



# The effects of exposure to high temperatures during pregnancy on adolescent mental health: Evidence from China<sup>☆</sup>

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## ABSTRACT

This paper provides the first study to explore the relationship between exposure to ambient temperatures during pregnancy and adolescent mental health in China. The results show that experiencing one more hot day relative to local historical contemporaneous average values during pregnancy significantly increases the likelihood of mental health disorders in adolescence. The impact is larger in the first and second trimesters. Individuals born in the northern region and whose mothers work in agriculture are more vulnerable to high temperatures. Prenatal exposure to hot days is more harmful to the mental health of older adolescents. Additionally, the adverse effects are similar for both men and women and individuals with rural and urban hukou. Biological effects, income effects, and human capital accumulation might be three operative channels of the impact. These findings add to the evidence on the lasting health effects of early life exposure to climatic shocks and call for policy interventions during pregnancy.

## 1. Introduction

Mental health disorders are causing huge economic losses and posing threats to the lives of younger and younger people.<sup>1</sup> Adolescence is a critical period of human brain growth and life development, closely related to changes in behavior and social interaction, maturation of brain structure and cognitive, and maturity of consciousness (Provensi, Schmidt, Boehme, et al., 2019; Whitaker, Vertes, Romero-Garcia, et al., 2016). Therefore, many lifetime disorders and psychological disorders first manifest during adolescence (Kessler et al., 2007). The detrimental effects of mental health disorders during childhood and adolescence on future's health and economic outcomes are more important and larger than that of common physical health problems (Currie, Stabile, Manivong, & Roos, 2010; Goodman, Joyce, & Smith, 2011; Smith & Smith, 2010). However, due to inadequate health care and

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<sup>1</sup> Around 13% of the disease burden in the world is constituted by different categories of mental disorder diagnoses (Collins et al., 2011). According to the official website of the World Health Organization, children and adolescents with mental health disorders account for around 20% worldwide, with suicide the second leading cause of death among 15–29-year-olds.

government health expenditure and insufficient awareness, adolescents are more severely affected by mental health disorders than physical health problems in low- and middle-income countries.<sup>2</sup> The overall prevalence of mental disorders among children and adolescents aged 6 to 16 is 17.5% in China (Zheng, 2021). Limited and underdeveloped treatment and support services for adolescents' mental health disorders, combined with the accelerated pace of life and the increasingly fierce social competition, have exacerbated the mental health problems of Chinese adolescents. Therefore, it is urgent to comprehensively explore the factors affecting adolescent mental health and take early interventions. Although many economic researchers have paid attention to the impact of exposure contemporaneous economic, environmental, and climate shocks on mental health, little is known about early-life determinants, particularly environmental conditions.

Global warming has become a considerable concern and attracted widespread attention of scholars and policymakers.<sup>3</sup> The recent economic literature has found that extreme heat is an important environmental risk that impairs adult mental health (Hua, Qiu, & Tan, 2022; Mullins & White, 2019). As the world's largest carbon emitter, China has experienced a noticeable rise in temperature with an average temperature warming rate of 0.26°C per decade from 1951 to 2020 (China Meteorological Administration (CMA), 2021). China's warming rate is higher than the global average rate over the same period, and the impact of climate change in China is particularly pronounced. In Chinese meteorology, high temperature is defined as daily maximum temperature reaching >35°C.<sup>4</sup> The existing literature shows that high temperature refers to daily average temperature above 30°C (Agarwal, Qin, Shi, Wei, & Zhu, 2021; Garg, Gibson, & Sun, 2020; He & Tanaka, 2023; Li, Ferreira, & Smith, 2020; Wang, Obradovich, & Zheng, 2020). Air conditioning is one of the most important avoidance behaviors against high temperatures. Due to the backward level of economic development and technology, the penetration rate of air conditioning in China in the last century was much lower than that of developed countries. Residents of developing countries are more vulnerable to high temperatures than those of developed countries because adaptation facilities are generally more limited.

This paper estimates the impacts of prenatal exposure to temperatures on adolescent mental health using a unique dataset from the 2010 wave of the China Family Panel Studies (CFPS). The CFPS 2010 provides detailed individual birth information, self-reported mental health status, and other demographic characteristics for 3045 individuals from 25 provinces. We use the Kessler Psychological Distress Scale (K6) instrument to measure self-reported mental health status. Based on birth of city and month, we merge individual dataset with city-level meteorological dataset. We find that exposure to high temperatures during pregnancy significantly increases the frequency of depressive symptoms in teens after including other meteorological variables, individual and parental demographic characteristics, and a series of two-way fixed effects. These impacts are more pronounced in the first and second trimesters. An extreme hot day in spring and autumn has a greater negative impact than that in summer during pregnancy.

Our main findings remain unchanged after conducting several robustness checks across various dimensions, including alternative fixed effects and clusters, alternative dependent and independent variables, alternative temperature intervals and sample, and placebo tests. Age heaping doesn't confound our main findings. Additionally, we rule out confounding factors of selective mortality, selective fertility, migration, and adaptive tools that may respond to temperatures and drive our results of mental health. In addition, the adverse effects of prenatal exposure to high temperatures are larger for adolescents born in the northern region and whose mothers work in farming. Older adolescents are more sensitive to high temperatures. Heterogeneous effects are absent across gender and hukou status. We also provide evidence that exposure to heat waves during in utero period reduces subjective happiness.

We then explore the influencing channels through which prenatal exposure to high temperatures affect adolescent mental health, including biological effects, income effects, and human capital accumulation. First, we show that exposure to high temperatures significantly reduces birth weight. Second, we check whether exposure to high temperatures affects annual net household income and the proportion of annual net household agricultural income. All the coefficients are significantly negative. Third, we explore the link between in utero exposure to extreme hot temperatures and test scores. The results suggest that prenatal exposure to heat waves significantly decreases cognitive performance during adolescence. Finally, we rule out other contemporary shocks, such as household shocks, household size, physical illness, and individual negative behaviors. Our mechanism analyses provide suggestive evidence for the biological effects, income effects, and human capital accumulation, which might be the main channels behind the deteriorating impact of in utero hot days exposure on adolescent mental health.

This paper contributes to the existing literature in three ways. First, it may be the first study to explore the relationship between exposure to ambient temperatures during pregnancy and adolescent mental health disorders by coupling meteorological variables with an individual dataset from a nationally representative survey in the largest developing country. Although existing literature examines the effects of temperatures on self-reported mental health and expressed sentiment (Baylis, 2020; Li, Ferreira, & Smith, 2020; Mullins & White, 2019; Obradovich, Migliorini, Paulus, & Rahwan, 2018), they mostly focus on the contemporary short-term effects of ambient temperature fluctuations in developed countries. Only limited research explores the day-to-day impacts of temperatures on individuals' expressed sentiment and the annual effects of temperature variability on individuals' depressive status in China. Xue, Zhu, Zheng, & Zhang (2019) demonstrates the association between an increase in temperature variability and higher probabilities of

<sup>2</sup> Nearly half of world's depressed people live in and >80% of non-fatal disease burden occurs in low-income and middle-income countries (World Health Organization, 2017).

<sup>3</sup> High temperatures pose a threat to economic outcomes and human health, including economic performance (Li, Gong, Gu, & Zhang, 2021), crop yields (Chen et al., 2016), industrial output (Chen & Yang, 2019), productivity (Zhang, Deschenes, Meng, & Zhang, 2018), cognitive performance (Zivin, Song, Tang, & Zhang, 2020), mortality (Yu et al., 2019), morbidity (Agarwal et al., 2021), expressed sentiment (Baylis et al., 2018), and mental health (Li et al., 2020).

<sup>4</sup> The daily maximum temperature generally occurs between 2 pm and 3 pm.

depression. Wang, Obradovich, & Zheng (2020) also suggests that temperature extremes lead to a reduction in city-level expressed sentiment constructed by social media posts. In this paper, we use the K6 score to capture symptoms of depression and mental disorders and explore whether prenatal exposure to high temperatures have long-lasting impacts on adolescent mental health status.

This paper is in line with Adhvaryu, Fenske, Kala, & Nyshadham (2019), which finds that one degree warmer than the local historical average in the calendar year before the year of birth increases depressive symptoms in adults using self-reported depression and anxiety data for 19 African countries. We and Adhvaryu, Fenske, & Nyshadham (2019) are interested in estimating the impact of exposure to temperatures during gestational period on mental health outcomes - but focus on individuals of different ages (adolescents aged 10–15 versus adults aged 18 or older) in different countries (China versus African countries). The conclusions of this paper and Adhvaryu, Fenske, Kala, & Nyshadham (2019) consistently demonstrate that elevated temperatures during pregnancy impair mental health in adolescence and adulthood. This paper finds that experiencing an additional day with daily average temperature over 30°C during pregnancy (9 months prior to birth) relative to local historical average values significantly increases the K6 score by 0.05 points compared with a day in the 20–25°C bin. Our conclusions are in line with Adhvaryu, Fenske, Kala, & Nyshadham (2019), that is, exposure to one degree warmer than the local historical average in one year before birth increases the constructed indicators of mental health by 0.03 standard deviations. Based on the method of Adhvaryu, Fenske, Kala, & Nyshadham (2019), we construct new indicators of mental health and temperatures to re-estimate the linear and nonlinear relationships between prenatal exposure to temperatures and adolescent mental health in Table A2. Our coefficients are larger than that of Adhvaryu, Fenske, Kala, & Nyshadham (2019). Additionally, Adhvaryu, Fenske, & Nyshadham (2019) uses an OLS model with temperature point and year of birth fixed effects and a vector of country time trends to explore the linear effects of in utero temperature in the year before birth, whereas this paper constructs the variables for the number of days with daily average temperature falling into eight 5°C temperature bins to explore the nonlinear effects of exposure to temperatures on mental health status. On the one hand, while there has been much research using nonlinear does-response function to explore whether extreme temperatures have larger impacts on physical health outcomes, little is known to the nonlinear link between temperature and mental health status. The existing studies have found that the health hazards of extreme temperatures are much greater than the average effect. This paper extends previous literature on the nonlinear relationship between temperature and health. On the other hand, the increased risk of frequent extreme weather shocks, such as persistent hot temperatures and heat waves, is an important threat to climate change, causing greater economic losses. Therefore, investigating the effects of extreme temperatures provides empirical evidence for policymakers and residents to formulate policies and take adaptive measures to reduce the hazards of climate change. A nonlinear does-response function can capture the effects of extreme temperatures.

This paper is also closest to Hua, Qiu, & Tan (2022). Based on the same data source (CFPS) and estimation specification, we investigate the nonlinear relationship between temperatures and the K6 score in China. But we focus on the effects of temperatures experienced at different times (pregnancy versus 30 days before the survey) on mental health of different individuals (adolescents aged 10–15 versus adults aged above 16). On the one hand, adolescence is an important transition period from childhood to adulthood. The mental health of adolescents is crucial to cultivating personality, forming spirit quality, and establishing ideals and beliefs. Effective early prevention and intervention of mental health problems in adolescence can help reduce health problems and welfare losses in adulthood. On the other hand, estimates for Chinese adults may not be simply extrapolated to Chinese adolescents due to different natural conditions and socioeconomic backgrounds, including natural adaptation to temperature shocks, living conditions, the levels of health care, and the awareness of mental health disorders. In addition, we deviate our interested meteorological variables from local historical contemporaneous average values. But these core meteorological variables in the previous 30 days used by Hua, Qiu, & Tan (2022) are not deviated from historical contemporaneous values. Hua, Qiu, & Tan (2022) finds that an additional day with daily average temperature over 30°C experienced one month before the survey date leads to an increase in the K6 score by 0.21 points. The absolute value is 4.2 times larger than the estimated coefficient of this paper. This difference may be due to the fact that we focus on different indicators of high temperatures during different periods. We further compare the results by using changes in standard deviations. The difference becomes smaller.

Second, the main finding of this paper extends to a growing economic literature on “fetal origins hypothesis” that early life conditions have profound effects on later life outcomes (Barker, 2001). A large body of literature has provided empirical evidence for the persistent adverse effects of early life negative shocks, such as high temperatures in utero (Isen, Rossin-Slater, & Walker, 2017), water drinking in utero (Li & Xiao, 2023), extreme floods in utero and in infancy (Rosales-Rueda, 2018), Ramadan in utero (Almond & Mazumder, 2011), infectious diseases in early childhood (Fink, Venkataramani, & Zanolini, 2021), hunger episodes in childhood (Cui, Smith, & Zhao, 2020; Kim, Fleisher, & Jessica, 2017), and wars in childhood (Akresh, Lucchetti, & Thirumurthy, 2012).<sup>5</sup> Additionally, several studies have also found that prenatal exposure to temperature shocks has negative effects on birth outcomes in both developed and developing countries (Barreca, Deschenes, & Guldi, 2018; Chen, Tan, Zhang, & Zhang, 2020; Deschênes, Greenstone, & Guryan, 2009). This paper complements the existing literature by investigating the medium-term impact of exposure to hot weather during pregnancy on adolescent mental health. The adverse effects of prenatal shocks on welfare losses extend from birth and childhood through adolescence into adulthood. Income effects, family inputs, and fetal selection have been empirically confirmed to be the main channels behind these adverse effects (Hu & Li, 2019; Rosales-Rueda, 2018; Wilde, Apouey, & Jung, 2017). Our mechanism analyses provide suggestive evidence that physiological and biological effects, income effects, and human capital accumulation may be the main channels through which exposure to high temperatures in utero period affects adolescent mental health after excluding other

<sup>5</sup> These studies found that these early life negative shocks have adverse effects on adult height (Akresh et al., 2012), weight (Cui et al., 2020), cognitive performance (Hu & Li, 2019), human capital (Fink et al., 2021), economic productivity (Fishman et al., 2019), and annual earnings (Isen et al., 2017).

contemporary shocks and selection issues, calling for health care for pregnant women.

Third, this paper adds to the literature on the early life determinants of mental health by investigating the link between prenatal exposure to high temperatures and adolescent mental health. Despite mounting research on the effects of a variety of contemporaneous economic and climatic shocks,<sup>6</sup> little is known about how early life shocks exposure drives individuals' mental health status. [Adhvaryu, Fenske, Kala, & Nyshadham \(2019\)](#) and [Singhal \(2019\)](#) are two exceptions, who find that early life income shocks (cocoa price fluctuations) and exposure to conflicts (American war in Vietnam) significantly have enduring effects on adult mental health. Understanding the early life contributors to mental health is crucial for early intervention and prevention of mental illness.

The rest of this paper is organized as follows. We describe data source and present summary statistics in [Section 2](#). Empirical specification is presented in [Section 3](#). [Section 4](#) reports the empirical results and rules out selection issues. We explore the potential influencing channels in [Section 5](#) and conclude in [Section 6](#).

## 2. Data

We first describe two main data sources. The first on adolescent mental health and the other on city-level weather variables. We then provide summary statistics.

### 2.1. Adolescent mental health

Our adolescent mental health data is obtained from the CFPS, which tracks the economic, social, health, and behavioral information of communities, families, and individuals. This nationally representative survey is conducted by the Institute of Social Science Survey of Peking University since 2010 and is held every two years. 25 provinces are included in this survey.<sup>7</sup> The total population of these 25 provinces accounts for 95% of the whole country ([Xie, 2012](#)). Individual-level surveys include adult questionnaires and child questionnaires. Adults aged 16 and above complete the former and children aged below 16 complete the latter. The CFPS includes individual demographic characteristics and household characteristics, including gender, age, nationality, years of education, self-reported physical and psychological well-being, self-reported behaviors, parental characteristics, household income, and so on.

We collect the individual depressive symptoms from the 2010 wave of CFPS, which uses the K6 score to measure self-reported mental health status. The K6 instrument, developed by [Kessler et al. \(2002\)](#) includes six questions about negative emotions and mental status experienced during the past month. The K6 instrument is highly correlated and effective with the K10 instrument and the K20 instrument ([Aggarwal et al., 2008](#); [Prochaska, Sung, Max, Shi, & Ong, 2012](#)). Many medical and economic studies have shown that the K6 instrument has sufficient properties as a screening tool for symptoms of depression and mental disorders ([Kessler et al., 2003](#); [Zhang, Zhang, & Chen, 2017](#)). Additionally, the K6 instrument has been widely used by a large number of international government surveys ([Chen, Oliva, & Zhang, 2018](#)). Adults and children aged 10–15 independently complete the survey. Guardians complete this survey on behalf of children aged under 10.

In this study, we focus on adolescents between the ages of 10 and 15, who answer the children's questionnaire independently themselves, for the following reasons. First, mental health problems among Chinese adolescents are becoming increasingly serious. A comprehensive understanding of the factors influencing adolescent mental health, including environmental shocks during pregnancy, can help to intervene earlier to alleviate the problem. Second, while mounting medical literature and clinical experiments demonstrate the negative effects of fetal health and maternal stress on physical and mental health status from infancy to adulthood, limited attention has been paid to the impact on adolescent health, especially mental health. Third, adolescents are less exposed to other forms of stresses than adults. Therefore, we could be better able to identify causal impacts on mental health.

The CFPS 2010 consists of the following six questions to measure the symptoms of depression and mental disorders:

- (1) During the past month, how often did you feel depressed that nothing could cheer you up?
- (2) During the past month, how often did you feel nervous?
- (3) During the past month, how often did you feel restlessness that nothing could calm you down?
- (4) During the past month, how often did you feel futureless?
- (5) During the past month, how often did you feel difficult that everything was an effort?
- (6) During the past month, how often did you feel meaningless?

Individuals between the ages of 10 and 15 have five options to choose, each option corresponds to a score, ranging from zero points to four points: none of the time (zero point), once a month (one point), two or three times a month (two points), two or three times a week (three points), and almost every day (four points). Therefore, the total K6 score is between zero and 24. Higher scores are associated with more frequent depressive symptoms and poorer mental health status in the past month.

The CFPS 2010 dataset also provides other individual demographic characteristics and parental characteristics, including place of birth, birth year and month, gender, age, nationality, parents' age at birth year, and parents' educational attainment. The gestation period is defined as the nine month (270 days) preceding the birth month, which doesn't include the birth month. To explore trimester

<sup>6</sup> These shocks include income shocks ([Gardner & Oswald, 2007](#)), economic crisis ([Friedman & Thomas, 2008](#)), local labor market fluctuations ([Charles & DeCicca, 2008](#)), migration policies ([Stillman, McKenzie, & Gibson, 2009](#)), and ambient temperatures ([Mullins & White, 2019](#)).

<sup>7</sup> The 25 provinces don't include Xinjiang, Tibet, Qinghai, Inner Mongolia, Ningxia, Hainan, Hong Kong, Macao, and Taiwan.

**Table 1**  
Summary statistics.

Variable	Obs.	Mean	Std. Dev	Min.	Max.
Panel A: Individual level variables					
K6 score	3045	2.964	3.915	0.000	24.000
Depressed	3045	0.694	1.042	0.000	4.000
Nervous	3045	0.699	1.079	0.000	4.000
Restless	3045	0.478	0.928	0.000	4.000
Futureless	3045	0.276	0.741	0.000	4.000
Difficult	3045	0.573	0.962	0.000	4.000
Meaningless	3045	0.244	0.725	0.000	4.000
Age	3045	12.592	1.728	10.000	15.000
Female (0/1)	3045	0.503	0.500	0.000	1.000
Han (0/1)	3045	0.883	0.322	0.000	1.000
Agriculture (0/1)	3045	0.824	0.381	0.000	1.000
Mother's age at birth	3045	25.890	4.352	13.000	44.000
Father's age at birth	3045	27.745	4.940	17.000	63.000
Mother's education years	3045	5.460	4.567	0.000	23.000
Father's education years	3045	7.059	4.128	0.000	19.000
Panel B: City level weather variables					
Number of days (AT $\geq 30^{\circ}\text{C}$ )	2401	1.776	8.226	-23.500	36.000
Number of days (AT $25\text{--}30^{\circ}\text{C}$ )	2401	0.004	4.109	-14.800	25.300
Number of days (AT $20\text{--}25^{\circ}\text{C}$ )	2401	0.057	9.653	-39.300	34.300
Number of days (AT $15\text{--}20^{\circ}\text{C}$ )	2401	0.295	8.030	-27.600	29.600
Number of days (AT $10\text{--}15^{\circ}\text{C}$ )	2401	-0.836	7.108	-30.700	27.800
Number of days (AT $5\text{--}10^{\circ}\text{C}$ )	2401	0.063	6.221	-22.200	21.900
Number of days (AT $0\text{--}5^{\circ}\text{C}$ )	2401	-0.622	6.400	-21.000	21.900
Number of days (AT $<0^{\circ}\text{C}$ )	2401	-7.737	5.513	-29.100	17.200
Precipitation (mm)	2401	0.005	0.577	-2.422	2.794
Relative humidity (%)	2401	-0.402	2.141	-8.382	7.257
Wind speed (m/s)	2401	0.015	0.118	-0.422	0.433
Sunshine duration (hour)	2401	0.012	0.353	-1.408	1.167
Air pressure (0.1 hPa)	2401	-0.747	7.117	-88.945	50.984

Notes: Our sample includes 3045 individuals, born in 126 cities across 25 provinces. In Panel A, “Depressed”, “Nervous”, “Restless”, “Futureless”, “Difficult”, and “Meaningless” represent self-reported the frequency of feeling depresses, nervous, restless, futureless, difficult, and meaningless during the previous month. “Female” is a dummy variable for gender, which equals to one when one child is female. “Han” is a dummy variable for nationality, which equals to one when one child is Han race. “Agriculture” is a dummy variable for mother’s job sector, which equals to one when one child’s mother’s occupation is agricultural work. In Panel B, “Number of days” is a relative indicator, equaling to the number of days falling into one temperature bin during pregnancy relative to the average number of days falling into the same temperature bin during the same pregnancy in 1980–1990. “AT” represents average temperature.

heterogeneity, we divide the entire gestation period into three trimesters: the seventh to ninth months before the month is the first trimester, the fourth to sixth months before the birth month is the second trimester, and the first to third months before the birth month is the third trimester. We also divide the four seasons of pregnancy to explore seasonal heterogeneous effects.<sup>8</sup>

## 2.2. Weather data

The 820 weather stations of the China Meteorological Data Sharing Service System (CMDSSS) provide weather data, including average temperature, total precipitation amount, average relative humidity, average wind speed, sunshine duration, and atmospheric pressure. Most of the existing economic literature uses meteorological data from ground monitoring weather stations to evaluate the effects of temperature in China (Agarwal, Qin, Shi, Wei, & Zhu, 2021; Chen, Tan, Zhang, & Zhang, 2020; Chen, Cui, & Gao, 2023; Yu, Lei, & Wang, 2019).

First, we use inverse distance weighting method to calculate city-level daily weather variables based on station-level weather variables. Next, we calculate each weather variable for the 270 days preceding each date in each city. We then calculate the mean values of each weather variable during pregnancy. We further calculate the number of days with daily average temperature falling into one of eight temperature bins ( $\geq 30^{\circ}\text{C}$ ,  $25\text{--}30^{\circ}\text{C}$ ,  $20\text{--}25^{\circ}\text{C}$ ,  $15\text{--}20^{\circ}\text{C}$ ,  $10\text{--}15^{\circ}\text{C}$ ,  $5\text{--}10^{\circ}\text{C}$ ,  $0\text{--}5^{\circ}\text{C}$ ,  $<0^{\circ}\text{C}$ ) during the 9 gestational months in our sample. We define the  $20\text{--}25^{\circ}\text{C}$  bin as the reference temperature bin and omit this bin in our regression to prevent multicollinearity. According to above methods and steps, we calculate the mean values of each weather variable and the number of days

<sup>8</sup> Spring is March, April, and May. Summer is June, July, and August. Autumn is September, October, and November. Winter is December, January, and February.

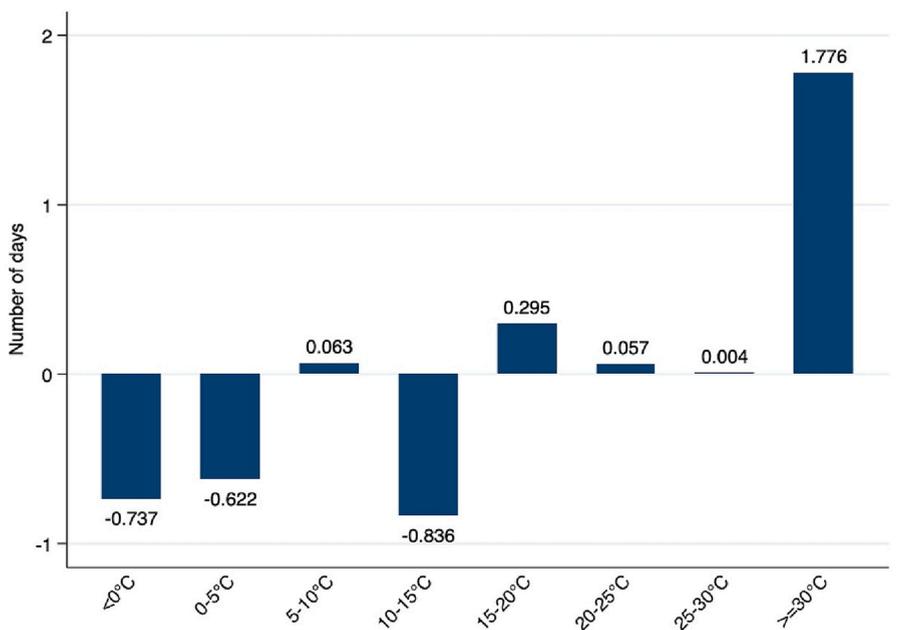


Fig. 1. Distribution of the number of days in eight temperature bins during the gestational period relative to local historical contemporaneous average values in our sample.

falling into eight temperature bins during previous 9 months from 1980 to 1990. Finally, we calculate the deviations of the number of days falling into each temperature bin and weather variables during pregnancy relative to local historical contemporaneous average values.

### 2.3. Summary statistics

The child dataset of CFPS 2010 consists of 8990 individuals aged 0–15, and 3464 of these 8990 individuals are 10 to 15 years old. We exclude sample with missing birth information and personal characteristics in our analysis. The final sample includes 3045 individuals from 25 provinces. We merge individual data and city-level weather data based on birth city and birth year and month. Table 1 provides the summary statistics. The mean value of the K6 score is 2.96. The average score on the six components, feeling depressed, nervous, restless, futureless, difficult, and meaningless is 0.69, 0.70, 0.48, 0.28, 0.57, and 0.24, respectively. The mean age of the sample is 12.59. 50.3% of the sample is female. 88.3% of the sample is Han race. 82.4% of adolescent mothers’ work is agricultural work. The average mother’s age at birth is 25.89 and the average father’s age at birth is 27.75. In addition, the average educational attainment of fathers and mothers is 9 and 10 years, respectively.

In Panel B, we provide descriptive statistics of weather variables at the city level. The mean values of the number of days falling into eight temperature bins relative to local historical contemporaneous average values during pregnancy are 1.78 for the  $\geq 30^\circ\text{C}$  bin, 0.00 for the  $25\text{--}30^\circ\text{C}$  bin, 0.06 for the  $20\text{--}25^\circ\text{C}$  bin, 0.30 for the  $15\text{--}20^\circ\text{C}$  bin,  $-0.84$  for the  $10\text{--}15^\circ\text{C}$  bin, 0.06 for the  $5\text{--}10^\circ\text{C}$  bin,  $-0.62$  for the  $0\text{--}5^\circ\text{C}$  bin, and  $-7.73$  for the  $<0^\circ\text{C}$  bin. Fig. 1 plots the distribution of the number of days in eight temperature bins. The mean values of other meteorological variables relative to local historical contemporaneous average values during pregnancy are 0.01 for precipitation,  $-0.42\%$  for relative humidity, 0.02 for wind speed, 0.01 for sunshine duration, and  $-0.75$  for air pressure.

Other variables used in the robustness checks and mechanism analyses will be introduced in Section 4 and Section 5. Table A1 in the appendix provides the summary statistics.

### 3. Empirical strategy

In order to investigate the nonlinear impacts of prenatal exposure to temperatures on the K6 score, we conduct the following regression model:

$$Y_{icmy} = \alpha + \sum_{k=1}^8 \beta_k Temp_{cmy,k} + \theta W_{cmy} + \gamma X_i + \lambda_{cq} + \pi_{my} + \varepsilon_{icmy} \tag{1}$$

where  $i$  represents individual,  $c$  represents city of birth,  $m$  and  $y$  represent birth month and year, and  $q$  represents quarter of birth. The mental health outcome  $Y_{icmy}$  is the K6 score of individual  $i$  born in city  $c$  in month  $m$  and year  $y$ . We also use a dummy variable for whether the individual’s K6 score is above ten as an indicator for severe mental illness.  $Temp_{cmy,k}$  is the number of days with daily

**Table 2**  
Impacts of prenatal exposure to temperatures on mental health.

	(1)	(2)	(3)	(4)
Number of days (AT $\geq$ 30°C)	0.036 (0.025)	0.035 (0.025)	0.035 (0.024)	0.052** (0.026)
Number of days (AT 25–30°C)	0.027** (0.013)	0.027** (0.013)	0.027** (0.013)	0.039*** (0.014)
Number of days (AT 15–20°C)	–0.004 (0.014)	–0.005 (0.014)	–0.003 (0.014)	–0.002 (0.013)
Number of days (AT 10–15°C)	–0.022 (0.021)	–0.023 (0.021)	–0.023 (0.021)	–0.016 (0.020)
Number of days (AT 5–10°C)	–0.020 (0.027)	–0.021 (0.027)	–0.020 (0.027)	–0.011 (0.024)
Number of days (AT 0–5°C)	–0.014 (0.030)	–0.015 (0.030)	–0.014 (0.029)	–0.000 (0.027)
Number of days (AT <0°C)	–0.027 (0.042)	–0.027 (0.042)	–0.026 (0.042)	–0.009 (0.037)
Female		–0.137 (0.161)	–0.130 (0.164)	–0.151 (0.166)
Age		–0.923 (0.954)	–0.863 (0.958)	–0.914 (0.914)
Han		0.109 (0.369)	0.126 (0.376)	0.279 (0.386)
Mother's age at birth			0.005 (0.032)	–0.003 (0.031)
Father's age at birth			0.030 (0.036)	0.036 (0.036)
Mother's education years			0.002 (0.026)	0.006 (0.025)
Father's education years			–0.026 (0.022)	–0.027 (0.022)
Precipitation				0.388* (0.205)
Relative humidity				0.023 (0.060)
Wind speed				–0.451 (1.055)
Sunshine duration				0.420 (0.381)
Air pressure				–0.021 (0.013)
City-quarter FE	Yes	Yes	Yes	Yes
Year-month FE	Yes	Yes	Yes	Yes
Observation	3045	3045	3045	3045
R <sup>2</sup>	0.235	0.236	0.238	0.240

Notes: The reference temperature bin is 20–25°C, which is omitted in regressions. Standard errors clustered at city level are reported in parentheses.

\*  $p < 0.10$ .

\*\*  $p < 0.05$ .

\*\*\*  $p < 0.01$ .

average temperature falling in  $k$ th temperature bin ( $\geq 30^\circ\text{C}$ ,  $25\text{--}30^\circ\text{C}$ ,  $20\text{--}25^\circ\text{C}$ ,  $15\text{--}20^\circ\text{C}$ ,  $10\text{--}15^\circ\text{C}$ ,  $5\text{--}10^\circ\text{C}$ ,  $0\text{--}5^\circ\text{C}$ ,  $<0^\circ\text{C}$ ) during the gestational period (9 months prior to birth month  $m$  and year  $y$ ) relative to local historical contemporaneous average values. We exclude the baseline bin  $20\text{--}25^\circ\text{C}$  in all regressions.  $W_{cmy}$  is a series of other meteorological control variables, including precipitation, relative humidity, wind speed, sunshine duration, and air pressure. We also control for a vector of individual demographic characteristics,  $X_i$ , including gender, age, race, parental age at delivery, and parental educational attainment.  $\lambda_{cq}$  is city of birth by quarter of birth fixed effects, which can control for seasonal confounding factors at city level that affect mental health.  $\pi_{my}$  is year of birth by month of birth fixed effects. The year-specific seasonal shocks are absorbed by year-month of birth two-way fixed effects. We further add four sets of other fixed effects (city-year of birth fixed effects, city-month of birth fixed effect, and year-month of birth fixed effects; city-quarter of birth fixed effects, year-quarter of birth fixed effects, and month of birth fixed effects; year-month of birth fixed effects, city of birth fixed effects, and month of birth fixed effects; city-quarter of birth fixed effects, year-month of birth fixed effects, and survey month fixed effects) to confirm the robustness of our main findings.  $\varepsilon_{icmy}$  is the error term, which captures time-varying and city-specific unobservable factors that influence mental health.  $\alpha$  is an intercept. All standard errors are clustered at city of birth level. In robustness checks, we also cluster the standard errors at city-year of birth and city-month of birth levels.

$\beta_k$  is the core coefficient of our interest. It can capture the nonlinear impacts of exposure to temperatures during pregnancy relative to local historical contemporaneous average values on the K6 score. When  $\beta_1$  is positive, it indicates that experiencing an additional hot day during gestational period relative to local historical contemporaneous average values increases the K6 score by  $\beta_1$  compared with a day in the baseline temperature bin.

We further conduct the following model to investigate the heterogeneous effects of prenatal exposure to temperatures on the K6 score across different trimesters:

$$Y_{icmy} = \alpha + \sum_{k=1}^8 \beta_k^{TR1} Temp_{cmy,k}^{TR1} + \sum_{k=1}^8 \beta_k^{TR2} Temp_{cmy,k}^{TR2} + \sum_{k=1}^8 \beta_k^{TR3} Temp_{cmy,k}^{TR3} + \theta^{TR1} W_{cym}^{TR1} + \theta^{TR2} W_{cym}^{TR2} + \theta^{TR3} W_{cym}^{TR3} + \gamma X_i + \lambda_{cq} + \pi_{my} + \varepsilon_{icmy} \quad (2)$$

where TR1, TR2, and TR3 represent the first, second, and third trimesters, respectively. In Eq. (2), we include the number of days in each temperature bin and other meteorological control variables separately for each trimester. Other variables are consistent with Eq. (1).

We also refine the model to estimate the seasonal heterogeneous effects of exposure to temperatures during pregnancy on the K6 score:

$$Y_{icmy} = \alpha + \sum_{k=1}^8 \beta_k^{Spring} Temp_{cmy,k}^{Spring} + \sum_{k=1}^8 \beta_k^{Summer} Temp_{cmy,k}^{Summer} + \sum_{k=1}^8 \beta_k^{Autumn} Temp_{cmy,k}^{Autumn} + \sum_{k=1}^8 \beta_k^{Winter} Temp_{cmy,k}^{Winter} + \theta^{Spring} W_{cym}^{Spring} + \theta^{Summer} W_{cym}^{Summer} + \theta^{Autumn} W_{cym}^{Autumn} + \theta^{Winter} W_{cym}^{Winter} + \gamma X_i + \lambda_{cq} + \pi_{my} + \varepsilon_{icmy} \quad (3)$$

where Spring, Summer, Autumn, and Winter are the indicators for four seasons during in utero period, respectively. We only include the number of days in each temperature bin and other meteorological control variables experienced during gestational period by season to identify the heterogeneous effects across each season. Other variables are the same as Eq. (1).

#### 4. Results

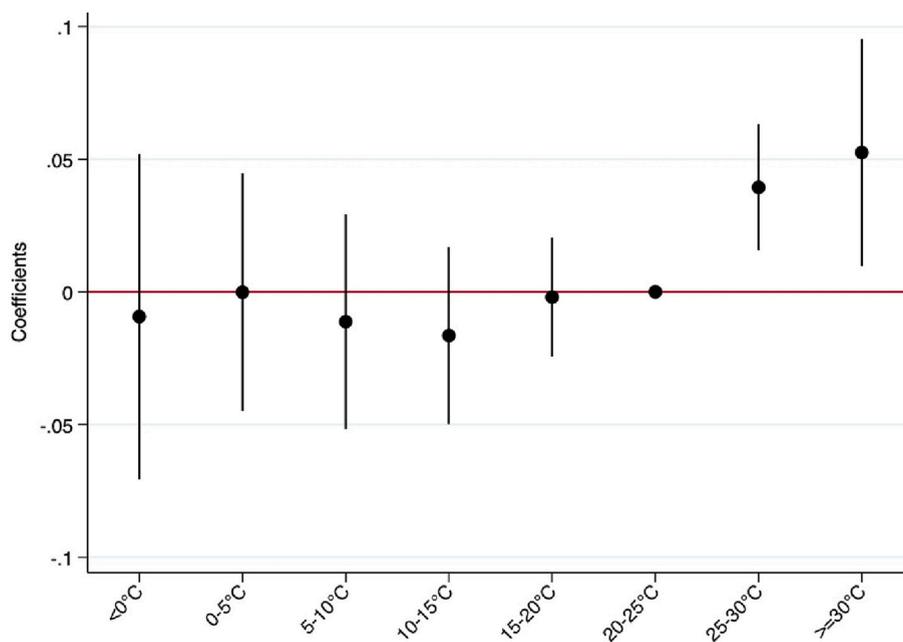
We first report the effects of exposure to temperatures during pregnancy on total K6 score and scores for the six components. We also present the estimated effects of exposure to temperatures by different gestational trimesters and seasons. Then, we show that our main results are consistent across a variety of robustness checks. We further show the heterogeneous effects of prenatal exposure to temperatures on the K6 score across individual demographic characteristics and climate regions.

##### 4.1. Main results

We first investigate the effects of exposure to temperatures during pregnancy on the frequency of depressive symptoms of adolescents by estimating Eq. (1). Table 2 provides the main results. The dependent variable is the K6 score. In column 1, we only include city-quarter of birth fixed effects and year-month of birth fixed effects. The estimated results show that in utero exposure to one 20–25 °C day and one over 30 °C day relative to local historical contemporaneous average values increases the K6 score by 0.04 points (1.21% of the mean value of the sample) and 0.03 points (0.91% of the mean value of the sample), respectively. In columns 2 to 4, we further add individual demographic characteristic control variables, parental demographic characteristic control variables, and other meteorological control variables. After adding other meteorological control variables, the estimated coefficients of extreme hot days become statistically significant in column 4. Replacing an additional day with daily average temperature over 30 °C during pregnancy that deviates from its historical contemporaneous values leads to a significant increase in the K6 score by 0.05 points (1.75% of the mean value of the sample). In utero exposure to an additional relative day with daily average temperature in the 25–30 °C bin significantly increases the K6 score by 0.04 points (1.32% of the mean value of the sample), compared with a baseline day. The number of extreme hot days with daily average temperature over 30 °C experienced during pregnancy increase by an average of 1.78 days relative to the historical average values for the same period. Based on our estimated coefficients, prenatal exposure to additional high temperatures relative to historical long-term temperature deviations significantly increases the K6 score of adolescents by 0.09 points.<sup>9</sup> These estimated results indicate that exposure to high temperatures during in utero period significantly increases the frequency of depressive symptoms, providing evidence for “fetal origins of mental health hypothesis”. We use the results of column 4 as our baseline results to compare with the following results due to the rigorous specification.

To place our findings in context, we compare our results with estimates of extant literature on the effects of temperatures on self-reported mental health. The most relevant to this paper is Adhvaryu, Fenske, and Nyshadham (2019), which investigates the effects of experiencing temperature shocks during pregnancy on depressive symptoms in adulthood in 19 African countries. One degree hotter during one year before delivery than the local historical average leads to an increase in the indicators of depression of adults nearly by 0.03 standard deviations. Based on their method, we also convert the K6 score into a standard normal variable with mean zero and standard deviation one. We first use this new mental health standard normal variable as dependent variable to estimate Eq. (1) in column (1) of Table A2. The estimates of the nonlinear effects of temperatures indicate that exposure to one more hot day with daily average temperature in the over 30 °C bin and the 20–25 °C bin during pregnancy than the local historical contemporaneous average values significantly increases this new measure of mental health by 0.07 standard deviations and 0.05 standard deviations, respectively. Then, we also calculate a relative indicator of average temperature during pregnancy that deviates from historical contemporaneous values. We use this indicator to estimate the linear effects in column (2) of Table A2, suggesting that prenatal exposure to

<sup>9</sup> This value is calculated by multiplying the estimated coefficient of the number of high temperature days (0.052) by the average number of high temperature days experienced during pregnancy (1.776).



**Fig. 2.** Estimated effects of prenatal exposure to temperatures on the K6 score.

Notes: The figure plots the estimated coefficients with 90% confidence intervals associated with each temperature bin identified from regressions in column 4 of Table 2. The temperature exposure window is defined as 9 months during pregnancy. The x-axis indicates the bins that the average temperature belongs to. The y-axis is the size of the coefficient. The full-length bars are the 90% confidence intervals. The reference temperature bin is 20–25°C and seven temperature bin variables are included in model. All regressions include child's demographic controls (gender, child age, and race), parental demographic controls (parents' age at delivery and education years), weather controls (precipitation, relative humidity, wind speed, sunshine duration, and atmospheric pressure), city-quarter FE, and year-month FE. Standard errors are clustered at the city level.

one degree warmer than the local historical average values leads to an increase in the K6 score of adolescents by 0.16 standard deviations. Our coefficients are larger than that of Adhvaryu, Fenske, & Nyshadham (2019). This paper is also related to Hua, Qiu, & Tan (2022), which finds that exposure to an additional extreme hot day in the previous month significantly increases adults' K6 score by 0.21 points (6.72% of sample mean) using the same identification strategy as we do. Our estimated coefficient, 1.75% of the mean value of the sample, is about 4 times smaller than the size of their estimate. The differences in this comparison may be due to the fact that we focus on different exposure periods (during pregnancy versus previous month) and use different indicators of the number of days in each temperature bin (deviations versus no deviations). We further compare the results by using changes in standard deviations. Our estimated results suggest that an increase of one standard deviation in prenatal exposure to extreme high temperatures leads to an increase in the K6 score by 0.14 standard deviations. The coefficients of Hua, Qiu, & Tan (2022) indicate that an increase of one standard deviation in exposure to hot days in the previous month significantly increases the K6 score by 0.21 standard deviations.<sup>10</sup> The difference of the magnitudes of the results becomes smaller.

Using the predicted daily average temperature from 2041 to 2099 from the Hadley GEM2-ES, our calculations show that the number of days with daily average temperature over 30°C every year (360 days) will increase roughly 56.38 days.<sup>11</sup> Based on our baseline coefficient, a back-of-the envelope calculation suggests that prenatal exposure to extreme hot days will increase the K6 score of adolescents by roughly 2.82 points in 2041–2099. Although the absolute value of the estimated coefficient is relatively small, the threat of global warming to mental health cannot be underestimated with increasingly frequent heatwaves. We need to be careful in interpreting this result, because we assume that the future temperature and adolescent mental health relationship will be the same as it is now.

Fig. 2 shows the estimated coefficients with 90% confidence intervals of variables for the number of days falling in each temperature bin identified from the regression in column 4 of Table 2. In addition, all individual and parental demographic characteristics do not have significant effects on adolescent mental health. Furthermore, many studies have found that other meteorological variables may influence expressed sentiment (Baylis et al., 2018). Our results show that only the coefficient of precipitation is significant at 5% level, suggesting that precipitation during gestational period may significantly worsen adolescent mental health.

Next, we estimate the effects of exposure to temperatures during pregnancy on the score for each component of total K6 score

<sup>10</sup> These changes in standard deviations are calculated by multiplying the estimated coefficient of the dependent variable by the standard deviation of the independent variable and then dividing by the mean of the dependent variable.

<sup>11</sup> Data source: <https://cera-www.dkrz.de/WDCC/ui/cersearch/q?query=CMIP5&page=0&rows=15>.

**Table 3**  
Impacts of prenatal exposure to temperatures on the K6 score components.

	Depressed	Nervous	Restless	Futureless	Difficult	Meaningless
	(1)	(2)	(3)	(4)	(5)	(6)
Number of days (AT $\geq$ 30°C)	0.009** (0.004)	0.014** (0.007)	0.002 (0.007)	0.008** (0.004)	0.012* (0.007)	0.004 (0.004)
Number of days (AT 25–30°C)	0.010 (0.007)	0.010*** (0.004)	0.005 (0.003)	0.006** (0.003)	0.002 (0.004)	0.003 (0.003)
Number of days (AT 15–20°C)	0.002 (0.004)	-0.002 (0.004)	0.002 (0.003)	-0.002 (0.003)	-0.002 (0.003)	-0.002 (0.003)
Number of days (AT 10–15°C)	-0.005 (0.006)	-0.004 (0.007)	-0.001 (0.005)	-0.004 (0.004)	-0.006 (0.005)	-0.002 (0.004)
Number of days (AT 5–10°C)	-0.004 (0.007)	-0.007 (0.007)	0.004 (0.006)	-0.006 (0.004)	-0.001 (0.006)	-0.003 (0.005)
Number of days (AT 0–5°C)	-0.008 (0.008)	-0.005 (0.009)	0.006 (0.008)	-0.002 (0.005)	-0.000 (0.006)	0.000 (0.006)
Number of days (AT <0°C)	-0.017 (0.011)	-0.007 (0.011)	0.006 (0.010)	-0.006 (0.006)	-0.000 (0.008)	-0.000 (0.008)
Child's demographic controls	Yes	Yes	Yes	Yes	Yes	Yes
Parental demographic controls	Yes	Yes	Yes	Yes	Yes	Yes
Weather controls	Yes	Yes	Yes	Yes	Yes	Yes
City-quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-month FE	Yes	Yes	Yes	Yes	Yes	Yes
Observation	3045	3045	3045	3045	3045	3045
R <sup>2</sup>	0.212	0.242	0.209	0.211	0.195	0.187

Notes: The reference temperature bin is 20–25°C, which is omitted in regressions. Child's demographic controls include gender, child age, and race. Parental demographic controls include parents' age at delivery and education years. Weather controls include precipitation, relative humidity, wind speed, sunshine duration, and atmospheric pressure. Standard errors clustered at city level are reported in parentheses.

\*  $p < 0.10$ .

\*\*  $p < 0.05$ .

\*\*\*  $p < 0.01$ .

separately. All the results of the impacts of extreme hot days on the frequency of all six depressive symptoms are positive. Four of the six symptoms are significantly affected by high temperatures. Relative to a comfortable 20–25°C day, exposure to one more extreme hot day during the gestational period than the local historical contemporaneous average values significantly increases the occurrence of feeling depressed, nervous, futureless, and difficult. The values of the coefficients of the occurrence of feeling nervous and difficult are larger. As shown in Table 3 and Fig. 3, the results suggest that the positive effects of high temperatures on total K6 score are not determined by a single symptom of depression.

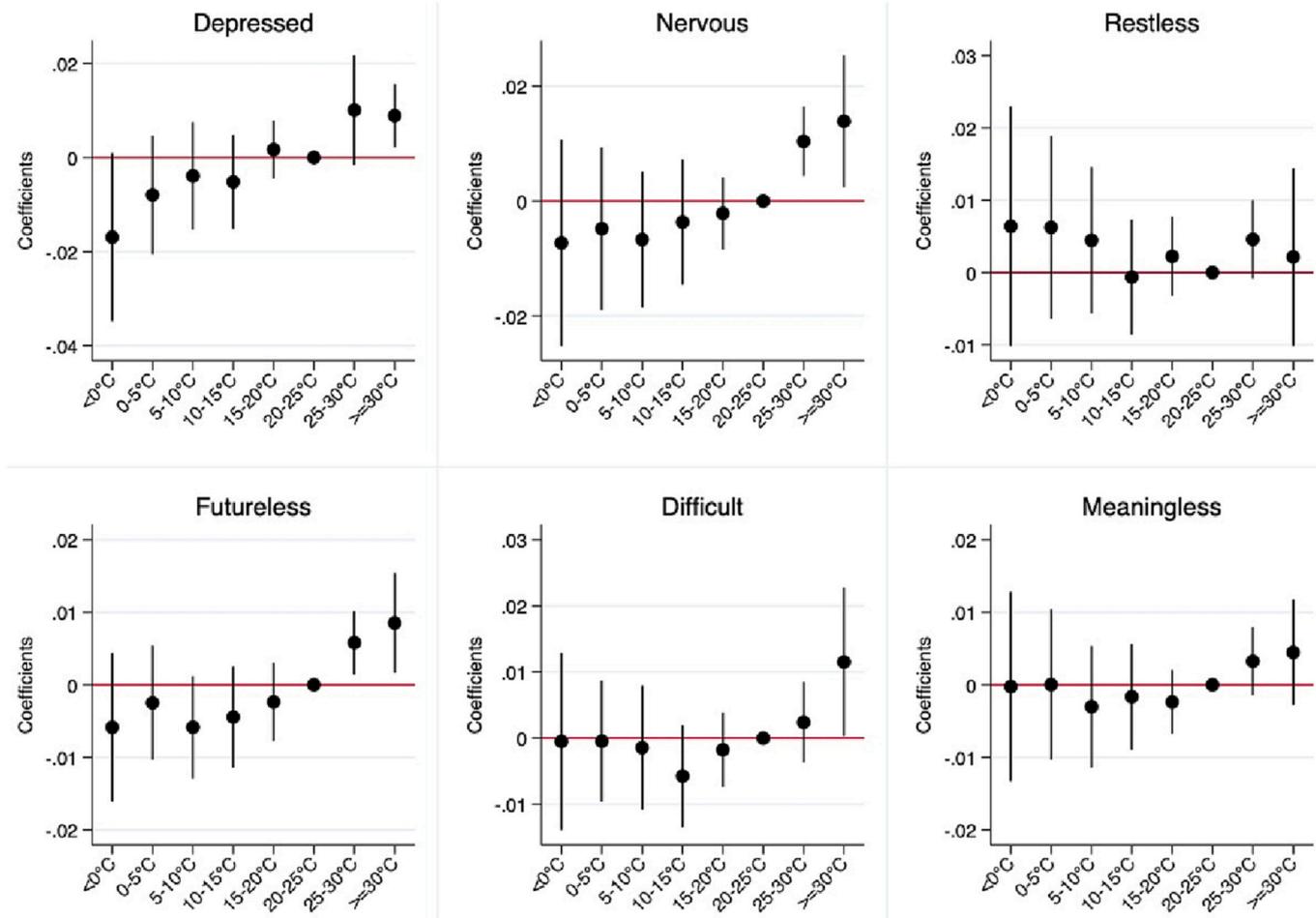
Then, we explore whether there are differences in the impacts of prenatal exposure to hot days on the K6 score in different trimesters by estimating Eq. (2) in Table 4 and Fig. 4. The results show that the impacts of hot days in the first and second trimesters are more significant and larger. However, the positive coefficients of in utero exposure to hot days in the third trimester are insignificant. A growing body of economic and medical literature has shown that fetuses may be sensitive to heat waves in the first and second trimesters (Hu & Li, 2019; Murray et al., 2000).

We further add the relative indicators of the number of days in each temperature bin and other meteorological control variables in each month of pregnancy to Eq. (1) instead of the variables for the entire 9 months of pregnancy to explore the more detailed heterogeneous impacts. Table 5 provides the estimated results. The coefficient of extreme high temperature first increases and then decreases, reaching a maximum in the fifth month. The adverse impact of hot days on the K6 score is statistically significant in the third to seventh months.

Finally, the seasonal heterogeneous effects are estimated by Eq. (3) to try to distinguish between the effects of objective extreme high temperatures (e.g., above 30°C) and the effects of the occurrence of abnormally high temperatures (e.g., 25–30°C winter) in different seasons. The estimated coefficients of exposure to high temperatures in each season during pregnancy are presented in Table 6. Experiencing one more extreme hot day in spring, summer, and autumn during pregnancy than the local historical contemporaneous average values significantly increases the K6 score by 1.46 points, 0.05 points, and 0.08 points, respectively. Extreme hot days (over 30°C) are missing in winter. Additionally, replacing one 20–25°C day with one 25–30°C day in summer, autumn, and winter during pregnancy relative to the local historical contemporaneous average values leads to a significant increase in the K6 score by 0.12 points, 0.03 points, and 0.28 points, respectively. Our estimates show that the adverse effects of objective extreme high temperatures and the occurrence of abnormally high temperatures both exist, indicating an obvious seasonal heterogeneity. Additionally, prenatal exposure to objective extreme hot days has larger harmful effects during the relatively mild season.

#### 4.2. Robustness checks

A series of robustness checks to show that the results remain robust to alternative specifications, alternative dependent and independent variables, alternative temperature intervals, alternative sample, age heaping, and placebo tests.



**Fig. 3.** Estimated effects of prenatal exposure to temperatures on the K6 score components.

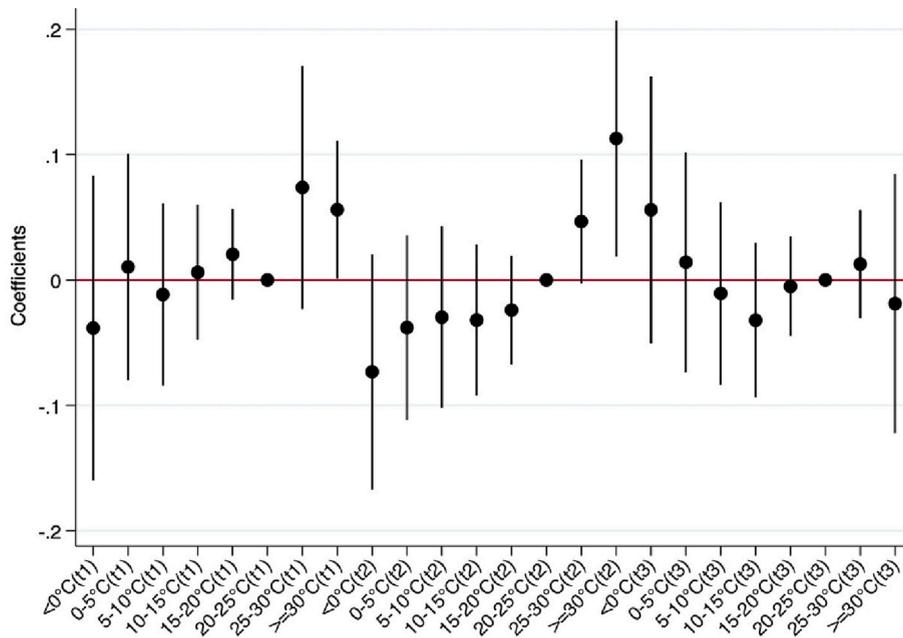
Notes: The figure plots the estimated coefficients with 90% confidence intervals associated with each temperature bin identified from regressions in Table 3. The temperature exposure window is defined as 9 months during pregnancy. The x-axis indicates the bins that the average temperature belongs to. The y-axis is the size of the coefficient. The full-length bars are the 90% confidence intervals. The reference temperature bin is 20–25 $^{\circ}\text{C}$  and seven temperature bin variables are included in model. All regressions include child’s demographic controls (gender, child age, and race), parental demographic controls (parents’ age at delivery and education years), weather controls (precipitation, relative humidity, wind speed, sunshine duration, and atmospheric pressure), city-quarter FE, and year-month FE. Standard errors are clustered at the city level.

**Table 4**  
Impacts of prenatal exposure to temperatures on mental health in each trimester.

	1st trimester	2nd trimester	3rd trimester
Number of days (AT ≥ 30 °C)	0.056* (0.033)	0.113** (0.057)	-0.019 (0.062)
Number of days (AT 25–30 °C)	0.074 (0.059)	0.047 (0.030)	0.013 (0.026)
Number of days (AT 15–20 °C)	0.020 (0.022)	-0.024 (0.026)	-0.005 (0.024)
Number of days (AT 10–15 °C)	0.006 (0.032)	-0.032 (0.036)	-0.032 (0.037)
Number of days (AT 5–10 °C)	-0.012 (0.044)	-0.030 (0.044)	-0.011 (0.044)
Number of days (AT 0–5 °C)	0.010 (0.054)	-0.038 (0.044)	0.014 (0.053)
Number of days (AT < 0 °C)	-0.038 (0.073)	-0.073 (0.057)	0.056 (0.064)
Child's demographic controls	Yes		
Parental demographic controls	Yes		
Weather controls	Yes		
City-quarter FE	Yes		
Year-month FE	Yes		
Observation	3045		
R <sup>2</sup>	0.247		

Notes: The reference temperature bin is 20–25°C, which is omitted in regressions. Child's demographic controls include gender, child age, and race. Parental demographic controls include parents' age at delivery and education years. Weather controls include precipitation, relative humidity, wind speed, sunshine duration, and atmospheric pressure. Standard errors clustered at city level are reported in parentheses.

\*  $p < 0.10$ .  
\*\*  $p < 0.05$ .



**Fig. 4.** Estimated effects of prenatal exposure to temperatures on the K6 score in each trimester.

Notes: The figure plots the estimated coefficients with 90% confidence intervals associated with each temperature bin identified from regressions in Table 4. The temperature exposure window is defined as 9 months during pregnancy. The x-axis indicates the bins that the average temperature belongs to. The y-axis is the size of the coefficient. The full-length bars are the 90% confidence intervals. The reference temperature bin is 20–25°C and seven temperature bin variables are included in model. All regressions include child's demographic controls (gender, child age, and race), parental demographic controls (parents' age at delivery and education years), weather controls (precipitation, relative humidity, wind speed, sunshine duration, and atmospheric pressure), city-quarter FE, and year-month FE. Standard errors are clustered at the city level.

**Table 5**

Impacts of prenatal exposure to temperatures on mental health in each month during pregnancy.

	1st month	2nd month	3rd month	4th month	5th month	6th month	7th month	8th month	9th month
Number of days (AT $\geq$ 30 °C)	0.110 (0.115)	0.132 (0.102)	0.164* (0.093)	0.231** (0.103)	0.117** (0.052)	0.091** (0.042)	0.021* (0.012)	0.019 (0.119)	-0.047 (0.048)
Number of days (AT 25–30 °C)	0.034 (0.057)	0.073 (0.055)	0.030 (0.050)	0.046 (0.111)	0.059 (0.056)	0.006 (0.047)	0.028 (0.101)	0.010 (0.054)	-0.044 (0.051)
Number of days (AT 15–20 °C)	0.034 (0.040)	-0.016 (0.049)	0.001 (0.045)	-0.065 (0.047)	0.013 (0.037)	-0.025 (0.052)	0.037 (0.048)	-0.016 (0.051)	-0.158 (0.105)
Number of days (AT 10–15 °C)	0.030 (0.057)	-0.017 (0.055)	-0.046 (0.064)	-0.047 (0.065)	0.025 (0.065)	-0.055 (0.076)	0.018 (0.076)	-0.060 (0.062)	-0.061 (0.076)
Number of days (AT 5–10 °C)	0.000 (0.076)	-0.026 (0.071)	-0.043 (0.092)	-0.101 (0.087)	0.032 (0.093)	-0.034 (0.106)	0.077 (0.090)	-0.052 (0.100)	-0.092 (0.096)
Number of days (AT 0–5 °C)	-0.089 (0.100)	-0.079 (0.094)	-0.061 (0.095)	-0.138 (0.093)	0.020 (0.104)	0.009 (0.124)	0.098 (0.104)	0.024 (0.105)	-0.077 (0.117)
Number of days (AT <0 °C)	-0.093 (0.105)	-0.107 (0.111)	-0.009 (0.144)	-0.187* (0.111)	-0.071 (0.118)	0.027 (0.151)	0.125 (0.117)	-0.030 (0.131)	-0.024 (0.142)
Child's demographic controls	Yes								
Parental demographic controls	Yes								
Weather controls	Yes								
City-quarter FE	Yes								
Year-month FE	Yes								
Observation	3045								
R <sup>2</sup>	0.273								

Notes: The reference temperature bin is 20–25°C, which is omitted in regressions. Child's demographic controls include gender, child age, and race. Parental demographic controls include parents' age at delivery and education years. Weather controls include precipitation, relative humidity, wind speed, sunshine duration, and atmospheric pressure. Standard errors clustered at city level are reported in parentheses.

\*  $p < 0.10$ .\*\*  $p < 0.05$ .**Table 6**

Impacts of prenatal exposure to temperatures on mental health in each season during pregnancy.

	Spring	Summer	Autumn	Winter
Number of days (AT $\geq$ 30 °C)	1.456* (0.761)	0.049** (0.020)	0.078** (0.035)	–
Number of days (AT 25–30 °C)	0.120* (0.065)	0.049 (0.034)	0.033* (0.017)	0.283*** (0.075)
Number of days (AT 15–20 °C)	-0.013 (0.029)	-0.046 (0.033)	0.053 (0.038)	-0.022 (0.040)
Number of days (AT 10–15 °C)	-0.011 (0.034)	-0.112 (0.082)	0.009 (0.051)	-0.004 (0.053)
Number of days (AT 5–10 °C)	-0.014 (0.038)	-0.118 (0.450)	0.041 (0.061)	-0.020 (0.061)
Number of days (AT 0–5 °C)	-0.011 (0.063)	-0.235 (15.872)	0.052 (0.071)	0.009 (0.067)
Number of days (AT <0 °C)	-0.040 (0.076)	–	0.029 (0.077)	0.015 (0.081)
Child's demographic controls	Yes			
Parental demographic controls	Yes			
Weather controls	Yes			
City-quarter	Yes			
Year-month FE	Yes			
Observation	3045			
R <sup>2</sup>	0.253			

Notes: The reference temperature bin is 20–25°C, which is omitted in regressions. Child's demographic controls include gender, child age, and race. Parental demographic controls include parents' age at delivery and education years. Weather controls include precipitation, relative humidity, wind speed, sunshine duration, and atmospheric pressure. Standard errors clustered at city level are reported in parentheses.

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

First, we use different two-way fixed effects to control for regional time trends and unobservable variables. In column 1 of Table 7, we replace city-quarter of birth fixed effects with city-year of birth fixed effects and city-month of birth fixed effects to capture unobserved regional time-specific confounding factors over time that might influence both temperature and mental health, such as economic shocks and policy interventions. We further control for city-quarter of birth fixed effects, year-quarter of birth fixed effects, and month of birth fixed effects in column 2 of Table 7 to capture year-specific seasonal fluctuations. Then, we include year-month of

**Table 7**  
Robustness checks: alternative specifications.

	Alternative fixed effects				Alternative clusters		Alternative controls	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Number of days (AT $\geq$ 30°C)	0.157** (0.074)	0.050* (0.026)	0.028** (0.012)	0.046* (0.026)	0.050** (0.023)	0.050* (0.028)	0.048* (0.025)	0.046* (0.024)
Number of days (AT 25–30°C)	0.054 (0.038)	0.035** (0.015)	0.033 (0.024)	0.035** (0.015)	0.035*** (0.014)	0.035** (0.015)	0.035** (0.015)	0.038** (0.015)
Number of days (AT 15–20°C)	–0.033 (0.041)	–0.005 (0.014)	–0.008 (0.011)	–0.005 (0.014)	–0.005 (0.013)	–0.005 (0.014)	–0.006 (0.014)	0.001 (0.015)
Number of days (AT 10–15°C)	–0.087* (0.049)	–0.022 (0.022)	–0.023 (0.019)	–0.022 (0.023)	–0.022 (0.020)	–0.022 (0.020)	–0.023 (0.022)	–0.035 (0.023)
Number of days (AT 5–10°C)	–0.067 (0.078)	–0.017 (0.027)	–0.023 (0.022)	–0.020 (0.027)	–0.017 (0.023)	–0.017 (0.026)	–0.019 (0.027)	–0.030 (0.027)
Number of days (AT 0–5°C)	–0.142 (0.112)	–0.011 (0.030)	–0.013 (0.026)	–0.016 (0.031)	–0.011 (0.026)	–0.011 (0.027)	–0.015 (0.031)	–0.026 (0.031)
Number of days (AT <0°C)	–0.146 (0.144)	–0.026 (0.042)	–0.015 (0.033)	–0.032 (0.043)	–0.026 (0.035)	–0.026 (0.036)	–0.031 (0.042)	–0.033 (0.042)
Child's demographic controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Parental demographic controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Weather controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Contemporary weather controls	No	No	No	No	No	No	No	No
Family investment and environment controls	No	No	No	No	No	No	Yes	Yes
School environment controls	No	No	No	No	No	No	No	Yes
Upbring controls	No	No	No	No	No	No	No	Yes
Personality traits	No	No	No	No	No	No	No	Yes
City-quarter FE	No	Yes	No	Yes	Yes	Yes	No	No
City-year FE	Yes	No	No	No	No	No	Yes	Yes
City-month FE	Yes	No	No	No	No	No	Yes	Yes
Year-quarter FE	No	Yes	No	No	No	No	No	No
Year-month FE	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes
City FE	No	No	Yes	No	No	No	No	No
Month FE	No	Yes	Yes	No	No	No	No	No
Survey month FE	No	No	No	Yes	No	No	No	No
Cluster	City	City	City	City	City-year	City-month	City	City
Observation	3045	3045	3045	3045	3045	3045	3045	2602
R <sup>2</sup>	0.600	0.225	0.138	0.249	0.240	0.240	0.249	0.250

Notes: The reference temperature bin is 20–25°C, which is omitted in regressions. Child's demographic controls include gender, child age, and race. Parental demographic controls include parents' age at delivery and education years. Weather controls include precipitation, relative humidity, wind speed, sunshine duration, and atmospheric pressure. Contemporary weather controls include the number of days in each temperature bin, average precipitation, average relative humidity, average wind speed, average sunshine duration, and average atmospheric pressure in the month before the survey month. Family investment and environment controls include the duration of breastfeeding, height-for-age z-scores, BMI-for-age z-score, and parent-child communication. School environment control includes school level. Upbring control includes time for left-behind children. Personality traits control includes naturally optimistic personality. In columns 1, 2, 3, 4, 7 and 8, standard errors clustered at city level are reported in parentheses. In column 5, standard errors clustered at city-year level are reported in parentheses. In column 6, standard errors clustered at city-month level are reported in parentheses.

\*  $p < 0.10$ .

\*\*  $p < 0.05$ .

\*\*\*  $p < 0.01$ .

birth fixed effects, month of birth fixed effects, and city of birth fixed effects to isolate high versus low temperatures for the same month in column 3 of Table 7. Additionally, we also add an additional survey month fixed effects in the baseline model to rule out any seasonal contemporary impacts on the K6 score in column 4 of Table 7. The estimated results remain consistent with our baseline findings.

Second, we next allow for two-way clustering of errors by city and year of birth and by city and month of birth in columns 5 and 6 of Table 7, respectively. Two-way clustering allows for serial correlation within each city-year of birth and each city-month of birth. The main results remain significant.

Third, we add contemporary weather control variables and other environment and personality controls in our baseline regression to examine whether these factors alter our main results. We calculate our interested meteorological variables in the previous month before the interview date. We include these variables and re-estimate Eq. (1) in column 7 of Table 7. We also add family investment and environment control variables, school environment control variables, upbringing control variables, and personality trait control variables in Eq. (1), including the duration of breastfeeding, height-for-age z-scores, BMI-for-age z-score, an indicator for parent-child

**Table 8**  
Robustness checks: alternative dependent and independent variables.

	Alternative dependent variables		Alternative independent variables	
	Ln K6	Severe depression	No temperature deviations	Maximum temperature
	(1)	(2)	(3)	(4)
				Number of days (MT $\geq 35^{\circ}\text{C}$ )
				0.024*
				(0.014)
Number of days (AT $\geq 30^{\circ}\text{C}$ )	0.007**	0.003*	0.047**	Number of days (MT 30–35 $^{\circ}\text{C}$ )
	(0.003)	(0.002)	(0.022)	0.017*
				(0.010)
Number of days (AT 25–30 $^{\circ}\text{C}$ )	0.010	0.002*	0.021**	Number of days (MT 25–30 $^{\circ}\text{C}$ )
	(0.006)	(0.001)	(0.010)	–0.008
				(0.011)
Number of days (AT 15–20 $^{\circ}\text{C}$ )	–0.001	–0.001	0.008	Number of days (MT 15–20 $^{\circ}\text{C}$ )
	(0.003)	(0.001)	(0.010)	–0.017
				(0.014)
Number of days (AT 10–15 $^{\circ}\text{C}$ )	–0.005	–0.002*	–0.004	Number of days (MT 10–15 $^{\circ}\text{C}$ )
	(0.005)	(0.001)	(0.012)	–0.006
				(0.021)
Number of days (AT 5–10 $^{\circ}\text{C}$ )	–0.003	–0.003	–0.011	Number of days (MT 5–10 $^{\circ}\text{C}$ )
	(0.007)	(0.002)	(0.016)	0.015
				(0.015)
Number of days (AT 0–5 $^{\circ}\text{C}$ )	–0.002	–0.001	–0.017	Number of days (MT 0–5 $^{\circ}\text{C}$ )
	(0.007)	(0.002)	(0.016)	0.007
				(0.018)
Number of days (AT $<0^{\circ}\text{C}$ )	–0.005	–0.002	–0.028	Number of days (MT $<0^{\circ}\text{C}$ )
	(0.010)	(0.003)	(0.022)	–0.004
				(0.023)
Child's demographic controls	Yes	Yes	Yes	Child's demographic controls
Parental demographic controls	Yes	Yes	Yes	Parental demographic controls
Weather controls	Yes	Yes	Yes	Weather controls
City-quarter FE	Yes	Yes	Yes	City-quarter FE
Year-month FE	Yes	Yes	Yes	Year-month FE
Observation	3045	3045	3045	Observation
R <sup>2</sup>	0.261	0.206	0.239	R <sup>2</sup>
				0.240

Notes: The reference temperature bin is 20–25 $^{\circ}\text{C}$ , which is omitted in regressions. Child's demographic controls include gender, child age, and race. Parental demographic controls include parents' age at delivery and education years. Weather controls include precipitation, relative humidity, wind speed, sunshine duration, and atmospheric pressure. Standard errors clustered at city level are reported in parentheses.

\*  $p < 0.10$ .

\*\*  $p < 0.05$ .

communication status, a dummy variable for school level, time for left-behind children, and a dummy variable for naturally optimistic personality.<sup>12</sup> Column 8 of Table 7 shows the estimates. The magnitude and significance of the estimated coefficients are in line with our baseline results. Despite we try to include sufficient control variables and fixed effects at different levels to solve the problem of omitted variables, we cannot completely solve this problem because of data limitations.<sup>13</sup> We leave these for future research.

Fourth, we use the natural logarithm of the K6 score as the dependent variable in column 1 of Table 8. In utero exposure to one more extreme hot day than the local historical contemporaneous average values leads to an increase in the K6 score by 0.7%, respectively. In column 2 of Table 8, we define a dummy variable representing severe depression, which equals to one when the K6 score is ten and above, and zero otherwise (Andresen, Malmgren, Carter, & Patrick, 1994). The results show that hot days significantly increase the probability of depressive by 0.3%, which is larger than that of Hua, Qiu, & Tan (2022) (0.2%).

Fifth, we use meteorological variables during pregnancy without considering historical deviations to re-estimate Eq. (1). The main finding remains unchanged in column 3 of Table 8. Additionally, extreme hot temperatures are more likely to be captured by the daily maximum temperature. Thus, we calculate the number of days with daily maximum temperature falling into each temperature bin to estimate Eq. (1) in column 4 of Table 8. Experiencing one more day with daily maximum temperature falling into the over 35 $^{\circ}\text{C}$  bin and the 30–35 $^{\circ}\text{C}$  bin during pregnancy than the local historical contemporaneous average values increases the K6 score by 0.02 points and 0.02 points, respectively.

Sixth, we use 3 $^{\circ}\text{C}$  and 4 $^{\circ}\text{C}$  temperature bins instead of 5 $^{\circ}\text{C}$  temperature bins to further capture the negative effects of extreme hot weather (over 33 $^{\circ}\text{C}$  and over 32 $^{\circ}\text{C}$ ). Table 9 provides the results. We find that prenatal exposure to extreme high temperatures with daily average temperature over 33 $^{\circ}\text{C}$  and over 32 $^{\circ}\text{C}$  relative to the local historical long-term average temperatures increases the K6 score by 0.18 points and 0.11 points, respectively. The coefficients are larger than that of the variables for the number of days falling into the 30–33 $^{\circ}\text{C}$  temperature bin and the 28–32 $^{\circ}\text{C}$  temperature bin.

Seventh, we further include individuals aged 16–17 in our sample by combining the child dataset and adult dataset and re-estimate Eq. (1) in column 1 of Table 10. The positive effects of the frequency of depressive symptoms remain robust.

Eighth, there is the tendency for individuals to inaccurately report their actual age or date of birth with a round and lucky number or a better meaning in traditional culture. Age heaping may confound our results by wrong pregnancy period. We exclude some

<sup>12</sup> We calculate height-for-age z-scores and BMI-for-age z-scores based on adolescents' actual height and BMI from the CFPS 2010 and international reference values from the World Health Organization. Other variables are defined in Table A1.

<sup>13</sup> For example, we cannot observe information about fetus and control all confounding factors that affect mental health as adolescents grow up, including environment, personality traits, and so on.

**Table 9**  
Robustness checks: alternative temperature intervals.

	3°C (1)		4°C (2)
Number of days (AT <sub>≥</sub> 33°C)	0.178* (0.104)	Number of days (AT <sub>≥</sub> 32°C)	0.112* (0.063)
Number of days (AT 30–33°C)	0.045* (0.027)	Number of days (AT 28–32°C)	0.033* (0.019)
Number of days (AT 27–30°C)	0.023 (0.022)	Number of days (AT 24–28°C)	0.013 (0.010)
Number of days (AT 24–27°C)	0.026 (0.017)	Number of days (AT 16–20°C)	−0.008 (0.012)
Number of days (AT 18–21°C)	0.008 (0.022)	Number of days (AT 12–16°C)	0.003 (0.017)
Number of days (AT 15–18°C)	0.010 (0.019)	Number of days (AT 8–12°C)	−0.012 (0.016)
Number of days (AT 12–15°C)	−0.007 (0.025)	Number of days (AT 4–8°C)	0.000 (0.018)
Number of days (AT 9–12°C)	−0.010 (0.028)	Number of days (AT 0–4°C)	0.025 (0.020)
Number of days (AT 6–9°C)	−0.000 (0.029)	Number of days (AT <0°C)	0.022 (0.024)
Number of days (AT 3–6°C)	−0.003 (0.035)		
Number of days (AT 0–3°C)	0.020 (0.037)		
Number of days (AT <0°C)	−0.001 (0.044)		
Child's demographic controls	Yes	Child's demographic controls	Yes
Parental demographic controls	Yes	Parental demographic controls	Yes
Weather controls	Yes	Weather controls	Yes
City-quarter FE	Yes	City-quarter FE	Yes
Year-month FE	Yes	Year-month FE	Yes
Observation	3045	Observation	3045
R <sup>2</sup>	0.240	R <sup>2</sup>	0.240

Notes: The reference temperature bin is 20–25°C, which is omitted in regressions. Child's demographic controls include gender, child age, and race. Parental demographic controls include parents' age at delivery and education years. Weather controls include precipitation, relative humidity, wind speed, sunshine duration, and atmospheric pressure. Standard errors clustered at city level are reported in parentheses.

\*  $p < 0.10$ .

samples to rule out evidence of age heaping in birth year and month. On the one hand, we exclude adolescents born in the Year of the Dragon and aged 12, 10, and 15 years old.<sup>14</sup> The results are shown in columns 2 to 5 of Table 10 and remain consistent with the baseline results. On the other hand, we exclude adolescents born in August, January, and February to rule out age heaping in birth month in columns 6 and 7 of Table 10.<sup>15</sup> The estimated results are similar to our main results.<sup>16</sup>

Ninth, we conduct a placebo test by simultaneously including our main meteorological variables during the nine-month period before conception, in gestation, and after birth. Table 11 and Fig. 5 provide the estimated results. As we expect, experiencing hot days before conception and after birth don't affect adolescent mental health. The deteriorating effects of hot days during pregnancy still remain robust, suggesting that controlling for lags and leads don't alter our main findings.

#### 4.3. Selection issues

It is important to discuss some selection issues that may bias our main findings. First, high temperatures may affect fecundity and decrease sexual activity, especially for people who don't get knowledge of weather and its adverse effects and cannot take measures to avoid heat hazards (Wilde, Apouey, & Jung, 2017). Therefore, less educated women may have lower fertility nine months after experiencing hot temperatures. We check whether exposure to high temperatures one month before conception is associated with maternal education attainment and age at birth. The results are presented in columns 1 and 2 of Table 12. We find that prenatal exposure to high temperatures before conception doesn't affect maternal years of education and age. In addition, exposure to high temperatures reduce time spend working in China, especially for women farmers (Garg, Gibson, & Sun, 2020). This is another potential

<sup>14</sup> First, the dragon is the auspicious zodiac sign of China. Second, age heaping occurs on a 12-year cycle among Han Chinese, which is consistent with preferred animal years of the Chinese calendar. Third, individuals prefer to report ages ending in 0 and 5.

<sup>15</sup> In China, children born in August can enter school to start compulsory education in September of that year when they are 6 years old, otherwise they will enter school in September of the following year. Additionally, January and February are generally the Chinese Lunar Spring Festival.

<sup>16</sup> We thank an anonymous referee for pointing out age heaping may confound our main findings.

**Table 10**  
Robustness checks: alternative sample and age heaping.

	Alternative sample		Age heaping				
	10–17	Year of the Dragon	12	10	15	August	January and February
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Number of days (AT ≥ 30°C)	0.025** (0.011)	0.048* (0.028)	0.045** (0.020)	0.048* (0.028)	0.053* (0.029)	0.061** (0.029)	0.057* (0.030)
Number of days (AT 25–30°C)	0.032 (0.022)	0.026 (0.017)	0.029 (0.035)	0.026 (0.017)	0.042*** (0.014)	0.040** (0.017)	0.029* (0.015)
Number of days (AT 15–20°C)	−0.003 (0.011)	−0.011 (0.015)	−0.012 (0.017)	−0.011 (0.015)	0.010 (0.015)	−0.004 (0.015)	−0.013 (0.015)
Number of days (AT 10–15°C)	−0.023 (0.017)	−0.024 (0.021)	−0.005 (0.024)	−0.024 (0.021)	−0.004 (0.023)	−0.018 (0.023)	−0.021 (0.021)
Number of days (AT 5–10°C)	−0.017 (0.019)	−0.020 (0.025)	0.004 (0.025)	−0.020 (0.025)	−0.011 (0.030)	−0.023 (0.029)	−0.017 (0.027)
Number of days (AT 0–5°C)	−0.004 (0.024)	−0.005 (0.028)	0.005 (0.028)	−0.006 (0.028)	0.007 (0.031)	−0.007 (0.033)	−0.010 (0.028)
Number of days (AT < 0°C)	−0.007 (0.031)	−0.035 (0.039)	−0.007 (0.036)	−0.034 (0.039)	0.015 (0.044)	−0.029 (0.045)	−0.015 (0.038)
Child's demographic controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Parental demographic controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Weather controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City-quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observation	3903	2567	2569	2575	2466	2759	2534
R <sup>2</sup>	0.209	0.254	0.270	0.254	0.272	0.255	0.258

Notes: The reference temperature bin is 20–25°C, which is omitted in regressions. Child's demographic controls include gender, child age, and race. Parental demographic controls include parents' age at delivery and education years. Weather controls include precipitation, relative humidity, wind speed, sunshine duration, and atmospheric pressure. Standard errors clustered at city level are reported in parentheses.

\*  $p < 0.10$ .

\*\*  $p < 0.05$ .

\*\*\*  $p < 0.01$ .

channel to affect fertility.<sup>17</sup> We estimate the nonlinear effects of exposure to hot weather in one month previous the survey on the natural logarithm of maternal working hours by matching maternal working hours to our dataset based on mothers' personal code in column 3 of Table 12. Extreme high temperatures don't significantly reduce maternal working time. Therefore, selection on fertility doesn't alter our main findings.

Second, selective mortality may be another confounding concern. It means that stronger and healthier fetuses are more likely to survive, leading to an underestimation of our main estimates. Compared with females, males are more fragile and need more maternal resource to develop (Catalano & Bruckner, 2006; Catalano, Bruckner, Anderson, & Gould, 2005). We use a dummy variable for whether an individual is female as dependent variable to directly examine the effects of exposure to high temperatures during pregnancy on sex ratio. The estimated insignificant coefficients, presented in column 4 of Table 12 don't support for the existence of fetus loss hypothesis, suggesting that selective mortality doesn't bias our main results.

Third, we check whether migration alters our findings. Ambient high temperature is an important environmental factor driving internal and international migration (Cai, Feng, Oppenheimer, & Pytlikova, 2016; Feng, Krueger, & Oppenheimer, 2010; Lu, 2020; Oliveira & Pereda, 2020). Migration is an adaptive measure with high investments to adapt to high temperatures. People with higher education attainment and income are more likely to choose to migrate. If those who couldn't migrate had worse mental health status, our estimates may be overestimated. However, migration cannot confound the estimated results in our context due to Chinese Hukou restrictions. Education and medical resources are closely linked to Hukou in China. In our sample, only 17 individuals' location of survey and their location of birth are not in the same city. Such low migration rate is unlikely to alter our main findings. We also define a dummy variable for migration, which equals to one if the city of survey and the city of birth are not the same, and otherwise equals to zero. We use the dummy variable as dependent variable. Column 5 of Table 12 suggests that hot days don't affect the probability of migration. We also exclude these migrated samples and re-estimate Eq. (1) in column 6 of Table 12. The results are consistent with those in column 4 of Table 2. These estimates provide evidence to support that migration is not a concern.

Forth, air conditioner and electric fan are very important and effective adaptive measures to mitigate the deteriorating effects of extreme hot weather. Unfortunately, we cannot observe information on the household possession of air conditioner and electric fan during pregnancy. Adolescents in this dataset were born between 1995 and 2001. The average number of air conditioners per 100 urban households at the end of the year ranged from 8.09 in 1995 to 35.79 in 2001. The average number of electric fans per 100 urban households at the end of the year ranged from 167.35 in 1990 to 170.74 in 2001.<sup>18</sup> The household possession of air conditioner and

<sup>17</sup> We thank an anonymous referee for pointing out time spend working may affect fertility.

<sup>18</sup> Data source: <http://www.stats.gov.cn>.

**Table 11**  
Robustness checks: Placebo tests.

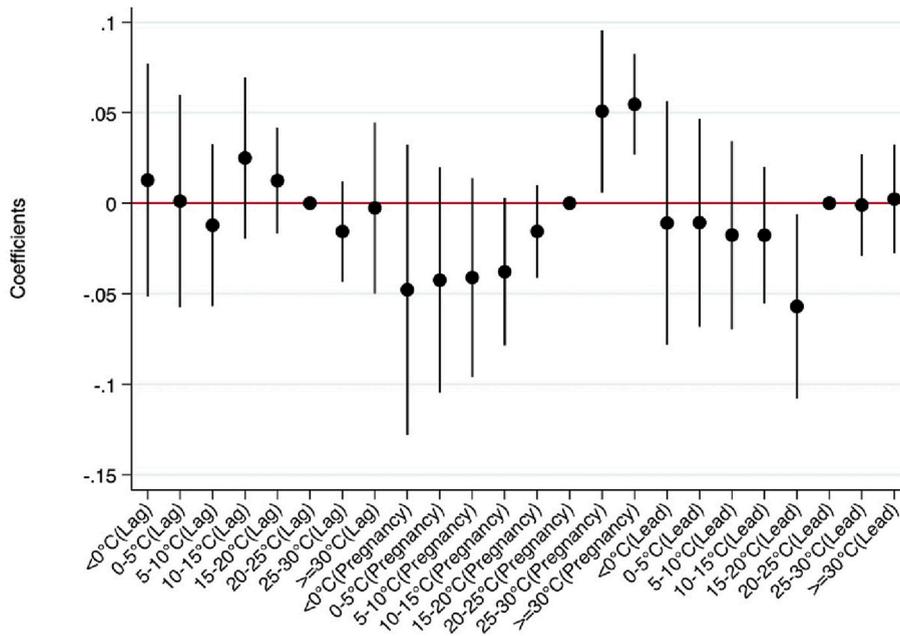
	(1)
Number of days (AT $\geq 30$ °C) (Lag 9 months)	−0.003 (0.029)
Number of days (AT 25–30 °C) (Lag 9 months)	−0.016 (0.017)
Number of days (AT 15–20 °C) (Lag 9 months)	0.012 (0.018)
Number of days (AT 10–15 °C) (Lag 9 months)	0.025 (0.027)
Number of days (AT 5–10 °C) (Lag 9 months)	−0.012 (0.027)
Number of days (AT 0–5 °C) (Lag 9 months)	0.001 (0.035)
Number of days (AT <0 °C) (Lag 9 months)	0.013 (0.039)
Number of days (AT $\geq 30$ °C) (Pregnancy)	0.055*** (0.017)
Number of days (AT 25–30 °C) (Pregnancy)	0.051* (0.027)
Number of days (AT 15–20 °C) (Pregnancy)	−0.016 (0.015)
Number of days (AT 10–15 °C) (Pregnancy)	−0.038 (0.025)
Number of days (AT 5–10 °C) (Pregnancy)	−0.041 (0.033)
Number of days (AT 0–5 °C) (Pregnancy)	−0.043 (0.038)
Number of days (AT <0 °C) (Pregnancy)	−0.048 (0.048)
Number of days (AT $\geq 30$ °C) (Lead 9 months)	0.002 (0.018)
Number of days (AT 25–30 °C) (Lead 9 months)	−0.001 (0.017)
Number of days (AT 15–20 °C) (Lead 9 months)	−0.057* (0.031)
Number of days (AT 10–15 °C) (Lead 9 months)	−0.018 (0.023)
Number of days (AT 5–10 °C) (Lead 9 months)	−0.018 (0.031)
Number of days (AT 0–5 °C) (Lead 9 months)	−0.011 (0.035)
Number of days (AT <0 °C) (Lead 9 months)	−0.011 (0.041)
Child's demographic controls	Yes
Parental demographic controls	Yes
Weather controls	Yes
City-quarter FE	Yes
Year-month FE	Yes
Observation	3045
R <sup>2</sup>	0.251

Notes: The reference temperature bin is 20–25 °C, which is omitted in regressions. Child's demographic controls include gender, child age, and race. Parental demographic controls include parents' age at delivery and education years. Weather controls include precipitation, relative humidity, wind speed, sunshine duration, and atmospheric pressure. Standard errors clustered at city level are reported in parentheses.

\*  $p < 0.10$ .

\*\*\*  $p < 0.01$ .

electric fan in rural areas is much lower than that in urban areas. Indoor cooling facilities were not widely available during the study period of this paper. We think that the low possession of adaptation tools does not influence our main conclusions. Electricity is the main energy source for the use of electric fans and air conditioners. Thus, we further use the natural logarithm of monthly household electricity consumption as the dependent variable to investigate whether hot temperatures in the previous month influence the household electricity consumption. Column 7 of Table 12 provides that estimated results, indicating that extreme hot temperatures have insignificant effects on electricity consumption. Our estimates provide suggestive evidence that limited adaptation tools don't alter our main findings.



**Fig. 5.** Estimated effects of prenatal exposure to temperatures on the K6 score before conception and after birth.  
 Notes: The figure plots the estimated coefficients with 90% confidence intervals associated with each temperature bin identified from regressions in Table 11. The temperature exposure window is defined as 9 months during pregnancy. The x-axis indicates the bins that the average temperature belongs to. The y-axis is the size of the coefficient. The full-length bars are the 90% confidence intervals. The reference temperature bin is 20–25°C and seven temperature bin variables are included in model. All regressions include child’s demographic controls (gender, child age, and race), parental demographic controls (parents’ age at delivery and education years), weather controls (precipitation, relative humidity, wind speed, sunshine duration, and atmospheric pressure), city-quarter FE, and year-month FE. Standard errors are clustered at the city level.

4.4. Heterogeneous effects

We explore heterogeneous impacts of in utero exposure to high temperatures on the prevalence of symptoms of depression across individual demographic characteristics (gender, Hukou status, and age), climate regions of birth, and mother’s occupation. We first define four dummy variables of individual, regional, and occupational characteristics (female, rural, southern, and agriculture). Then, we include the interaction term for the dummy variable and variables for the number of days with daily average temperature falling into each temperature bin in Eq. (1).

First, many studies have found that the expressed sentiment and mental health status of females are more sensitive to high temperatures than those of males (Basu, Gavin, Pearson, Ebisu, & Malig, 2017; Wang, Obradovich, & Zheng, 2020). Additionally, there are differences in family investments between males and females in early life, which may lead to heterogeneous effects of prenatal exposure to high temperatures. In column 1 of Table 12, there are no significant differences in the harmful effects of in utero exposure to heat waves on adolescent mental health of males and females.

Second, rural individuals have less adaptive resources than urban individuals due to lower income and little knowledge on the detrimental effects of hot weather. In column 2 of Table 12, we conduct heterogeneity analyses to explore whether hot days have a different effect on the mental health of urban-born adolescents and those born in rural areas. The coefficients of the interaction terms suggest that heterogeneous effects are absent between rural- and urban-born individuals.

Third, we divide the sample into individuals born in the northern region and individuals born in the southern region based on the Huai River and Qinling Mountain range. In column 3 of Table 13, experiencing one more day with daily average temperature over 30°C than the local historical contemporaneous average values significantly reduces the K6 score of individuals born in the southern region by 0.26 points more than that of individuals born in the northern region, relative to a day in the 20–25°C bin. The results suggest that the deteriorating effects are more salient for those born in the northern region. This may be due to southern pregnant women’s natural adaptation and tolerance to hot weather.

Fourth, agricultural work is a type of high-intensity outdoor work. Mothers who work in agriculture are more likely to work outdoors and have higher intensity exposure to hot weather. Therefore, we explore the heterogeneous effects between mothers who work in agriculture and mothers who engage in nonagricultural work. The mental health of adolescents whose mothers are engaged in agricultural work is impaired more than the mental health of adolescents whose mothers are engaged in nonagricultural work by exposure to extreme high temperatures during pregnancy in column 4 of Table 13. Our results suggest that more attention and intervention should be provided to pregnant women who work outdoors.

Finally, we perform sub-sample analysis by dividing our sample into six groups to explore if there are age differences in the harmful

**Table 12**  
Selection issues: Fertility, mortality, migration, and adaptation.

	Selection on fertility			Selection on mortality	Selection on migration		Selection on adaptation
	Mother's education years	Mother's age at birth	Mother's time spent working	Female	Migration	K6 score	Electricity consumption
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Number of days (AT <sub>≥</sub> 30°C)	0.107 (0.099)	-0.095 (0.121)	0.099 (0.065)	-0.000 (0.004)	0.001 (0.001)	0.048* (0.026)	0.031 (0.022)
Number of days (AT 25–30°C)	0.022 (0.044)	0.027 (0.053)	0.005 (0.034)	-0.001 (0.002)	0.000 (0.000)	0.035** (0.015)	-0.008 (0.015)
Number of days (AT 15–20°C)	-0.045 (0.041)	-0.042 (0.045)	-0.007 (0.030)	-0.003 (0.002)	-0.000 (0.000)	-0.006 (0.014)	-0.004 (0.013)
Number of days (AT 10–15°C)	-0.050 (0.051)	-0.075 (0.060)	0.003 (0.030)	-0.003 (0.003)	-0.000 (0.000)	-0.023 (0.022)	-0.008 (0.015)
Number of days (AT 5–10°C)	-0.059 (0.078)	-0.086 (0.083)	0.006 (0.068)	-0.002 (0.004)	0.000 (0.000)	-0.018 (0.028)	0.005 (0.029)
Number of days (AT 0–5°C)	-0.057 (0.102)	-0.106 (0.101)	-0.106 (0.089)	-0.004 (0.004)	-0.001* (0.000)	-0.011 (0.031)	-0.023 (0.034)
Number of days (AT <0°C)	-0.112 (0.107)	-0.227* (0.125)	-0.423 (0.648)	-0.004 (0.005)	-0.001 (0.001)	-0.025 (0.042)	0.114 (0.284)
Child's demographic controls	No	No	No	No	Yes	Yes	No
Parental demographic controls	No	No	No	Yes	Yes	Yes	No
Individual controls	No	No	Yes	No	No	No	No
Household controls	No	No	Yes	No	No	No	Yes
Weather controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City-quarter FE	Yes	Yes	No	Yes	Yes	Yes	No
Year-month FE	Yes	Yes	No	Yes	Yes	Yes	No
Individual FE	No	No	Yes	No	No	No	No
Survey city-year FE	No	No	Yes	No	No	No	Yes
Survey city-month FE	No	No	Yes	No	No	No	Yes
Survey year-month FE	No	No	Yes	No	No	No	Yes
Observation	3045	3045	2362	3045	3045	3028	2317
R <sup>2</sup>	0.474	0.247	0.626	0.182	0.434	0.242	0.508

Notes: The reference temperature bin is 20–25°C, which is omitted in regressions. Child's demographic controls include gender, child age, and race. Parental demographic controls include parents' age at delivery and education years. Individual controls include mother's age and quadratic polynomials in age, years of education, and employment status. Household controls include annual net household income, and household size. Weather controls include precipitation, relative humidity, wind speed, sunshine duration, and atmospheric pressure. Standard errors clustered at city level are reported in parentheses.

\*  $p < 0.10$ .

\*\*  $p < 0.05$ .

effects of extreme hot days. The estimated results in Table 14 and Fig. 6 indicate that the detrimental effects of prenatal exposure to extreme temperatures on the K6 score are insignificant in adolescents aged 10 and 11. However, in utero exposure to an additional day with daily average temperature over 30°C relative to the local historical contemporaneous average values significantly increases the K6 scores of adolescents aged 12, 13, 14, and 15 by 0.02 points, 0.07 points, 0.01 points, and 0.03 points, respectively. Our estimates indicate that in utero exposure to extreme hot days may worsen the mental health of the older adolescents.

## 5. Discussion

We first discuss the potential channels through which in utero exposure to hot days leads to an increase in the frequency of depressive symptoms. Then, we also investigate the impacts of experiencing hot weather during gestational period on other health status.

### 5.1. Mechanisms

Exploring the influencing channels is essential to taking measures to protect adolescents from adverse effects of exposure to high temperatures. Several channels may explain this impact, including physiological and biological effects, income effects, and human

Table 13

Heterogeneous effects of prenatal exposure to temperatures on mental health: by gender, Hukou status, climate region, and mother's occupation.

	Gender (Female = 1)	Hukou status (Rural = 1)	Region (Southern = 1)	Mother's occupation (Farmer = 1)
	(1)	(2)	(3)	(4)
Number of days (AT ≥ 30 °C) × Dummy	-0.013 (0.038)	0.007 (0.043)	-0.256*** (0.086)	0.057* (0.031)
Number of days (AT 25–30 °C) × Dummy	0.025 (0.022)	0.019 (0.026)	-0.026 (0.025)	-0.014 (0.031)
Number of days (AT 15–20 °C) × Dummy	0.015 (0.028)	0.031 (0.024)	-0.021 (0.029)	0.022 (0.035)
Number of days (AT 10–15 °C) × Dummy	0.006 (0.034)	0.042 (0.029)	-0.037 (0.037)	-0.024 (0.042)
Number of days (AT 5–10 °C) × Dummy	-0.023 (0.034)	0.004 (0.032)	-0.031 (0.036)	-0.017 (0.046)
Number of days (AT 0–5 °C) × Dummy	-0.006 (0.034)	0.049 (0.034)	-0.073** (0.034)	0.062 (0.041)
Number of days (AT <0 °C) × Dummy	-0.019 (0.040)	0.006 (0.039)	-0.038 (0.046)	0.014 (0.048)
Dummy	-0.190 (0.190)	0.036 (0.233)	-6.736 (5.024)	0.346 (0.260)
Number of days (AT ≥ 30 °C)	0.058* (0.035)	0.042 (0.035)	0.083** (0.032)	0.024 (0.049)
Number of days (AT 25–30 °C)	0.023 (0.019)	0.024 (0.020)	0.055*** (0.020)	0.046 (0.031)
Number of days (AT 15–20 °C)	-0.012 (0.023)	-0.025 (0.017)	0.003 (0.020)	-0.024 (0.032)
Number of days (AT 10–15 °C)	-0.025 (0.028)	-0.052* (0.029)	-0.009 (0.025)	-0.003 (0.044)
Number of days (AT 5–10 °C)	-0.006 (0.032)	-0.021 (0.035)	-0.008 (0.033)	-0.000 (0.049)
Number of days (AT 0–5 °C)	-0.008 (0.031)	-0.044 (0.036)	0.017 (0.032)	-0.056 (0.045)
Number of days (AT <0 °C)	-0.017 (0.044)	-0.033 (0.047)	-0.017 (0.048)	-0.033 (0.060)
Child's demographic controls	Yes	Yes	Yes	Yes
Parental demographic controls	Yes	Yes	Yes	Yes
Weather controls	Yes	Yes	Yes	Yes
City-quarter FE	Yes	Yes	Yes	Yes
Year-month FE	Yes	Yes	Yes	Yes
Observation	3045	3045	3045	3045
R <sup>2</sup>	0.241	0.242	0.243	0.243

Notes: The reference temperature bin is 20–25 °C, which is omitted in regressions. In column 1, child's demographic controls include child age and race. In columns 2, 3, and 4, child's demographic controls include gender, child age, and race. Parental demographic controls include parents' age at delivery and education years. Weather controls include precipitation, relative humidity, wind speed, sunshine duration, and atmospheric pressure. Standard errors clustered at city level are reported in parentheses.

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

capital accumulation. We also rule out other shocks that may alter our main conclusions.

### 5.1.1. Physiological and biological effects

Exposure to high temperatures during pregnancy may not only directly restrict intrauterine growth and affect fetal development, but also cause negative effects on growth of fetuses through maternal stress and health. On the one hand, adverse and abnormal in utero environment and prenatal growth have durable effects on human brain development and biological vulnerability to psychological disorders through disease-related genes variants (Caspi & Moffitt, 2006; Gleason, Liu, Bruening, et al., 2010; Gluckman, Hanson, Cooper, & Thornburg, 2008; Raznahan, Greenstein, Lee, Clasen, & Giedd, 2012). Because fetal thermoregulatory and sympathetic nervous systems are not fully developed (Knobel & Holditch-Davis, 2007; Young, 2002), prenatal exposure to the anomalous environment of heat waves may impair fetal development of neural networks and brain, especially brain circuitry regulating stress, further reducing the self-healing power of psychological trauma and increasing the vulnerability of mental illness. On the other hand, a significant association between maternal prenatal stress and sensitive to stress in offspring has been proved by clinical research and animal studies, leading to an increased vulnerability to mental illness disorders (Goldstein, Cohen, & Mareckova, 2021). Additionally, maternal prenatal stress also influences offspring fetal neurodevelopment and increases a risk for mental disorders (O'Donnell, Glover, Barker, & O'Connor, 2014; Walsh, McCormack, Webster, et al., 2019). A large body of literature has found that exposure to high temperatures impair individuals' mental health and expressed sentiments both in developed and developing countries (Baylis et al.,

**Table 14**  
Heterogeneous effects of prenatal exposure to temperatures on mental health: by age.

	10	11	12	13	14	15
	(1)	(2)	(3)	(4)	(5)	(6)
Number of days (AT $\geq$ 30°C)	0.004 (0.067)	0.028 (0.026)	0.016* (0.009)	0.068* (0.040)	0.013* (0.007)	0.026* (0.015)
Number of days (AT 25–30°C)	0.033 (0.027)	0.028 (0.020)	0.010 (0.006)	−0.023 (0.020)	0.008* (0.005)	0.001 (0.061)
Number of days (AT 15–20°C)	0.012 (0.023)	0.012 (0.018)	0.010* (0.006)	−0.025 (0.022)	0.002 (0.005)	0.004 (0.019)
Number of days (AT 10–15°C)	0.006 (0.037)	0.008 (0.025)	0.003 (0.009)	−0.022 (0.037)	0.002 (0.006)	−0.002 (0.030)
Number of days (AT 5–10°C)	0.013 (0.050)	0.009 (0.036)	−0.004 (0.010)	−0.059 (0.043)	0.002 (0.005)	0.028 (0.047)
Number of days (AT 0–5°C)	0.034 (0.052)	0.011 (0.039)	0.012 (0.012)	−0.030 (0.062)	0.000 (0.007)	0.008 (0.052)
Number of days (AT <0°C)	0.039 (0.058)	0.025 (0.048)	0.009 (0.023)	−0.036 (0.076)	0.004 (0.008)	−0.002 (0.054)
Child's demographic controls	Yes	Yes	Yes	Yes	Yes	Yes
Parental demographic controls	Yes	Yes	Yes	Yes	Yes	Yes
Weather controls	Yes	Yes	Yes	Yes	Yes	Yes
City-quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-month FE	Yes	Yes	Yes	Yes	Yes	Yes
Observation	470	515	476	488	517	579
R <sup>2</sup>	0.754	0.590	0.720	0.657	0.662	0.620

Notes: The reference temperature bin is 20–25°C, which is omitted in regressions. Child's demographic controls include gender and race. Parental demographic controls include parents' age at delivery and education years. Weather controls include precipitation, relative humidity, wind speed, sunshine duration, and atmospheric pressure. Standard errors clustered at city level are reported in parentheses.

\*  $p < 0.10$ .

2018; Hua, Qiu, & Tan, 2022; Li, Ferreira, & Smith, 2020; Mullins & White, 2019; Wang, Obradovich, & Zheng, 2020; Xue, Zhu, Zheng, & Zhang, 2019). Prenatal exposure to high temperatures may increase depressed maternal mood and mental stress, thus leading to the increased risk for adolescent mental health.

We use birth weight as a proxy variable for fetal environment and maternal stress to examine the biological channels. Estimates of birth weight and the indicator of low birth weight are presented in columns 1 and 2 in Table 15.<sup>19</sup> Compared with a day falling into the 20–25°C bin, experiencing one more gestational day with daily average temperature over 30°C relative to the local historical contemporaneous average values significantly reduces birth weight by 0.018 (0.28% of the mean value of the sample) and increases the probability of low birth weight by 0.6%, coinciding with that of Chen, Tan, Zhang, & Zhang (2020). Extreme heat exposure can influence birth weight through fetal development in many ways. Heat can directly have adverse effects on maternal physiological and psychological health and indirectly affect mother's appetite, nutrient intake, infectious disease, and food availability (Blom, Ortiz-Bobea, & Hoddinott, 2022; Ebi, Capon, Berry, et al., 2021; Herman, 1993; Schlenker & Roberts, 2009; Zivin & Shrader, 2016). Our estimates suggest that adolescent mental health may be worsened by in utero exposure to extreme hot days through physiological and biological effects.

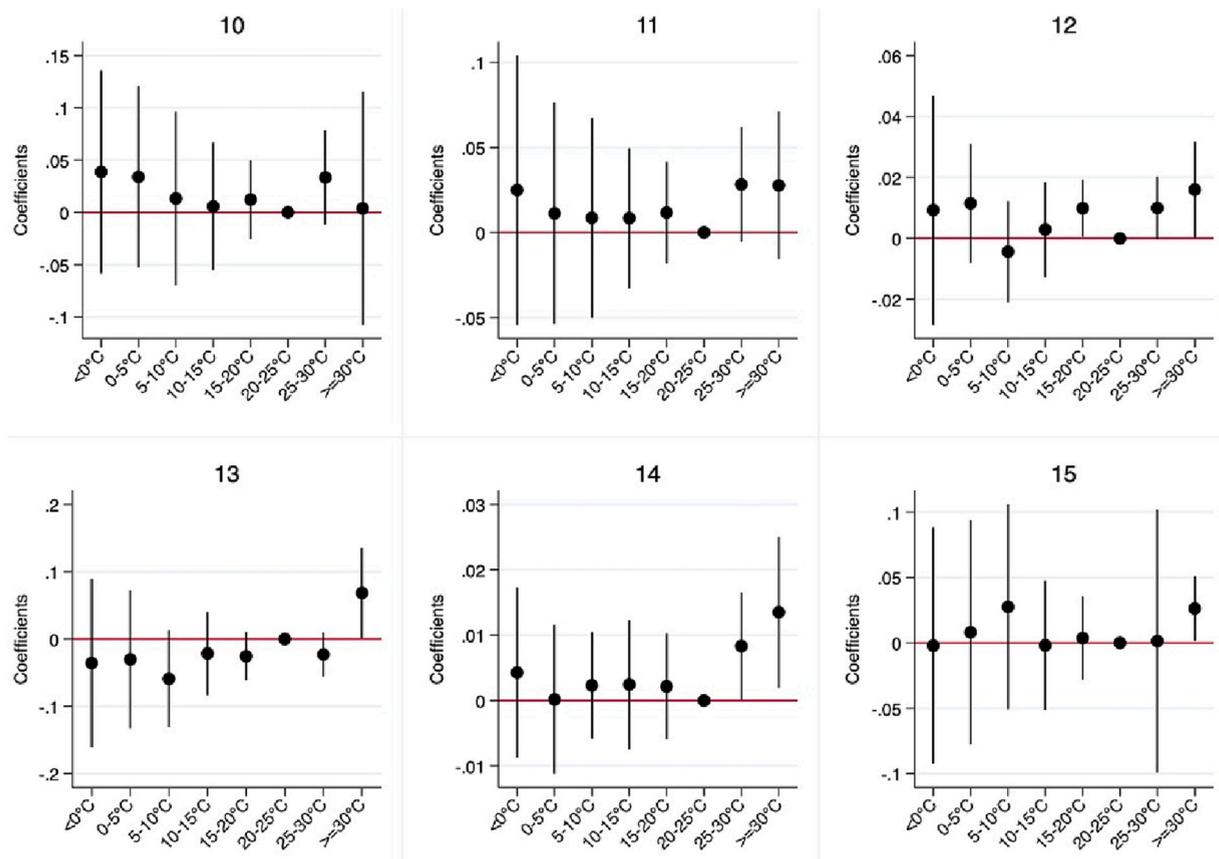
### 5.1.2. Income effects

Malnutrition during pregnancy and early-life stage is related to mental health status in later life (Adhvaryu, Fenske, Kala, & Nyshadham, 2019). Household income is the main economic security for pregnant mothers' and fetuses' nutrition. Mounting evidence has demonstrated that extreme heat is harmful for crop yields, agricultural productivity, and land values (Burke & Emerick, 2016; Chen, Chen, & Xu, 2016; DePaula, 2020). Since we don't have data on household income during pregnancy, we only can examine the effect of hot weather on household income during the survey period. The CFPS collects information on household income during the past year in the household dataset. Based on matched family datasets and child datasets, we use the natural logarithm of annual net household total income and the natural logarithm of the proportion of annual net household agricultural income as dependent variables to investigate whether ambient high temperatures affect household income and household agricultural income in columns 3 and 4 of Table 15. Our results show that replacing a day with daily average temperature 20–25°C with a day over 30°C relative to the local historical contemporaneous average values significantly reduces annual net household total income and the proportion of annual net household agricultural income by 37.6% and 3.2%, respectively. Our estimated results show that household income is another potential channel through which exposure to high temperatures impairs adolescent mental health.

### 5.1.3. Human capital accumulation

Given the literature on the negative relationship between prenatal exposure to high temperatures and cognitive ability (Almond &

<sup>19</sup> We define a dummy variable of low birth weight. When birth weight is below 5 jin (2500 g), it equals to one, otherwise it equals to zero.



**Fig. 6.** Estimated effects of prenatal exposure to temperatures on the K6 score across different age groups. Notes: The figure plots the estimated coefficients with 90% confidence intervals associated with each temperature bin identified from regressions in Table 14. The temperature exposure window is defined as 9 months during pregnancy. The x-axis indicates the bins that the average temperature belongs to. The y-axis is the size of the coefficient. The full-length bars are the 90% confidence intervals. The reference temperature bin is 20–25°C and seven temperature bin variables are included in model. All regressions include child’s demographic controls (gender, child age, and race), parental demographic controls (parents’ age at delivery and education years), weather controls (precipitation, relative humidity, wind speed, sunshine duration, and atmospheric pressure), city-quarter FE, and year-month FE. Standard errors are clustered at the city level.

Mazumder, 2011; Fishman, Carrillo, & Russ, 2019; Hu & Li, 2019), poor academic performance may lead to a higher reported incidence of depression. Due to the pressure of limited entrance chances and the expectations of parents, learning is one of the main sources of stress for Chinese adolescents. The CFPS 2010 collects data on the math-test score and word-test score. We further examine the effects of heat exposure during in utero period on these variables in columns 5 and 6 of Table 15. There is strong evidence of the negative effects of in utero exposure to hot days on adolescent test scores, indicating that human capital accumulation contributes to our main findings.<sup>20</sup>

5.1.4. Other contemporary shocks

Finally, we rule out other potential explanations, including death of parents, household size, and negative behaviors. First, the CFPS 2010 asks individuals whether their parents are alive. Therefore, we define two dummy variables, equaling to one when the parent is alive, otherwise equaling to zero. The results of high temperature days, presented in columns 1 and 2 of Table 16 are close to zero and are insignificant. Second, we merge household dataset and child dataset to check whether household size drives our results. The estimates in column 3 of Table 16 show that prenatal exposure to high temperatures doesn’t affect current household size. Third, we further check whether contemporary physical shocks result in mental disorders. The CFPS 2010 collects information on the number of times the adolescent was sick in the last month. We control this variable and re-estimate Eq. (1) and find that physical illness doesn’t alter our main findings in column 4 of Table 16. Fourth, we collect information on negative behaviors to test if these behaviors might explain our baseline results. Each adolescent is asked to answer the following questions: How many times did you drink last year? How many times did you smoke last year? How many times did you quarrel with your parents last month? We include these behavioral

<sup>20</sup> We thank an anonymous referee for pointing out human capital accumulation may be an influencing channel.

**Table 15**  
Mechanisms: Biological effects, income effects, and human capital accumulation.

	Birth weight	Low birth weight	Annual net household total income	The proportion of annual net household agricultural income	Math-test score	Word-test score
	(1)	(2)	(3)	(4)	(5)	(6)
Number of days (AT <sub>≥</sub> 30°C)	−0.018** (0.009)	0.006* (0.003)	−0.376*** (0.078)	−0.032** (0.015)	−0.051*** (0.019)	−0.058* (0.032)
Number of days (AT 25–30°C)	−0.004 (0.004)	0.002 (0.002)	0.051*** (0.017)	−0.016** (0.007)	0.004 (0.011)	−0.011 (0.016)
Number of days (AT 15–20°C)	0.000 (0.005)	0.001 (0.002)	−0.119** (0.047)	0.020 (0.022)	−0.011 (0.012)	−0.008 (0.016)
Number of days (AT 10–15°C)	−0.007 (0.007)	0.001 (0.003)	0.019 (0.029)	0.047*** (0.011)	−0.021 (0.022)	0.008 (0.029)
Number of days (AT 5–10°C)	0.007 (0.009)	−0.002 (0.003)	−0.045*** (0.015)	0.036*** (0.009)	−0.001 (0.024)	0.000 (0.037)
Number of days (AT 0–5°C)	−0.007 (0.010)	0.004 (0.004)	−0.007 (0.007)	−0.006* (0.003)	−0.002 (0.029)	−0.024 (0.040)
Number of days (AT <0°C)	−0.015 (0.013)	0.005 (0.005)	−0.007 (0.012)	−0.029*** (0.007)	0.004 (0.036)	0.009 (0.044)
Child's demographic controls	Yes	Yes	No	No	Yes	Yes
Parental demographic controls	Yes	Yes	Yes	Yes	Yes	Yes
Household controls	No	No	Yes	Yes	No	No
Weather controls	Yes	Yes	Yes	Yes	Yes	Yes
City-quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-month FE	Yes	Yes	Yes	Yes	Yes	Yes
Household FE	No	No	Yes	Yes	No	No
Survey city-year FE	No	No	Yes	Yes	No	No
Survey city-month FE	No	No	Yes	Yes	No	No
Survey year-month FE	No	No	Yes	Yes	No	No
Observation	2274	2274	2863	2863	2954	2954
R <sup>2</sup>	0.357	0.295	0.407	0.460	0.610	0.446

Notes: The reference temperature bin is 20–25°C, which is omitted in regressions. Child's demographic controls include gender and race. Household controls include family size. Weather controls include precipitation, relative humidity, wind speed, sunshine duration, and atmospheric pressure. In columns 1, 2, 5, and 6, parental demographic controls include parents' age at delivery and education years. In columns 3 and 4, parental demographic controls include parents' age and education years. Standard errors clustered at city level are reported in parentheses.

\*  $p < 0.10$ .

\*\*  $p < 0.05$ .

\*\*\*  $p < 0.01$ .

control variables in Eq. (1) and find little evidence that these negative behaviors influence our main results in column 5 of Table 16.

## 5.2. Other outcomes

The CFPS 2010 asks each respondent the following questions: (1) How good do you think your relationship is? (2) How happy do you feel? (3) How confident are you in your future? Each question has five options from one point (not at all) to five points (very). We use these points, chosen by respondents as dependent variables to examine whether in utero hot days exposure alters their self-reported feelings in Table 17. We find that exposure to high temperatures during gestational period significantly reduces self-reported subjective happiness. Replacing a day with daily average temperature 20–25°C with a day over 30°C relative to the local historical contemporaneous average values significantly leads to a reduction in subjective happiness score by 0.02 points. These results provide some evidence that in utero exposure to extreme hot days has adverse effects on other self-reported happiness outcomes as well as mental health.

## 6. Conclusions

In this paper, we examine the adverse effects of ambient temperature anomalies during pregnancy on adolescent mental health. Using a dataset from the 2010 wave of CFPS, we find that individuals experienced an additional extreme hot day during pregnancy, especially in the first and second trimester, are more likely to have depressive symptoms in adolescence. Prenatal exposure to high

**Table 16**  
Mechanisms: Other contemporary shocks.

	Father alive	Mother alive	Household size	K6 score	K6 score
	(1)	(2)	(3)	(4)	(5)
Number of days (AT $\geq$ 30°C)	-0.000 (0.001)	0.000 (0.001)	0.003 (0.010)	0.049* (0.026)	0.049* (0.026)
Number of days (AT 25–30°C)	-0.000 (0.000)	0.000 (0.000)	-0.008 (0.005)	0.034** (0.015)	0.035** (0.015)
Number of days (AT 15–20°C)	0.000 (0.000)	0.001 (0.000)	0.006 (0.005)	-0.005 (0.014)	-0.005 (0.014)
Number of days (AT 10–15°C)	0.000 (0.001)	-0.000 (0.000)	0.008 (0.008)	-0.022 (0.022)	-0.022 (0.022)
Number of days (AT 5–10°C)	-0.001 (0.001)	-0.001 (0.001)	0.013 (0.011)	-0.017 (0.027)	-0.020 (0.027)
Number of days (AT 0–5°C)	0.000 (0.001)	-0.000 (0.001)	0.013 (0.012)	-0.010 (0.030)	-0.015 (0.030)
Number of days (AT <0°C)	-0.001 (0.001)	-0.001 (0.001)	0.023* (0.013)	-0.026 (0.042)	-0.031 (0.041)
Child's demographic controls	Yes	Yes	Yes	Yes	Yes
Parental demographic controls	Yes	Yes	Yes	Yes	Yes
Weather controls	Yes	Yes	Yes	Yes	Yes
Physical illness	No	No	No	Yes	No
Risky behaviors	No	No	No	No	Yes
City-quarter FE	Yes	Yes	Yes	Yes	Yes
Year-month FE	Yes	Yes	Yes	Yes	Yes
Observation	3045	3045	3045	3045	3045
R <sup>2</sup>	0.182	0.199	0.341	0.241	0.249

Notes: The reference temperature bin is 20–25°C, which is omitted in regressions. Child's demographic controls include gender, child age, and race. Parental demographic controls include parents' age at delivery and education years. Weather controls include precipitation, relative humidity, wind speed, sunshine duration, and atmospheric pressure. Physical illness is self-reported frequency of being ill during the previous month. Risky behaviors include drink, smoke, and quarrel. Standard errors clustered at city level are reported in parentheses.

\*  $p < 0.10$ .

\*\*  $p < 0.05$ .

**Table 17**  
Impacts of prenatal exposure to temperatures on other health measures.

	Relationship	Subjective happiness	Confidence
	(1)	(2)	(3)
Number of days (AT $\geq$ 30°C)	-0.009 (0.006)	-0.018** (0.007)	0.006 (0.005)
Number of days (AT 25–30°C)	-0.002 (0.003)	-0.009* (0.005)	-0.001 (0.004)
Number of days (AT 15–20°C)	0.004 (0.003)	0.002 (0.003)	-0.005 (0.003)
Number of days (AT 10–15°C)	0.006 (0.005)	0.007 (0.004)	-0.005 (0.004)
Number of days (AT 5–10°C)	0.005 (0.006)	0.002 (0.004)	-0.006 (0.006)
Number of days (AT 0–5°C)	0.004 (0.006)	0.002 (0.006)	-0.005 (0.006)
Number of days (AT <0°C)	0.008 (0.007)	-0.005 (0.003)	-0.003 (0.008)
Child's demographic controls	Yes	Yes	Yes
Parental demographic controls	Yes	Yes	Yes
Weather controls	Yes	Yes	Yes
City-quarter FE	Yes	Yes	Yes
Year-month FE	Yes	Yes	Yes
Observation	3042	3043	3039
R <sup>2</sup>	0.233	0.252	0.243

Notes: The reference temperature bin is 20–25°C, which is omitted in regressions. Child's demographic controls include gender, child age, and race. Parental demographic controls include parents' age at delivery and education years. Weather controls include precipitation, relative humidity, wind speed, sunshine duration, and atmospheric pressure. Standard errors clustered at city level are reported in parentheses.

\*  $p < 0.10$ .

\*\*  $p < 0.05$ .

temperatures also worsens subjective happiness. Physiological and biological effects, income effects, and human capital accumulation may be three main influencing mechanisms to explain our main findings. Due to data limitations, we cannot directly demonstrate every potential mechanism to explain the harmful effects of prenatal exposure to climatic shocks. Exploring the influencing channels is critical for future research.

It is crucial for policy makers, then, given the importance of adolescent mental health, to gain a better understanding of their origins and formulate targeted and effective policies. Our estimations have important and timely policy implications for governments that effective health interventions for pregnant women and measures to prevent exposure to heat during pregnancy can mitigate health and welfare losses in later life. First, it is necessary to educate pregnant women about the dangers of heat exposure and install an extreme hot weather warning system to improve their awareness of self-protection and adaptation to high temperatures (Hajdu & Hajdu, 2023). Second, investments in increasing the penetration rate of adaptive measures such as air conditioners and electric fans should be increased (Chen, Tan, Zhang, & Zhang, 2020; Hua, Qiu, & Tan, 2022; Yu, Lei, & Wang, 2019). Third, more attention should be paid to pregnant rural women. The availability of health care services for them and adequate maternal nutrition are two key factors to mitigate the adverse health effects of prenatal exposure to high temperatures (Banerjee & Maharaj, 2020). The relevant policies and programs are essential in developing countries.

## Data availability

The authors do not have permission to share data.

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## Appendix A. Appendix

**Table A1**

Additional summary statistics for other mental health measures and demographic variables.

Variable	Obs.	Mean	Std. Dev	Min.	Max.
Panel A: Other mental health measures					
Ln (K6 score)	3045	0.945	0.920	0.000	3.219
Severe mental illness (0/1)	3045	0.076	0.265	0.000	1.000
Relationship	3042	3.926	0.862	1.000	5.000
Subjective happiness	3043	4.177	0.877	1.000	5.000
Confidence	3039	4.131	0.870	1.000	5.000
Panel B: Other demographic variables					
Birth weight	2274	6.323	1.150	1.000	12.800
Low birth weight (0/1)	2274	0.248	0.432	0.000	1.000
Math-test score	2954	11.219	4.429	0.000	24.000
Word-test score	2954	21.719	7.080	0.000	24.000
Breastfeeding	3003	13.861	8.731	0.000	72.000
Height-for-age z-score	2960	-0.946	1.911	-14.332	4.011
BMI-for-age z-score	2848	-2.732	51.363	-91.061	1742.259
Drink	3045	0.077	0.601	0.000	6.000
Smoke	3045	0.017	0.289	0.000	6.000
Quarrel	3045	0.523	2.025	0.000	40.000
Illness	3045	0.298	0.814	0.000	10.000
Father alive (0/1)	3045	0.985	0.122	0.000	1.000
Mother alive (0/1)	3045	0.988	0.108	0.000	1.000
Communication	3045	0.924	0.264	0.000	1.000
Selective schools	3045	0.042	0.201	0.000	1.000
Time for left-behind children	3023	2.962	9.975	0.000	54.000
Optimism	3045	0.950	0.217	0.000	1.000
Mother's time spent working	2512	130.212	100.634	0.000	440.000
Migration (0/1)	3045	0.006	0.075	0.000	1.000
Rural (0/1)	3045	0.593	0.491	0.000	1.000
South (0/1)	3045	0.411	0.492	0.000	1.000
Annual net household total income	2893	27,212.660	32,105.200	15.000	842,465.000
The proportion of annual net household farm income	2893	0.285	0.331	0.000	1.000
Household size	3045	4.862	1.627	2.000	14.000

Notes: In Panel A, “Relationship”, “Subjective happiness”, and “Confidence” represent self-reported the degree of relationship, happiness, confidence in the future. In Panel B, “Low birth weight” is a dummy variable, which equals to one when one child’s birth weight <2500 g (5 jin in Chinese) pounds. “Breastfeeding” is the duration of breastfeeding. “Drink” and “Smoke” represent self-reported frequency of drinking and smoking during the previous year. “Quarrel” represents self-reported frequency of quarreling with parents during the previous month. “Illness” is self-reported frequency of being ill during the previous month. “Father alive” and “Mother alive” are dummy variables for whether one child’s parent is alive, which equals to one when a parent is alive. “Communication” is a dummy variable for whether parents communicate with their children; “Selective schools” is a dummy variable whether a child is in a selective school. “Time for left-behind children” is the longest consecutive time that neither parent lived with their child was (weeks) last year. “Optimism” is a dummy variable for whether a child is optimistic by nature. “Migration” is a dummy variable for migration, which equals to one when one child’s survey city is not the birth city. “Rural” is a dummy variable for Hukou status, which equals to one when one child is rural to Hukou.

Table A2

Impacts of prenatal exposure to temperatures on mental health standard normal variable.

	(1)		(2)
Number of days (AT $\geq$ 30°C)	0.067** (0.033)	Average temperature	0.159* (0.086)
Number of days (AT 25–30°C)	0.050*** (0.018)		
Number of days (AT 15–20°C)	–0.003 (0.017)		
Number of days (AT 10–15°C)	–0.021 (0.026)		
Number of days (AT 5–10°C)	–0.014 (0.031)		
Number of days (AT 0–5°C)	–0.000 (0.035)		
Number of days (AT <0°C)	–0.012 (0.047)		
Child’s demographic controls	Yes	Child’s demographic controls	Yes
Parental demographic controls	Yes	Parental demographic controls	Yes
Weather controls	Yes	Weather controls	Yes
City-quarter FE	Yes	City-quarter FE	Yes
Year-month FE	Yes	Year-month FE	Yes
Observation	3045	Observation	3045
R <sup>2</sup>	0.240	R <sup>2</sup>	0.238

Notes: The reference temperature bin is 20–25°C, which is omitted in regressions. Child’s demographic controls include gender, child age, and race. Parental demographic controls include parents’ age at delivery and education years. Weather controls include precipitation, relative humidity, wind speed, sunshine duration, and atmospheric pressure. Standard errors clustered at city level are reported in parentheses.

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

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