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Effects of temperature on mental health: Evidence and mechanisms from China

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ABSTRACT

We study how temperature exposure affects mental health in a developing country using data from China Family Panel Studies (CFPS). We find that exposure to high temperatures leads to worse mental health. Specifically, one additional day above 27 °C during the past week would increase individuals' total CESD 8 score by 1.5%, and the likelihood of having severe mental illness by 6.2% relative to a day in the reference temperature bin. We further estimate the potential mitigating effects of air conditioning on the relationship between temperature and mental health. We find that the identified relationship is mitigated by installing air conditioning. We also test some mechanisms through which temperature might impact mental health, including physical health status and sleep. We further discuss the overall health expenditure burden associated with climate change.

1. Introduction

Mental health is an important component of human health. Mental health is a state of well-being in which a person can cope with stress, work productively, and contribute to the community (WHO, 2014). Mental illness causes significant economic and health losses. The WHO (2017) estimated that at least 300 million people suffer from mental disorders around the world. In 2010, mental illness costs reached USD 2.5 trillion, which was nearly 50% of the global health spending (WHO, 2010). People with severe mental illness could die 10–20 years earlier than the normal population (WHO, 2018).

This paper estimates the causal effects of temperature on mental health in the largest developing country, China. Mental health has become a major public health and social problem in China. The current prevalence of mental disorders among adults in China is 17.5%. However, the rate of diagnosis and treatment is relatively low, with an average treatment rate of 0.15% (Que, Lu, and Shi, 2019). The estimated health care expenditure for mental disorders in 2013 was $88.8 billion, which accounted for over 15% of the total health care expenditure in China. Given that millions of Chinese people suffer from untreated mental illnesses and psychiatric disorders, the potential economic costs could be much higher than the actual estimated mental health treatment costs (Xu, Wang, Wimo, and Qiu, 2016).

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Our primary analyses are based on self-reported mental health status data from the China Family Panel Studies (CFPS), which is one of the most comprehensive surveys in China. Since 2010, the CFPS has interviewed approximately 16,000 households across 162 counties in China. The CFPS asked eight questions regarding mental health performance, including depression, effortlessness, poor sleep quality, unhappiness, loneliness, not enjoying life, sadness and the inability to get started on a task. All the eight questions form the total mental health score (CESD 8 scale), which is extensively used as a clinical screening tool for determining the presence of major depression.

This paper measured the linear and nonlinear effects of temperature on mental health. First, we tested the linear relationship between temperature and mental health. We used daily average temperature to explore the impacts of temperature on self-reported mental illness. Second, we utilized a semiparametric approach, which counts the number of days during the past week that falls into 3 °C wide temperature bins (Barreca, Clay, Deschenes, Greenstone, and Shapiro, 2016; Mullins and White, 2019). We find that high temperature increases the CESD 8 scores and the probability of severe mental health problems using linear and nonlinear methods. Our results are both statistically significant and economically significant. Specifically, an additional day above 27 °C during the past week would lead to individuals reporting 0.0783 higher scores of the total CESD 8 scores (1.5% to the mean) and 0.62%age points higher of reporting severe mental illness (6.2 percent to the mean), relative to a day in the reference temperature bin (18–21 °C). Our results reveal adverse effects of high temperature on mental health, consistent with the existing studies such as Mullins and White (2019).

We further estimate the factors that might mitigate the relationship between heat and mental health. We specifically use individual-level air conditioning as a means of adaptation. Our models include a temperature and time trend interaction term to allow air conditioning ownership to vary over time. Our results show that installing air conditioning could mediate the adverse effects of excess heat on mental health.

In addition, we explore the heterogeneous effects of excess heat on mental health by splitting our samples into different subgroups by gender, age, education, and living in urban/rural areas. Our results do not find dramatic heterogeneous impacts of temperature on mental health outcomes among different demographic groups. Finally, we further investigate the indirect channels that might affect the relationship between temperature and mental health status. We found that high temperature significantly affected mental health outcomes through general physical health status, sleep quality, and sleep hours. Our results remain the same for many robustness checks.

This paper contributes to the literature in three ways. First, it adds to the limited literature on climate change and mental health by providing a study on a developing country, China. The existing limited studies that estimate extreme weather effects on mental health mainly focus on developed countries (Burke et al., 2018; Mullins and White, 2019; Obradovich, Migliorini, Paulus, and Rahwan, 2018), while studies on developing countries are lacking. This question is crucial for developing countries. First, the developing world will experience disproportionately higher temperatures, and most residents work in climate-exposed environments (Harrington et al., 2016). In addition, people in developing countries have difficulty smoothing their consumption across aggregate weather shocks (Bhugra et al., 2017; Cole et al., 2013; Deaton, 1997).

Second, unlike Obradovich et al. (2018) and Mullins and White (2019), who use a randomly sampled, pooled cross-section of respondents, we use nationally representative panel data, which controls individual fixed effects. Identifying the causal effect of high temperature on mental health would not be accurate due to the failure to include unobservable attributes that could affect mental health outcomes, such as individuals' personalities and temperaments. Individual fixed effects can eliminate self-selection bias and significantly improve identification.

Third, we use individual-level air conditioning data to estimate the modifying effects of temperature on mental health. Earlier attempts to estimate adaptation assume that the relationship between temperature and health is the same for people with and without air conditioning and that the relationship is also constant over time in the absence of increasing air conditioning penetration (Barreca et al., 2016; Mullins and White, 2019). We are the first study to relax the above assumptions by using individual-level air condition data from CFPS to provide evidence regarding adaptation.

The remainder of the paper is organized as follows. Section 2 describes the direct and indirect channels through which high temperature might affect mental health. Section 3 analyses the empirical models, and Section 4 discusses our data. Section 5 shows our main results, and Section 6 discusses the policy and welfare implications and concludes the paper.

2. Mechanisms

Temperature can affect mental health in both direct and indirect ways (Berry, Bowen, and Kjellstrom, 2010). Directly, heat can cause poorer concentration and elevated fatigue (Howarth and Hoffman, 1984) and further lead to aggression (Anderson and Anderson, 1998). Researchers find that high temperatures are associated with higher rates of criminal and aggressive behavior (Cheatwood, 1995; Cohn, Rotton, Peterson, and Tarr, 2004), suicide, and mental and behavioral disorders (Hansen et al., 2008; Maes, Meyer, Thompson, Peeters, and Cosyns, 1994).

There are several indirect ways through which temperature could affect mental health. First, high ambient temperature could cause excessive core body temperature (Leihead and Lind, 1964) and dehydration (Schrier et al., 1970), which could further reduce people's capacity to undertake physical and mental tasks (Bridger, 2008; Kjellstrom, Holmer, and Lemke, 2009). The loss of work capacity and the resulting loss of income can cause mental health problems as well (Kjellstrom, 2009).

Second, temperature could affect mental health through physical health and behavioral channels. Physical and mental health are causally and reciprocally associated (Miller, Chen, and Cole, 2009; Prince et al., 2007). Excessive heat can cause heat stroke and dehydration and cardiovascular, respiratory, and cerebrovascular diseases (U.S. EPA, 2017). Anxiety and depression may occur because of stress, fear, and misinterpretation of physical symptoms. On the other hand, heat exposure could disturb sleep (Kovats and Hajat, 2008; Obradovich et al., 2018), which may further cause mental issues (Arimura, Imai, Okawa, Fujimura, and Yamada, 2010; Reid et al., 2006).

Third, temperature might affect mental health outcomes through other indirect channels. For example, there is evidence to show that high temperature significantly reduces workers' productivity (Zhang, Deschenes, Meng, and Zhang, 2018) and might further reduce their income. Income is a critical determinant factor affecting mental health outcomes (Gardner and Oswald, 2007; Golberstein, 2015). The reduction in worker productivity and income caused by excess heat may cause additional job-related stress and fear of job loss. Both of these factors result in decreased mental health (Kopp, Stauder, Purebl, Janszky, and Skrabski, 2008; Paul and Moser, 2009; Wang, Lesage, Schmitz, and Drapeau, 2008).

3. Data

3.1. Mental health

We use data drawn from the China Family Panel Studies (CFPS), which is a nationally representative survey conducted by Peking University. To date, there have been five waves of the survey in 2010, 2012, 2014, and 2016 and 2018.[2] During each wave, approximately 27,000 residents were surveyed across 162 counties in 25 provinces in China. The CFPS collects detailed health information, including self-reported mental health status, physical health outcomes and personal demographic background, such as education, gender, and residence location. Our estimation sample includes individuals who were above 18 years old at the time of the interview.

The key independent variable, i.e., self-reported mental health status, is reflected by eight questions that were asked regarding the state of an individual's mental health in wave 2012 and wave 2016.[3] Specifically, the respondents were asked about how often they had the following feelings over the past week: "I felt depressed;" "I felt everything I did was an effort;" "My sleep was restless;" "I enjoyed life;" "I felt lonely;" "I was happy;" "I felt sad;" and "I could not get going." For each question, the interviewee could choose one of the following answers: never (zero points), sometimes (one point), often (two points), or most of the time (three points). The answers to these questions are typically called CESD scores. One can then aggregate all points into a single score, namely, the CESD 8 score.[4] The CESD 8 score thus ranges from 0 to 24, with a higher number indicating the presence of a severe mental disorder. The advantage of using CFPS self-reported mental health outcomes is that the recall period is only for one week, which is much closer to the interview date than most other survey data, which collect self-reported mental health outcomes during the past month. The respondents are less likely to have biased recall on their mental health problems when recalling the feelings.

The Center for Epidemiologic Studies Depression scale (CESD) score was initially developed by Laurie Radloff for research use. It has been widely used in the health literature and by government agencies as a clinical screening tool for the presence of major depression. CESD is currently one of the most widely used measures in psychiatric epidemiology. The full version of CESD has 20 items in total.[5] Including all 20 items may mean that a longer length of time is necessary for respondents to complete the survey and, thus, may reduce the respondents' motivation to participate (Karim, Weisz, Bibi, Rehman, and ur., 2015). Shortened versions of the CESD have been developed (Andresen, Malmgren, Carter, and Patrick, 1994; Santor and Coyne, 1997; Van, Levecque, and Bracke, 2009), and the most commonly used abbreviated version is CESD 8 (Turvey, Wallace, and Herzog, 1999).[6] The short version of the CESD 8 has the same level of reliability and validity as the CESD 20 scale (O'Halloran, Kenny, and King-Kallimanis, 2014).

CFPS collected both CESD 20 and CESD 8 in wave 2012 and wave 2016; however, the number of observations is significantly larger for CESD 8. We mainly focus on the estimation of CESD 8 due to the much larger number of observations. Although CESD 8 scores are not a direct measure of psychiatric disorders, they have at least two strengths. First, the measure is spatially and temporally referenced so that one can merge it precisely with the weather data. Second, unlike medical data, which can capture only clinical mental illness, this measure is able to capture both clinical and subclinical mental illness (Lewinsohn, Seeley, Roberts, and Allen, 1997). We defined a

[2] The estimation of this paper requires us to use the interview dates and county residence data, which are the restricted data from CFPS. We only obtained the restricted data for waves 2010, 2012, 2014, and 2016. The restricted data from the newly released 2018 wave is not available yet, so we can not utilize the samples from the 2018 wave.

[3] CFPS interviewed their samples' mental health outcomes in all available waves, however the questions are quite different among different waves. In 2010 and 2014 waves, CFPS asked six questions about mental health during the past 30 days. They are typical questions of Kessler Psychological Distress Scale (K6). Please see vac802e.xft (vac-acc.gc.ca) for specific questions. In 2012 and 2016 waves, CFPS used the mental health measures of Center for Epidemiological Studies Depression (CESD) during past seven days. The two different systems of mental health measurements avoid us to use all the available waves of CFPS data.

[4] Among the eight symptoms of depression, two of them are measured in the positive way ("I enjoyed life" and "I was happy"). We reverse coded these two measures.

[5] The list of the CESD 20 items can be found at Center for Epidemiologic Studies Depression Scale (CES-D) (brown.edu).

[6] The 8 items include symptoms of sadness, loss of interest, appetite, sleep, thinking/concentration, worthlessness, fatigue, and movement.

dummy variable for severe mental illness when the CESD 8 score was equivalent to or above 11.[7] As shown in Table 1, the average CESD 8 score was 5.25, and 10% of our samples reported having severe mental illness. Fig. 1 illustrates the distribution of total CESD 8 scores, and the red line denotes the cutoff of 11 for severe mental illness.

3.2. Weather

The weather data are obtained from the National Meteorological Information Center of China (NMICC). The NMICC publishes daily weather variables, including temperature, precipitation, relative humidity, wind speed, sunshine duration and atmospheric pressure, for approximately 800 weather stations in China. We use the inverse distance weighting (IDW) method to convert weather data from station to county. The IDW method has been widely used in the related literature (e.g., Deschênes and Greenstone, 2011).[8] We then matched the weather data with the CFPS data according to the county residence and interview date. We use the mean of the daily average temperature in our baseline regression. Since the CFPS asked the interviewees to self-report their mental health conditions during the past week, we took the average of the daily mean temperature for the past seven days (interviewed date included) as our primary interest. We also took the mean relative humidity, wind speed, and sunshine duration by county during the past week. For precipitation, we took the summation of daily precipitation over the past week.

Table 1, Panel A presents the summary statistics of the weather variables during the past week. The mean of daily average ctemperature during the past week was 21.31 °C.[9] The histogram of the past week average temperature is plotted in Fig. 2. We specifically plot the average temperature histogram figure by urban and rural areas. The figure shows that the average temperature during the past week ranged from negative 28.9 °C to 33.8 °C, with a peak at approximately 25 °C for rural samples and slightly higher than 25 °C for urban samples. We further construct the number of days during the past week that daily average temperature falls into the 3 °C wide bins: below 0 °C, 0–3 °C, 3–6 °C, 6–9 °C, 9–12 °C, 12–15 °C, 15–18 °C, 18–21 °C, 21–24 °C, 24–27 °C, and above 27 °C. As shown in Table 1 of Panel A, we have ten temperature bins in total. The minimum of the number of days for each bin is zero and the maximum number of days for each bin is seven days over the past week.

4. Empirical method

4.1. Baseline analysis

The relationship between temperature and self-reported mental health at the individual level is depicted by the following equation:

$$MH_{ict} = \beta_0 + \beta_1 TEM_{ict} + \beta_2 \mathbf{W}_{ct} + \alpha_i + \gamma_t + \rho_c + \varepsilon_{it} \tag{1}$$

In the above model, i stands for each individual, c denotes the county where the individual lives, and t is the year-by-month of the interview. MH_{ict} stands for self-reported mental health outcomes.

We have two measures for self-reported mental health. One is the total score of CESD 8. The higher number of CESD 8 indicates the presence of a severe mental disorder. And we also created a dummy variable for severe mental illness that was equal to one if an individual's total CESD 8 score was equivalent to or >11, and zero otherwise. Because the respondents were asked about their mental health status over the past week in the interview, all the weather variables were constructed within the prior week, including the day of interview. The variable of interest is TEM_{ict}, which is the mean of the daily average temperature for individual i living in county c during the past week.

The vector, $\boldsymbol{W}_{ct}$, includes controls for other climatic variables, namely, precipitation, relative humidity, wind speed, atmospheric pressure and sunshine duration. All weather variables are averaged over the past week using daily values. The advantage of including the individual fixed effects (α_i) is that any time-invariant, individual-specific characteristics that might affect their mental health, such as personalities and temperaments, are controlled. ρ_c stands for county fixed effects to control for any county-specific time-invariant characteristics, including geography or cultural features. We use γ_t, i.e., the year-by-month fixed effects, to control for nationwide monthly shocks. People who were interviewed during holiday seasons were more likely to have better mental health performance (Ajdacic-Gross et al., 2006; Fang, Lei, Lin, and Zhang, 2021). In our robustness checks, we also include county-specific linear trends in the model to control for any county-level and time-variant factors that may contaminate our estimations. The standard errors, ε_{it}, are clustered at both county-year-month and individual levels. Last, the baseline regression models are weighted by the sample weights of each individual, which is the ratio between the county population and the interviewed population, to make our estimates nationally representative. Our coefficient of interest is β_1. The linear estimation of temperature represents the change in the total CESD score or the likelihood change of having severe mental illness when the daily average temperature during the past week increased by 1 °C.

[7] The cutoff for CESD 20 was 16 out of 60 for possible depression, and the cutoff for severe mental illness was 28 out of a total score of 60, which is indicated by the Center for Epidemiologic Studies Depression Scale. We followed the traditional proportional strategy to convert the cutoff of severe mental illness from CESD 20 to CESD 8 (Steffick, Wallace, and Herzog, 2000). The total score for CESD 8 is 24. Hence the cutoff of severe mental illness for CESD 8 is equivalent to 11, which is proportionally equal to 28 when the total CESD score is 60. See *CESD-R: Center for Epidemiologic Studies Depression Scale Revised Online Depression Assessment » CESD-R Explanation.*

[8] The basic algorithm takes the weighted average for all weather stations within a given radius (200 km) based on the county centroid, where the weights are the inverse distance from each weather station to the county centroid.

[9] As plotted in Figure A1, most of the interviews were conducted during July and August, so the average temperature is relatively high.

Table 1
Summary statistics.

	Obs.	Mean	SD	Min	Max
Panel A: Weather during the past week					
Number of days below 0 °C	41,416	0.47	1.64	0	7
Number of days between 0 and 3 °C	41,416	0.14	0.66	0	7
Number of days between 3 and 6 °C	41,416	0.14	0.69	0	7
Number of days between 6 and 9 °C	41,416	0.16	0.73	0	7
Number of days between 9 and 12 °C	41,416	0.15	0.70	0	7
Number of days between 12 and 15 °C	41,416	0.14	0.61	0	7
Number of days between 15 and 18 °C	41,416	0.27	0.91	0	7
Number of days between 18 and 21 °C	41,416	0.58	1.35	0	7
Number of days between 21 and 24 °C	41,416	1.10	1.74	0	7
Number of days between 24 and 27 °C	41,416	1.62	2.01	0	7
Number of days above 27 °C	41,416	2.22	2.80	0	7
Average temperature past week (°C)	41,416	21.31	10.19	−28.92	33.82
Relative humidity (%)	41,416	74.67	9.60	23.75	98.32
Wind speed (m/s)	41,416	2.11	0.72	0.59	7.74
Sunshine duration (hour)	41,416	6.16	2.47	0	12.71
Pressure (hpa)	41,416	956.42	63.03	777.58	1031.71
Precipitation (mm)	41,416	30.00	37.26	0	295.97
Panel B: Mental health outcomes					
CESD 8 score (0–24)	41,416	5.25	4.03	0	24
Severe mental illness (CESD 8 ≥11)	41,416	0.10	0.30	0	1
Depression (0-never; 3-most times)	41,416	0.65	0.76	0	3
Effortless (0-never; 3-most times)	41,416	0.69	0.86	0	3
Poor sleep (0-never; 3-most times)	41,416	0.73	0.90	0	3
Unhappy (0-never; 3-most times)	41,416	1.14	0.98	0	3
Loneliness (0-never; 3-most times)	41,416	0.40	0.71	0	3
Did not enjoy life (0-never; 3-most times)	41,416	1.01	0.96	0	3
Sadness (0-never; 3-most times)	41,416	0.44	0.67	0	3
Not get going (0-never; 3-most times)	41,416	0.19	0.53	0	3
Panel C: Demographic controls					
Age	41,414	49	15	18	96
Male	41,238	0.48	0.50	0	1
Married	41,234	0.45	0.50	0	1
Years of schooling	41,389	6.72	4.84	0	22
Urban	41,414	0.86	0.35	0	1
Employed	40,869	0.68	0.47	0	1
Own air conditioner	20,708	0.29	0.45	0	1

Notes: The summary of the data is derived from CFPS, which covers 162 counties from 2012 to 2016. The CFPS interviewed their respondents regarding their feelings of mental health well-being (CESD) during the past week. For each question, the interviewee could choose from the following options: never (0 points), sometimes (1 point), often (2 points), and most of the time (3 points). We defined a severe mental illness dummy that equal to one if the total CESD 8 score was >11. The temperature bins measure the number of days in which the temperature falls into each bin during the past week.

Second, to measure the nonlinear effects of temperature, we further use the binned approach that is followed by Barreca et al. (2016) and Mullins and White (2019). The estimation is presented in the following form.

$$MH_{ict} = \beta_0 + \sum_{j=1}^{10} \beta_j TEM_{ict} + \beta_2 \mathbf{W}_{ct} + \alpha_i + \gamma_t + \rho_c + \varepsilon_{it} \tag{2}$$

All the definitions are the same as we described in Eq. (1). We generated a series of 3 °C bins, which measure the number of days that the daily average temperature falls into 3 °C wide bins. There are ten bins in total, ranging from below 0 °C to above 27 °C. We use the 3 °C bins to replace the daily average temperature during the past week. The temperature bin 18–21 °C is omitted in the regressions as the reference. The interpretation of the coefficients of interest would be the change in the total score of CESD 8 or the probability of having severe mental illness if one additional day falls into the bin relatives to a day in the omitted bin (18–21 °C). Panel A of Table 1 shows that the average number of days above 27 °C is 2.22, and the average number of days below 0 °C is 0.47. This trend is consistent with the skewed temperature distribution shown in Fig. 2.

We use the one-week exposure window in the baseline model since the questions asked are concerned with mental well-being over the week prior to the interview date. We further changed the exposure window to the past one month, two months, three months, and four months to explore whether the effect of temperature on mental health was short-lived or accumulative. Last, we use the lead exposure window, i.e., the temperature after the interview date, as the placebo test.

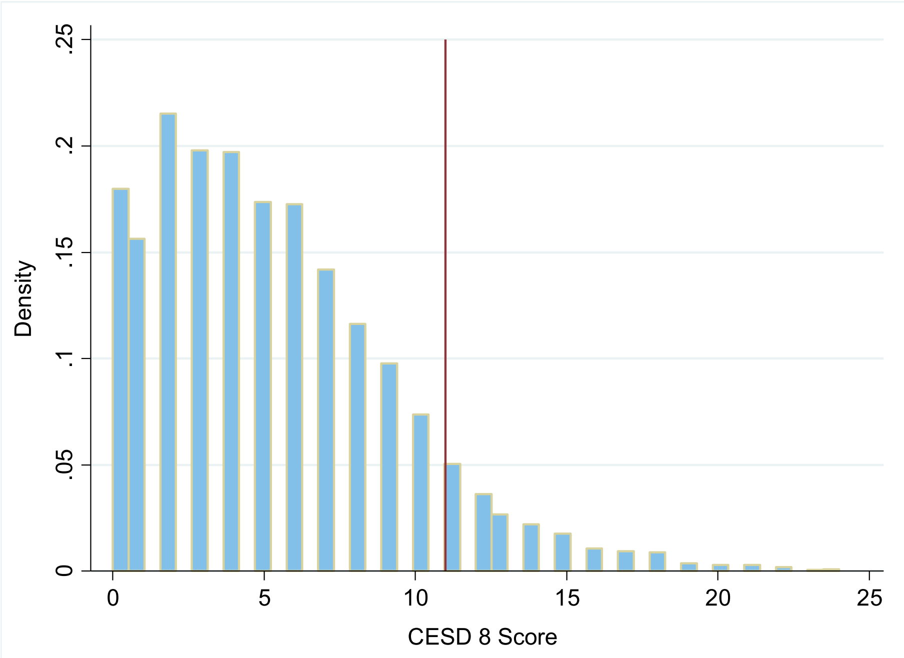


Fig. 1. Histogram of CESD 8.
Notes: This figure plots the histogram of the CESD 8 score, which ranges from 0 to 24. The vertical red line indicates the cutoff of 11. We defined the severe mental illness dummy by the cutoff of 11. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

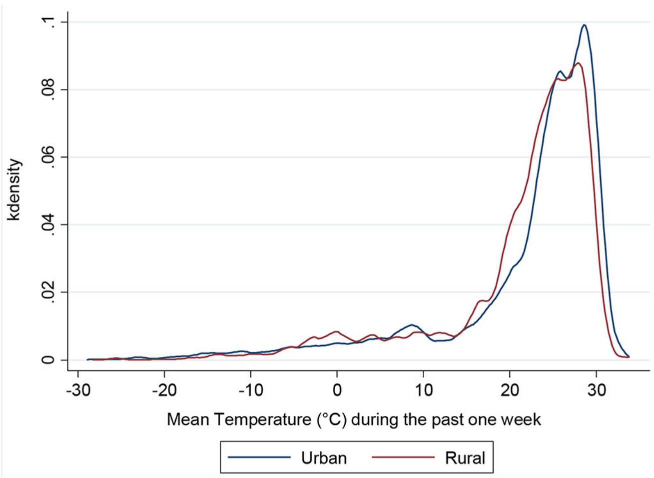


Fig. 2. Histogram of the average temperature in urban/rural areas in the past week.
Notes: This figure depicts the distribution of the mean temperature over the past week during the 2012–2016 waves of the CFPS. The mean temperature is calculated based on the daily average temperature.

4.2. Adding air conditioning for adaptation

Recent research has attempted to identify the factors that might serve as modifiers for the harm of excess heat. If factors that can modify the relationship between ambient temperature and human health are identified, policy-makers could implement interventions to benefit society as a whole, especially for the most vulnerable subgroup populations. Existing studies have tested factors, such as electricity, air conditioning penetration, and access to mental health care professionals, that might moderate the relationship between temperature and health and, thus, protect the human body from the harms caused by heat waves in the U.S. context (Barreca et al., 2016). They specifically use state-level electricity and air conditioning penetration rates to conduct empirical specifications for the relationship between temperature and mortality rates. Air conditioning might also improve mood or overall mental health outcomes during hot days. In this section, we consider whether air conditioning medigates the positive relationship between temperature and mental health problems.

One particular advantage of our estimation is that we use individual-level air conditioning information instead of state-level air conditioning penetration rates in this study. This is the first study that attempts to identify the effects of temperature on health by including individual fixed effects and using individual-level air conditioning information. The model used to test the adaptation of air conditioning is as follows:

$$MH_{ict} = \alpha_0 + \delta_1 TEM_{ict} + \delta_2 AC_{it} + \delta_3 TEM_{ict}{*}AC_{it} + \theta \mathbf{W}_{ct} + \alpha_i + \gamma_t + \rho_c + \varepsilon_{ict} \tag{3}$$

In Eq. (3), MH_{ict} represents the self-reported mental health outcomes in county c at time t for individual i. AC_{it} represents the dummy of owning an air conditioner for individual i living in county c at time t. We interact AC_{it} with the average temperature over the past week, and our primary coefficient of interest in this estimation is δ_3. If we find that the coefficient of the interaction term δ_3 is significantly different from zero, then air conditioning significantly alleviates the effects of temperature on mental health outcomes.

Our strategy for testing the adaptation of air conditioning presented in Eq. (3) is similar to that of Barreca et al. (2016) and Mullins and White (2019) but with some differences. Both Barreca et al. (2016) and Mullins and White (2019) used the state-level air conditioning penetration rate, while we used individual-level air conditioning data and controlled for individual fixed effects. However, the approach used by Barreca et al. (2016) and Mullins and White (2019) cannot be interpreted as a causal effect of air conditioning on the relationship between temperature and mental health due to strict assumptions. First, they assume that the relationship between temperature and mental health is the same for people who own air conditioners and those without air conditioning. Second, the relationship between temperature and mental health would be constant over time in the absence of increasing air conditioning penetration.

Hence, we use the following strategy to relax these two assumptions. First, to allow the relationship between temperature and mental health to vary across people with and without air conditioning, we additionally control a dummy for air conditioning switchers. Specifically, we create a variable Switcher_i that is time-invariant and equals one for those people who changed their air conditioner ownership status between waves 2012 and 2016. By including the interaction term of temperature and switcher, we allow for time-invariant differences in the effects of temperature across switchers and non-switchers. We specifically estimate the following equation:

$$MH_{ict} = \alpha_0 + \delta_1 TEM_{ict} + \delta_2 AC_{it} + \delta_3 (TEM_{ict}{*}AC_{it}) + \delta_4 (TEM_{ict}{*}Switcher_i) + \theta \mathbf{W}_{ct} + \alpha_i + \gamma_t + \rho_c + \varepsilon_{ict} \tag{4}$$

Second, we include the interaction of temperature with time fixed effects (or the interaction term of temperature with a time trend) to allow the effects of temperature change over time to vary in a way that is common to each individual. Particularly, we employ the following equation:

$$MH_{ict} = \alpha_0 + \delta_1 TEM_{ict} + \delta_2 AC_{it} + \delta_3 (TEM_{ict}{*}AC_{it}) + \delta_4 (TEM_{ict}{*}\mu_t) + \theta \mathbf{W}_{ct} + \alpha_i + \gamma_t + \rho_c + \varepsilon_{ict} \tag{5}$$

Finally, we include both the interaction term of temperature with the time trend and the interaction term of temperature with the dummy of switchers in the same regression to relax both of the discussed assumptions above. The specific estimation is as follows:

$$MH_{ict} = \alpha_0 + \delta_1 TEM_{ict} + \delta_2 AC_{it} + \delta_3 (TEM_{ict}{*}AC_{it}) + \delta_4 (TEM_{ict}{*}Switcher_i) + \delta_5 (TEM_{ict}{*}\mu_t) + \theta \mathbf{W}_{ct} + \alpha_i + \gamma_t + \rho_c + \varepsilon_{ict} \tag{6}$$

Specifically, the CFPS asked the interviewers whether they have air conditioning units in their house during waves 2012 and 2014. Our CESD 8 questions were asked in wave 2012 and wave 2016; hence, our original data could not be used to obtain panel data for whether the participant had air conditioning. To analyze the panel data, we assume that the individuals that owned an air conditioner in wave 2016 are the same as those that owned an air conditioner in 2014.[10] As shown in Table 1, the average rate of owning an air conditioner is 29%.

5. Results

5.1. Baseline results

We present the baseline results in Table 2. We first estimate the linear relationship between temperature and mental health by using the past week's average temperature. Columns (1) and (2) present the effects of past week's average temperature on the total CESD 8 score and the dummy of severe mental illness. All models include individual fixed effects, county fixed effects, interview year-month fixed effects, and weather controls, such as sunshine, rainfall, and relative humidity, in our estimations. As shown in Columns (1) and (2), high temperature has a statistically significant adverse impact on mental health. Specifically, a 1 °C increase in the past week's average temperature would increase the total CESD score by 0.0458 points (0.9% to the mean) and the probability of having severe mental illness by 0.23 percentage points (2.3% to the mean). In other words, we find that a one-standard-deviation increase in the average temperature in the past week leads to the CESD 8 score and the likelihood of reporting severe mental health increase by 0.12 and 0.08 standard deviations, respectively.

[10] We replace the dummy of owing air conditioning in 2016 with the data in wave 2014. We assume the individuals who owned air conditioners in 2014 continued to own air conditioners in 2016.

Table 2
The effects of temperature during the past week on self-reported mental health.

	(1)	(2)	(3)	(4)
	Total CESD 8 score	Severe mental illness	Total CESD 8 score	Severe mental illness
Panel A: Average temperature past week				
Average temperature	0.0458***	0.0023**		
	(0.0151)	(0.0009)		
Panel B: Temperature bins				
Number of days below 0 °C			−0.1110*	−0.0080*
			(0.0567)	(0.0042)
Number of days between 0 and 3 °C			0.0825	0.0020
			(0.0631)	(0.0045)
Number of days between 3 and 6 °C			0.0180	−0.0044
			(0.0742)	(0.0047)
Number of days between 6 and 9 °C			−0.0211	−0.0043
			(0.0592)	(0.0046)
Number of days between 9 and 12 °C			0.0875	−0.0061
			(0.0559)	(0.0045)
Number of days between 12 and 15 °C			−0.0886	−0.0022
			(0.0681)	(0.0044)
Number of days between 15 and 18 °C			0.0574	0.0016
			(0.0531)	(0.0038)
Number of days between 21 and 24 °C			0.0630	0.0045
			(0.0388)	(0.0028)
Number of days between 24 and 27 °C			0.0928***	0.0063***
			(0.0342)	(0.0023)
Number of days above 27 °C			0.0783**	0.0062**
			(0.0387)	(0.0025)
Observations	40,108	40,108	41,416	41,416
Individual FE	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
Year-by-month FE	Yes	Yes	Yes	Yes
Weather controls	Yes	Yes	Yes	Yes

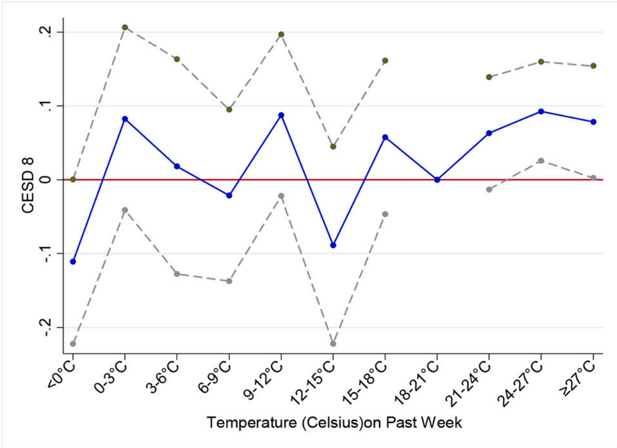
Notes: Columns (1) and (2) use the average temperature during the past week as an independent variable, and Columns (3) and (4) use the binned approach to explore the nonlinear relationship between temperature and mental health. All the regressions include individual fixed effects, county fixed effects, interview year-by-month fixed effects and other weather control variables. The weather controls include relative humidity, wind speed, sunshine duration, atmospheric pressure and precipitation. We take the summation of precipitation during the past week and the average of the other weather controls in the past week. Standard errors are clustered by both county-year-month and individual levels. ***$p < 0.01$, **$p < 0.05$, and *$p < 0.1$.

In Columns (3) and (4), we estimate the nonlinear relationship between temperature and mental health using the binned approach. Our primary interests are the estimates on the temperature bin that is above 27 °C. The estimates for bins between 24 and 27 °C and above 27 °C are statistically significant and positive for both the total CESD 8 score and the dummy of severe mental illness. Specifically, the estimate for the hottest bin implies that one additional day above 27 °C would lead to individuals reporting 0.0783 higher scores of the total CESD 8 (1.5% to the mean) and 0.62%age points higher of reporting severe mental illness (6.2 percent to the mean), relative to a day in the reference temperature bin (18–21 °C). We also plot the estimates on the different temperature bins in Fig. 3. The circles in Fig. 3 indicate the point estimates, and the whiskers denote the 95% confidence intervals. As shown in Panel A of Fig. 3, we find statistically significant positive effects of high temperature on the total CESD 8 scores for the hottest bins. Panel B also presents that the estimates are statistically significant when the temperature falls into the hottest two bins (24–27 °C and above 27 °C). Regardless of whether the relationship was linear or nonlinear, all estimates reach a similar conclusion: higher temperature harms human mental health.

5.2. Dynamic effects

The above baseline results of Table 2 mainly explore the effects of high temperature on mental health during the week before the interview date. In this session, we further test whether lagged temperatures by different exposure windows would affect mental health outcomes. In Fig. 4, we plot the impacts of temperature on CESD 8 and severe mental illness by different exposure windows, which ranged from one week to four months; therefore, we can check whether the impacts of temperature on mental health are cumulative or not. That being said, we use the exposure window variation to test whether the impacts of temperature on mental health are permanent

Panel A: The estimates of temperature on the total CESD 8 scores



Panel B: The estimates of temperature on the dummy of severe mental illness

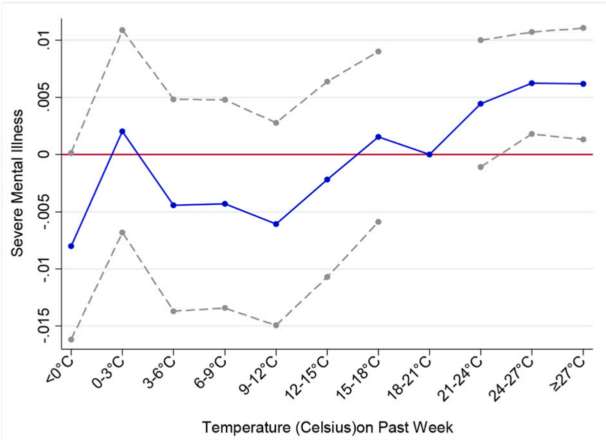


Fig. 3. The effects of high temperature on mental health-binned approach.
Notes: The Fig. 3 shows the non-linear effects of temperature on total CESD scores (upper panel) and the dummy for severe mental illness (lower panel). Each point estimate represents the effects of additional day with temperature in the corresponding interval compared with the reference interval (18–21 °C). Whiskers denote the 95% confidence interval. All the regressions include individual fixed effects, county fixed effects, interview year-month fixed effects and other weather control variables. Standard errors are clustered by both county-year-month and individual levels.

or temporary. The circles in Fig. 4 indicate the estimates of the hottest temperature bin (above 27 °C), and the whiskers denote the 95% confidence intervals.[11] Each line represents a separate regression. To save space, we only present the estimates for the hottest temperature bin (above 27 °C) the Fig. 4. The baseline effect is shown by a one-week lag. Panel A shows the impacts of temperature on the total CESD 8 scores, and Panel B presents the impacts of temperature on the dummy of severe mental illness. We observe significant effects of temperature on the total score of CESD 8 and the dummy of severe mental illness by one week lag; however, the significant effects disappear when we extend the exposure window to one month until four months. The results become insignificant from zero beyond one week. Similar trends are found for the lead effects. When we use temperature one week, one month until four months after the interviewed dates, the magnitudes are not statistically significant either.

5.3. Robustness checks

To investigate the robustness of our results, we conduct a number of different specifications in Table 3. In Panel A, we present the estimates for the total CESD 8 score, and in Panel B, we show the estimates for the dummy of severe mental illness. To save space, we only show the estimates for the bin above 27 °C in Table 3. Column (1) shows our baseline results, which employ two-way clustering by

[11] The estimates for the other temperature bin, i.e. bin <0 °C, 0–3 °C, 3–6 °C, 6–9 °C, …0.24–27 °C are not shown in Fig. 4.

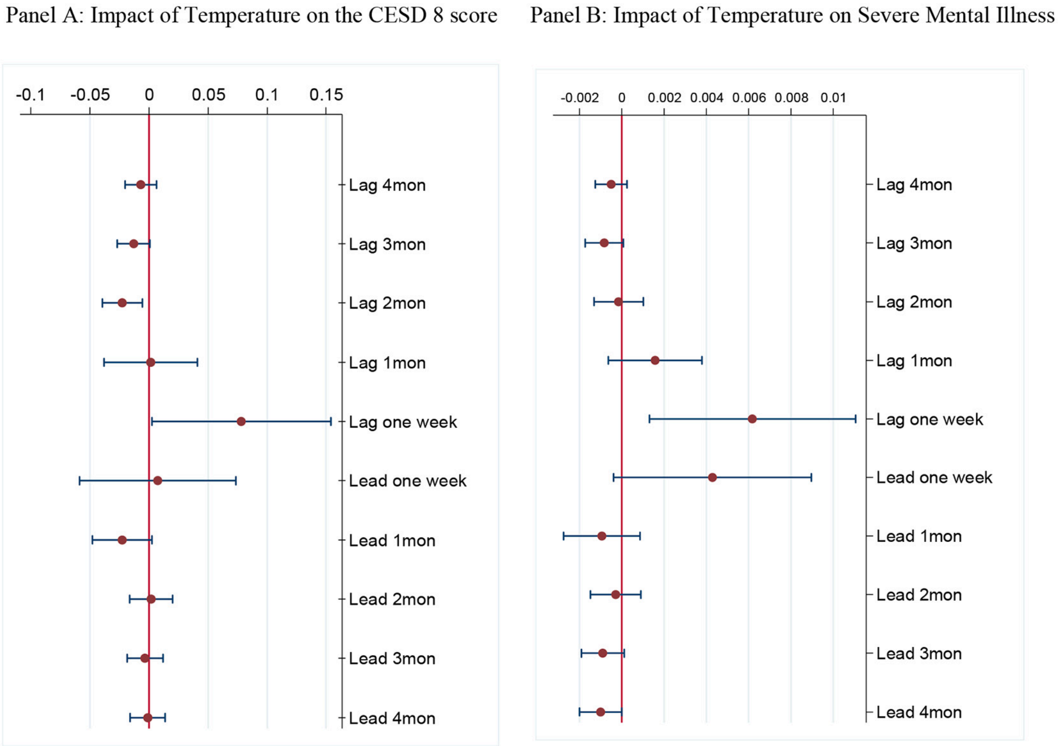


Fig. 4. Dynamic effects of temperature on mental health.
Notes: This figure depicts the effects of temperature on the total CESD 8 score and the dummy of severe mental illness. The exposure windows change from four-month lag of the interviewed to four-month lead. The red circle denotes the point estimate and the whisker denotes the 95% confidence interval. Our baseline result is denoted by a one-week lag. We use the binned approach to divide daily average temperature into 3 °C bin during the past week. Each line represents a separate regression, and we only present the estimates for the hottest bin (above 27 °C). All the regressions include individual fixed effects, county fixed effects, interview year-month fixed effects and other weather control variables. The weather controls include relative humidity, wind speed, sunshine duration, atmospheric pressure and precipitation. We take the summation of precipitation during the exposure windows and the average of the other weather controls in the exposure windows. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

county-interviewed year-month and individual in the main specifications. First, we alter the clustering method by county-interviewed date and individual in Column (2). The magnitude is similar for the dummy of severe mental illness and slightly higher for the total CESD 8 score.

Moreover, in Column (3), we exclude other weather control variables, and our results are robust to the baseline again. In Column (4), we additionally include county-specific linear time trends to control for any county-level time-variant variables that might contaminate our results. We find significant effects of temperature on CESD 8 score and the dummy of severe mental illness, and the magnitudes are similar to our baseline results. In Column (5), we further drop the counties with the largest (top 5 percentiles) and smallest (bottom 5 percentiles) sample sizes.[12] In Column (6), we drop the largest and smallest counties in terms of county territory area.[13] The magnitudes are almost identical to our baseline results. At last, in Column (7), we only include the samples interviewed during the summer. The magnitudes for the estimations focused on the summer-interviewed samples are similar to our baseline results. However, we only find statistically significant effects of high temperature on the dummy of severe mental illness.[14] To conclude, our estimates suggest a robust and causal adverse effects of ambient temperature on mental health.

5.4. Mechanism tests

As discussed in the previous section, temperature could directly affect mental health by causing poor concentration and fatigue. It could also indirectly affect mental health by decreasing work capacity and productivity, damaging physical health and disturbing sleep. Note that we cannot test the productivity channel, as no accurate measure of a person’s productivity can be obtained from our dataset. Using income as a proxy for productivity is not desirable because most individuals earn income through wages, which are

[12] We drop the counties with samples are above top 95 percentiles and the counties with samples are below bottom 5 percentiles.
[13] We drop the counties’ area above the top 5 percentile and below the bottom 5 percentiles over all the counties in CFPS.
[14] When we focus on the summer interviewed samples only, we lose about 32% of the samples.

Table 3
Robustness checks.

	(1) Baseline	(2) Cluster by county-date	(3) No weather controls	(4) Add county-specific linear trends	(5) Winsorize (county sample sizes)	(6) Winsorize (county area)	(7) Interviewed in summer only
Panel A: Total CESD 8 score							
Bin ≥ 27 °C	0.0783**	0.1422***	0.0976**	0.0540*	0.0797**	0.0702*	0.0662
	(0.0387)	(0.0411)	(0.0456)	(0.0308)	(0.0392)	(0.0404)	(0.0466)
Panel B: Dummy for severe mental illness							
Bin ≥ 27 °C	0.0062**	0.0069**	0.0059**	0.0067***	0.0062**	0.0059**	0.0071**
	(0.0025)	(0.0034)	(0.0026)	(0.0023)	(0.0025)	(0.0026)	(0.0032)
Observations	41,416	40,108	40,108	41,416	40,272	38,412	27,412
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-by-month FE	Yes	No	Yes	Yes	Yes	Yes	Yes
Date FE	No	Yes	No	No	No	No	No
Weather controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Panel A shows the estimation for the total CESD 8 score, and Panel B shows the results for the dummy of severe mental illness. Column (1) presents the baseline results. The baseline estimation uses a two-way cluster of county-year-month and individual levels. Column (2) changes the cluster by county-date and individual level. Column (3) does not include other weather controls (relative humidity, wind speed, sunshine duration, atmospheric pressure and precipitation) in the regression. In Column (4), we additionally include county-specific linear trends. In Column (5), we drop the smallest (county sample size bottom 5 percentiles) and largest counties (county sample size above top 5 percentiles) in terms of county sample sizes. In Column (6), we drop the smallest (area below 5% quantiles) and largest counties (area above top 5 percentiles) in terms of county area and at last in Column (7) we include only the samples who were interviewed during the summer. Standard errors are clustered by both county-year-month and individual levels except Column (2). ***$p < 0.01$, **$p < 0.05$, and *$p < 0.1$.

Table 4
Mechanisms-the effects of temperature on physical health and sleep.

	(1) Sick very serious	(2) Poor health status	(3) Bad sleep quality	(4) Bed hours	(5) Sleep <7 h
Number of days below 0 °C	−0.0065	0.0083	−0.0346***	−0.0404	0.0041
	(0.0053)	(0.0054)	(0.0117)	(0.0260)	(0.0069)
Number of days between 0 and 3 °C	0.0010	0.0231***	−0.0044	−0.0009	−0.0051
	(0.0069)	(0.0068)	(0.0137)	(0.0314)	(0.0083)
Number of days between 3 and 6 °C	−0.0031	0.0021	−0.0135	−0.0794***	0.0142*
	(0.0069)	(0.0062)	(0.0166)	(0.0283)	(0.0072)
Number of days between 6 and 9 °C	−0.0123*	0.0065	−0.0274**	−0.0105	0.0049
	(0.0068)	(0.0061)	(0.0121)	(0.0249)	(0.0067)
Number of days between 9 and 12 °C	−0.0054	0.0131**	−0.0057	−0.0446*	0.0085
	(0.0063)	(0.0063)	(0.0121)	(0.0238)	(0.0061)
Number of days between 12 and 15 °C	0.0092	0.0037	−0.0111	−0.0268	0.0038
	(0.0065)	(0.0056)	(0.0130)	(0.0242)	(0.0058)
Number of days between 15 and 18 °C	−0.0047	0.0044	−0.0221**	−0.0337*	0.0081*
	(0.0049)	(0.0055)	(0.0111)	(0.0196)	(0.0048)
Number of days between 21 and 24 °C	−0.0020	0.0008	0.0024	−0.0248	0.0013
	(0.0037)	(0.0034)	(0.0073)	(0.0193)	(0.0039)
Number of days between 24 and 27 °C	0.0046	0.0031	0.0069	−0.0432***	0.0086**
	(0.0034)	(0.0032)	(0.0071)	(0.0162)	(0.0036)
Number of days above 27 °C	0.0059	0.0033	0.0180**	−0.0325*	0.0089**
	(0.0039)	(0.0039)	(0.0085)	(0.0190)	(0.0044)
Observations	41,412	41,414	41,416	28,794	28,794
Mean of Dep.Var	0.2433	0.3782	0.7327	7.6208	0.1892
S·D of Dep.Var	0.4291	0.4849	0.8992	1.4692	0.3917
Individual FE	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes
Year-by-month FE	Yes	Yes	Yes	Yes	Yes
Weather controls	Yes	Yes	Yes	Yes	Yes

Table 5
Heterogeneity for all samples.

	(1)	(2)		(3)	(4)		(5)	(6)		(7)	(8)
	Total CESD 8 score	Severe mental illness		Total CESD 8 score	Severe mental illness		Total CESD 8 score	Severe mental illness		Total CESD 8 score	Severe mental illness
	Gender			Age			Urban/Rural			Education	
Panel A: Bin-approach											
Bin >27 °C*Male	0.0137	0.0009	Bin >27 °C*Elderly	−0.0017	−0.0027	Bin >27 °C*Urban	−0.0066	0.0021	Bin >27 °C*High-edu	0.0243	0.0036
	(0.0365)	(0.0025)	(Elderly- age≥60)	(0.0465)	(0.0042)		(0.0262)	(0.0018)	(High-edu≥9 yr)	(0.0464)	(0.0037)
Observations	41,060	41,060		41,412	41,412		41,076	41,076		41,366	41,366
Panel B: Average temperature											
Avg. Temp.*Male	−0.0077	−0.0005	Avg. Temp. *Elderly	0.0056	0.0008	Avg. Temp. *Urban	−0.0024	0.0011*	Avg. Temp.*High-edu	0.0084	0.0007
	(0.0059)	(0.0004)		(0.0083)	(0.0006)		(0.0089)	(0.0006)		(0.0081)	(0.0006)
	39,758	39,758		40,106	40,106		39,804	39,804		40,070	40,070
Individual FE	Yes	Yes		Yes	Yes		Yes	Yes		Yes	Yes
County FE	Yes	Yes		Yes	Yes		Yes	Yes		Yes	Yes
Year-by-month FE	Yes	Yes		Yes	Yes		Yes	Yes		Yes	Yes
Weather controls	Yes	Yes		Yes	Yes		Yes	Yes		Yes	Yes

Note: The estimates used bin approach are in Panel A and the estimates used the linear model are shown in Panel B. Regression models are estimated separately for each subsample. The weather controls include relative humidity, wind speed, sunshine duration, atmospheric pressure and precipitation. We take the summation of precipitation during the past week and the average of the other weather controls in the past week. Standard errors are clustered by both county-year-month and individual levels. ***$p < 0.01$, **$p < 0.05$, and *$p < 0.1$.

Table 6
Add air conditioner.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Total CESD score	Severe mental illness	Total CESD score	Severe mental illness	Total CESD score	Severe mental illness	Total CESD score	Severe mental illness	Total CESD score	Severe mental illness
	Add temperature*AC		Add temperature*AC switcher		Add temperature*time trend		Add temperature*year-month FE		Add Temperature*time trend and temperature*AC switcher	
Temperature	0.0411***	0.0019**	0.0411***	0.0019**	0.0540***	0.0018*	−0.0219	0.0039	0.0540***	0.0018*
	(0.0123)	(0.0008)	(0.0123)	(0.0008)	(0.0151)	(0.0010)	(0.0423)	(0.0029)	(0.0152)	(0.0010)
Air conditioner	0.2569	0.0072	0.2239	0.0034	0.2242	0.0075	0.2019	0.0101	0.1907	0.0037
	(0.1884)	(0.0127)	(0.1929)	(0.0131)	(0.1884)	(0.0129)	(0.1921)	(0.0134)	(0.1928)	(0.0133)
Temperature*AC	−0.0217***	−0.0007	−0.0215***	−0.0007	−0.0196***	−0.0007	−0.0197***	−0.0009	−0.0195***	−0.0007
	(0.0072)	(0.0005)	(0.0072)	(0.0005)	(0.0072)	(0.0005)	(0.0074)	(0.0005)	(0.0072)	(0.0005)
Observations	37,560	37,560	37,560	37,560	37,560	37,560	37,560	37,560	37,560	37,560
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Weather controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Column (1) and Column (2) include the interaction term of temperature and air conditioning in the regressions. In Columns (3) and (4), we include the interaction term of temperature and AC switcher. We define an AC switcher by identifying the status change of owning an air conditioner. In Columns (5) and (6), we include the interaction term of temperature and trends by year. Column (7) and Column (8) include the interaction term of temperature and year-month FE. Finally, Columns (9) and (10) include both the interaction term of temperature and the time trend along with the interaction of temperature and the AC switcher dummy. Standard errors are clustered by both county-year-month and individual levels. ***$p < 0.01$, **$p < 0.05$, and *$p < 0.1$.

typically fixed in the short run. In Table 4, we test the two direct channels, including physical health and sleep.

First, we tested whether temperature affects physical health. The CFPS asked the respondents whether they were severely sick during the past two weeks and self-rated their physical health status over the past month. The self-reported health status rate ranges from one (very healthy) to five (very poor). We define the dummy of poor health status equals one if the individual reports having a poor or very poor health status during the past month. The identification strategy is the same as the model we described before. As shown in Column (1), we find positive effects of temperature on being severely sick in the past two week. Although the estimates are not significant, the signs suggest a positive relationship between high temperature and being severely sick. Column (2) shows the estimates for the dummy with poor health status. The estimates of Column (2) imply positive effects of high temperature on the probability of having a poor physical health status. For example, an additional day that average temperatures above 27 °C during the past week increases the likelihood of reporting a poor physical health status by 0.33 percentage points (or 0.9% to the mean) relative to a day in the omitted category (18–21 °C). To compare the magnitudes of the effects of temperature on various channels, we convert the estimated impact to standard deviation units. In particular, a one-standard-deviation increase in the number of days above 27 °C would increase the probability of reporting a poor health status by 0.02 standard deviations.

Second, we test whether temperature affects sleep. We have three different measures of sleep in this section. First, CFPS asked each individual about the hours of sleep on a typical day. The question was, "Usually, how many hours do you sleep every day?". Second, the CFPS asked their respondents about their sleep quality during the past week. Third, other than using typical daily hours of sleep, the CFPS also collected the typical number of hours of sleep on working days. The question is, "Usually, how many hours do you sleep during your working days?" Thus, we create a dummy variable on working days for abnormal sleep, i.e., sleep <7 h.

We found that higher temperatures significantly reduced sleep quality and sleep hours during the past week. Specifically, a one-standard-deviation increase of days in the bin above 27 °C during the past week increases the scales of sleep quality by 0.06 standard deviations. In addition, an increase in the days fall in the bin above 27 °C in the past week (one standard deviation) led to a reduction in sleeping hours (0.06 standard deviations) and the probability of sleeping <7 h on working days (0.06 standard deviations).

In Table 4, we explore the relationship between temperature and physical health/sleep. Next, we test the relationship between physical health status and mental health outcomes using the CFPS individual data. Poor overall physical health is a significant factor likely to affect mental well-being (USGCRP, 2016). In addition, sleeping has been discussed as one primary channel that affects mental health and well-being (Mullins and White, 2019; Obradovich et al., 2018).

We first estimate the effects of physical health (i.e., whether sick severely during the past two weeks and the dummy of poor physical health status) on mental health outcomes. The estimations include individual-level demographic characteristics (i.e., age, gender, urban, education, marital status, employed), individual fixed effects, county fixed effects, and year-by-month fixed effects. The results are shown in Table A1 of Columns (1) to Column (4). We find a statistically significant positive impact of poor physical health on mental health problems. Specifically, people who reported having poor physical health status during the past month have a higher score of CESD 8 and are more likely to be in severe mental illness than those with good physical health status. Our results are consistent with the existing related literature (Ohrnberger, Fichera, and Sutton, 2017; Shao, Chen, and Ma, 2022). We additionally explored the relationship between sleep and mental health outcomes. Similar to the above estimations, we include individual-level demographic controls, individual fixed effects, county fixed effects, and year-by-month fixed effects when we evaluate the relationship between sleep and mental health outcomes. As shown from Column (5) to Column (10) of Table A1, poor sleep experiences increase the total CESD 8 score and the chances of reporting severe mental illness. Particularly, people who sleep less or are reported to sleep in worse quality have higher scores of total CESD 8 and are more likely to be in severe mental illness (João, de Jesus, Carmo, and Pinto, 2018; Wang et al., 2021).

5.5. Heterogeneous effects

Because temperature affects mental health differently, there might be heterogeneous effects across different demographic groups. In particular, we estimate heterogeneous effects by gender, age, education levels, and living in urban/rural in Table 5. We use the temperature bins interacted with different demographic groups to estimate the heterogeneous effects. To save space, we only present the interaction term of the hottest temperature bin (above 27 °C) with the dummy of each demographic group in Table 5. In Panel A, we present the nonlinear interaction terms, and in Panel B, we show the estimates of average temperature during the past week interacted with each demographic group dummies. We find little evidence of heterogeneous effects among various groups no matter for linear estimation or nonlinear estimation. Specifically, as shown in Columns (1) and (2) of Table 5, no significant differences were found between males and females. Similarly, our estimates, as shown in Column (3) and Column (4), do not suggest any statistically significant differences between young cohorts (aged between 18 and 60) and elderly cohorts (aged over 60).

In Table 5 of Column (5) and Column (6), we further interact the temperature with the dummy of living in rural and urban areas. Again, we do not find any statistically significant effects across the rural and urban populations. When we look at the effects of high temperature by highly educated (years of education >9) and less educated (years of education equal to or <9) individuals in Columns (7) and (8), we find no statistically significant effects for lower educated groups compared to their higher educated counterparts. To conclude, our results do not suggest any dramatic heterogeneous impacts across different demographic groups.

5.6. Adding air conditioning as a means of avoidance

We now estimate the alleviating effects of temperature on mental health outcomes by considering whether air conditioning is present in living places. We estimate the moderating effects of temperature on mental health through the approaches discussed in Section 4. In Column (1) of Table 6, we present the estimates that include the interaction of the dummy of owing an air conditioner and the average temperature during the past week, as expressed in Eq. (3). Our primary interest is the coefficient on the interaction term. Particularly, the negative and significant coefficient of the interacting term suggests that owning an air conditioner moderates the negative effects of high ambient temperatures on the CESD 8 score. The estimates for the likelihood of having severe mental illness are negative but not statistically significant as shown in Column (2). In Columns (3) and (4), we further consider air conditioning switchers to allow the relationship between temperature and mental health to vary across people with and without air conditioning. We defined air conditioning switchers as individuals who reported having air conditioning in the previous wave but reported not having air conditioning in the next wave or as respondents who did not own an air conditioner in previous wave, but reported owning an air conditioner in the next wave. Both of these cases are defined as "AC Switchers". We employ Eq. (4) in Columns (3) and (4). The interaction term shows very similar moderating effects of temperature on mental health due to owning an air conditioner. We additionally add the interaction term of average temperature with specific year trends (Column (5) and Column (6)) and the interaction term of average temperature with year-month fixed effects (Column (7) and Column (8)) to allow the effects of temperature to change over time in a way that is the same for each individual, as presented in Eq. (5). We found similar modifying effects of temperature on the total CESD 8 score and the probability of having severe mental illness. Finally, we add the interaction of temperature with time trends and the interaction of temperature with air conditioning switchers in the same regression as expressed in Eq. (6), and we find the same results. Our results are consistent with the findings from Barreca et al. (2016) that there are moderating effects of air conditioning on the relationship between temperature and health. However, this finding is in contrast with the results of Mullins and White (2019), which found no substantial evidence of adaptation.

6. Discussion and conclusion

This paper provides causal evidence of a positive relationship between high temperature and mental health problems by using nationally representative data from the CFPS in China. Specifically, an additional day above 27 °C during the past week would lead to individuals reporting 0.0783 higher scores of the total CESD 8 (1.5% to the mean) and 0.62%age points higher of reporting being severe mental illness (6.2 percent to the mean), relative to a day in the reference temperature bin (18–21 °C). The population of adults in China is 1.14 billion.[15] Thus, our estimates imply that an additional day above 27 °C during the past week would increase the number of adults who experience severe mental illness by 70.7 million. The estimated cost of mental illness in China was approximately USD 3665 for each patient in 2013 (Xu et al., 2016). Therefore, the estimated economic cost of treating all patients with severe mental illness would be 259 billion dollars if one additional day above 27 °C relatives to a day in the bin of 18–21 °C over the past week.

We further find convincing evidence of an avoidance strategy that can mitigate the relationship between excess heat and mental health. Our approach provides a reliable estimation of the role of air conditioning in mitigating the negative relationship between high temperature and mental health outcomes. We find that installing air conditioning units in living places can significantly reduce the total score of CESD 8. Our results are robust when we relax the assumptions that the relationship between temperature and heath is constant over time and is the same for individuals who own and do not own air conditioners.

The studies most closely related to our paper are Mullins and White (2019), Obradovich et al. (2018) and Wang, Obradovich, and Zheng (2020). We first compare our results with those of Mullins and White (2019). Mullins and White (2019) estimate a broad measure of mental health outcomes in the US, including mental health-related emergency department visits, suicides and self-reported mental health. Since the primary measure for mental health well-being in our study was self-reported mental illness, we mainly focused on the comparison of this measure. Mullins and White (2019) find that a 1 °F increase in the mean temperature increases the number of days with reported poor mental health by 0.00185. However, when they use the binned specification, they failed to find any statistically significant effects of high temperature on mental health. Our magnitude (1.5%) is slightly larger than Mullins and White's estimation of self-reported mental health well-being. One possible explanation for our different magnitudes may be due to the different study contexts. The economic conditions and GDP per capita in the US are larger than those in China. In addition, Mullins and White (2019) use state-level air conditioning penetration rate data and find no substantial evidence of adaptation. Our results show that there are significant mitigating effects of air conditioning, which is consistent with the findings from Barreca et al. (2016).

We also compare the results with Obradovich et al. (2018). They use the same mental health data source, i.e., BRFSS, in the US from 2002 to 2012 and find that a 1 °C increase in the average temperature over 5 years would increase the probability of having mental health issues by 2%. The magnitude is similar to our results. Similar to Mullins and White (2019), they estimate the relationship between temperature and mental health by using pooled cross-session data that fail to control individual specific characteristics that might bias the estimation.

In addition to those two studies, another finding related to our study is that of Wang et al. (2020), who evaluated the temperature on emotional sentiment by using 43 million people's information from one of the largest social media platforms in China (*Weibo*). They find that high temperature is associated with worse emotional sentiment in posts on social media in China. Since the emotional sentiment index that they constructed measures the mood when the individuals post on social media, which is different from the self-reported mental health measures that are used as clinical tools to screen mental health illness, we cannot compare the magnitude of the

[15] The adult population data is from China Statistical Yearbook, 2015.

findings of Wang et al. (2020) with ours.

Our study has important policy implications that can help the government to implement optimal strategies for coping with climate change. On the one hand, emerging studies have already shown that high temperatures adversely impact people's physical and mental health, including our study. However, most Chinese provinces have not undertaken climate health risk assessment and adaptation planning. China's health system is not adequately prepared for the challenge. Health authorities, like the newly formed National Bureau of Disease Control and Pretension, should develop appropriate policies and actions to improve China's climate health adaptation.

On the other hand, media coverage and personal engagement on health and climate change remain low in China, and knowledge dissemination and engagement are limited. On July 28, the United Nations General Assembly adopted a historic resolution declaring that a clean, healthy, and sustainable environment is a universal human right. Appropriate mitigation measures may save lives in the short term. First, the policymakers should inform the public to be fully aware of the potential physical and mental health risks of climate change, for example, heat stroke, cardiovascular disease, stress, etc. More importantly, the government should familiarize people with mitigating measures, such as reducing outdoor activities during heat waves and evidence-based personal adaptation behaviors, including soaking the body, clothes, or feet, and the preferred cooling strategies of using fans and air conditioning. As indicated by this study, air conditioning can be an effective way to adapt to hot days. However, their strategies are not well known by the public. Hence, government agencies and the media should be more active in reporting and informing the public about heat risks and protection methods.

Data availability

The data that has been used is confidential.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.chieco.2023.101953.

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