.406	0.302
		(1.057)	(1.158)	(1.146)	(1.149)	(1.168)	(1.197)	(1.162)
AT 5–10℃ (Lag 1 day)		-0.189	-0.466	-0.677	-0.548	-0.329	-0.248	-0.031
		(1.978)	(2.305)	(2.381)	(2.314)	(2.315)	(2.295)	(2.307)
AT 0–5℃ (Lag 1 day)		-2.175	-1.896	-2.419	-2.714	-3.281	-3.070	-2.383
		(3.033)	(3.621)	(3.800)	(3.845)	(3.847)	(3.672)	(3.751)
AT<0℃ (Lag 1 day)		-4.538	-5.710	-6.805	-7.311	-8.664*	-8.831*	-8.607*
		(4.085)	(4.687)	(4.877)	(4.760)	(5.062)	(4.881)	(4.810)
AT >=30℃ (Lag 2 day)			1.785**	1.709**	1.741**	1.789**	1.876**	1.844**
			(0.776)	(0.812)	(0.803)	(0.810)	(0.803)	(0.798)
AT 25–30℃ (Lag 2 day)			-0.128	-0.309	-0.340	-0.364	-0.378	-0.390

	(0.460)	(0.438)	(0.439)	(0.435)	(0.434)	(0.434)
AT 15–20℃ (Lag 2 day)	-0.323	-0.546	-0.602	-0.619	-0.627	-0.619
	(0.557)	(0.497)	(0.521)	(0.521)	(0.518)	(0.516)
AT 10–15℃ (Lag 2 day)	0.131	-0.442	-0.562	-0.460	-0.507	-0.569
	(1.235)	(1.387)	(1.339)	(1.279)	(1.243)	(1.282)
AT 5–10℃ (Lag 2 day)	0.412	0.802	0.677	0.541	0.459	0.642
	(1.862)	(1.821)	(1.792)	(1.837)	(1.854)	(1.836)
AT 0–5℃ (Lag 2 day)	-1.051	1.018	1.285	0.760	0.496	0.870
	(3.610)	(3.501)	(3.520)	(3.556)	(3.574)	(3.370)
AT<0℃ (Lag 2 day)	2.664	5.633	6.238	5.711	4.995	5.458
	(4.517)	(6.573)	(6.283)	(6.471)	(6.413)	(6.165)
AT >=30℃ (Lag 3 day)		1.072*	1.086*	1.150*	1.144*	1.139*
		(0.603)	(0.626)	(0.612)	(0.609)	(0.602)
AT 25–30℃ (Lag 3 day)		0.543	0.467	0.510	0.509	0.498
		(0.443)	(0.432)	(0.431)	(0.436)	(0.437)
AT 15–20℃ (Lag 3 day)		0.263	-0.300	-0.258	-0.244	-0.229
		(0.622)	(0.718)	(0.715)	(0.718)	(0.713)
AT 10–15℃ (Lag 3 day)		1.255	-0.259	-0.267	-0.241	-0.328
		(1.245)	(1.538)	(1.514)	(1.495)	(1.476)
AT 5–10℃ (Lag 3 day)		-0.059	-3.555**	-3.306**	-3.204*	-3.336*
		(1.400)	(1.621)	(1.628)	(1.685)	(1.687)
AT 0–5℃ (Lag 3 day)		-2.710	-7.430***	-7.074***	-6.626**	-6.921**
		(3.043)	(2.408)	(2.559)	(2.594)	(2.690)
AT<0℃ (Lag 3 day)		-3.003	-7.834	-6.727	-6.416	-6.888
		(5.223)	(4.976)	(5.075)	(5.160)	(4.871)
AT >=30℃ (Lag 4 day)			1.501**	1.677***	1.671***	1.621**
			(0.585)	(0.630)	(0.639)	(0.645)
AT 25–30℃ (Lag 4 day)			0.201	0.184	0.160	0.139
			(0.399)	(0.412)	(0.414)	(0.414)
AT 15–20℃ (Lag 4 day)			0.888	1.260*	1.292*	1.296*
			(0.629)	(0.671)	(0.685)	(0.684)
AT 10–15℃ (Lag 4 day)			2.227*	2.594*	2.614*	2.648*
			(1.304)	(1.403)	(1.421)	(1.449)
AT 5–10℃ (Lag 4 day)			5.036**	4.788**	4.649**	4.458**

	(1.998)	(1.930)	(1.933)	(2.066)
AT 0–5℃ (Lag 4 day)	6.402***	2.771	2.123	2.250
	(2.062)	(2.159)	(2.333)	(2.299)
AT<0℃ (Lag 4 day)	6.269	1.146	0.057	-0.669
	(4.181)	(5.706)	(5.896)	(5.426)
AT >=30℃ (Lag 5 day)		1.520**	1.306*	1.259*
		(0.630)	(0.695)	(0.694)
AT 25–30℃ (Lag 5 day)		-0.111	-0.247	-0.262
		(0.372)	(0.383)	(0.384)
AT 15–20℃ (Lag 5 day)		-0.780	-0.828	-0.792
		(0.573)	(0.586)	(0.576)
AT 10–15℃ (Lag 5 day)		-0.760	-0.310	-0.321
		(0.990)	(1.057)	(1.040)
AT 5–10℃ (Lag 5 day)		-0.236	1.562	1.677
		(1.394)	(1.506)	(1.451)
AT 0–5℃ (Lag 5 day)		6.592**	8.972***	8.931***
		(2.780)	(3.199)	(3.106)
AT<0℃ (Lag 5 day)		7.208	8.710	8.644*
		(4.886)	(5.271)	(5.110)
AT >=30℃ (Lag 6 day)			1.477**	1.679**
			(0.650)	(0.715)
AT 25–30℃ (Lag 6 day)			0.346	0.365
			(0.399)	(0.401)
AT 15–20℃ (Lag 6 day)			0.161	0.121
			(0.570)	(0.629)
AT 10–15℃ (Lag 6 day)			-0.664	-0.368
			(0.881)	(0.938)
AT 5–10℃ (Lag 6 day)			-2.714	-1.191
			(1.850)	(2.046)
AT 0–5℃ (Lag 6 day)			-3.457	-0.689
			(2.403)	(2.594)
AT<0℃ (Lag 6 day)			-0.447	1.335
			(3.159)	(3.492)
AT >=30℃ (Lag 7 day)				1.263**

								(0.622)
AT 25–30℃ (Lag 7 day)								0.043
								(0.433)
AT 15–20℃ (Lag 7 day)								0.109
								(0.472)
AT 10–15℃ (Lag 7 day)								-0.376
								(1.016)
AT 5–10℃ (Lag 7 day)								-2.063
								(0.958)
AT 0–5℃ (Lag 7 day)								-3.958
								(2.445)
AT<0℃ (Lag 7 day)								-0.611
								(4.277)
Mean of dependent variable	3.139	3.139	3.139	3.139	3.139	3.139	3.139	3.139
Demographic characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Other meteorological variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-by-month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Linear and quadratic monthly trends	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observation	34,314	34,314	34,314	34,314	34,314	34,314	34,314	34,314
R^2	0.164	0.172	0.174	0.177	0.186	0.199	0.204	0.208

Table A8: Mechanisms of the depression effects of high temperature exposure: mediation analysis

Mediator	(1) No. of Physical Exercise	(2) Physical Exercise (0/1)	(3) Sleep Time (hour)	(4) Inadequate Sleep (0/1)
Number of Days (AT >=30°C)×Mediator	0.017	0.059	-0.039***	0.327***
	(0.014)	(0.085)	(0.013)	(0.105)
Number of Days (AT 25–30°C)×Mediator	-0.006	0.024	-0.016***	0.110**
	(0.008)	(0.043)	(0.006)	(0.049)
Number of Days (AT 15–20°C)×Mediator	-0.022**	-0.082	0.009	-0.067
	(0.009)	(0.054)	(0.007)	(0.057)
Number of Days (AT 10–15°C)×Mediator	0.011	0.082	0.003	-0.040
	(0.012)	(0.089)	(0.010)	(0.084)
Number of Days (AT 5–10°C)×Mediator	0.023	0.117	-0.015	0.077
	(0.025)	(0.188)	(0.019)	(0.146)
Number of Days (AT 0–5°C)×Mediator	-0.014	0.029	0.014	0.007
	(0.024)	(0.166)	(0.010)	(0.089)
Number of Days (AT<0°C)×Mediator	-0.008	-0.137	-0.022**	0.213***
	(0.024)	(0.133)	(0.010)	(0.081)
Mediator	0.145	0.000	-0.015	-0.825
	(0.124)	(0.763)	(0.102)	(0.818)
Number of Days (AT >=30°C)	0.186**	0.196**	0.475***	0.134**
	(0.089)	(0.092)	(0.102)	(0.059)
Number of Days (AT 25–30°C)	0.046	0.029	-0.117**	0.013
	(0.052)	(0.055)	(0.046)	(0.034)
Number of Days (AT 15–20°C)	-0.028	-0.037	-0.119**	-0.047
	(0.063)	(0.065)	(0.054)	(0.048)
Number of Days (AT 10–15°C)	-0.131*	-0.140*	0.022	0.044
	(0.077)	(0.079)	(0.061)	(0.063)
Number of Days (AT 5–10°C)	-0.185	-0.184	0.058	-0.031
	(0.241)	(0.250)	(0.107)	(0.136)
Number of Days (AT 0–5°C)	-0.101	-0.128	-0.014	0.054
	(0.162)	(0.164)	(0.067)	(0.073)
Number of Days (AT<0°C)	0.002	0.035	0.066	-0.122*
	(0.164)	(0.174)	(0.057)	(0.074)
Mean of dependent variable	3.139	3.139	3.139	3.139
Demographic characteristics	Yes	Yes	Yes	Yes
Other meteorological variables	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes
Year-by-month FE	Yes	Yes	Yes	Yes
Linear and quadratic monthly trend	Yes	Yes	Yes	Yes
Observation	34,314	34,314	34,314	34,314
R^2	0.187	0.187	0.188	0.186

Note: The baseline temperature bin is 20–25°C. Demographic characteristics include household per capita income, self-reported relative income level and social status. Other meteorological variables include precipitation, relative humidity, wind speed, sunshine duration, and atmospheric pressure. Robust standard errors clustered at the city level in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A9: Examine the influencing mechanism of sleep

	(1)
Average minimum temperature in the previous 30-day period	0.536*
	(0.315)
Average maximum temperature in the previous 30-day period	0.296
	(0.337)
Mean of dependent variable	3.139
Demographic characteristics	Yes
Other meteorological variables	Yes
Individual FE	Yes
City FE	Yes
Year-by-month FE	Yes
Linear and quadratic monthly trends	Yes
Observation	34,314
R^2	0.172

Note: Demographic characteristics include household per capita income, self-reported relative income level and social status. Other meteorological variables include precipitation, relative humidity, wind speed, sunshine duration, and atmospheric pressure. Robust standard errors clustered at the city level in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.