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Source: *Weather, Climate, and Society* , October 2021, Vol. 13, No. 4 (October 2021), pp. 709-727

Published by: American Meteorological Society

Stable URL: https://www.jstor.org/stable/10.2307/27205552

Impact of Temperature on Physical and Mental Health: Evidence from China

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(Manuscript received 25 February 2021, in final form 23 April 2021)

ABSTRACT: Climate may significantly affect human society. Few studies have focused on the temperature impact on residents' health, especially mental health status. This paper uses 98 423 observations in China to study the relationship between temperature and health, based on the China Family Panel Studies survey during 2010–16. We analyze the health effects of extreme hot and cold weather and compare the effects under different social demographic factors including gender, age, and income. We find that temperature and health status exhibit a nonlinear relationship. Women and low-income households are more likely to be impacted by extreme cold, whereas men, the elderly, and high-income households are more sensitive to extreme heat. Our results highlight the potential effects of extreme temperatures on physical and mental health and provide implications for future policy decisions to protect human health under a changing climate.

KEYWORDS: Social Science; Damage assessment; Societal impacts; Climate change

1. Introduction

The potential impact margins of climate change are wide and far-reaching (Deschênes 2014). The University College London (UCL)–Lancet Commission on Managing the Health Effects of Climate Change called climate change ''the biggest global health threat of the 21st century'' (Costello et al. 2009). Fossil fuels have led to substantive emissions of greenhouse gases since the industrial age, which result in a dramatic increase in average temperatures and more frequent extreme weather events (Zivin and Shrader 2016; Oppenheimer and Anttila-Hughes 2016) where the daily temperatures exceed the upper and lower limits of a certain range (Yan et al. 2002; Zhang et al. 2011). Extreme temperature events are expected to become more frequent and intense as climate changes continue, at least in certain regions (Chen et al. 2014). The damage of extreme heat and cold to human health has been recognized as one of the most important areas of concern and become a focus of global research (Deschênes 2014; Yang et al. 2019a).

Abnormal temperature is a threat to physical health. Recent studies have analyzed the impact of temperature on mortality and morbidity (Deschênes and Greenstone 2011; Allen and Sheridan 2015; Marsha et al. 2018; Yang et al. 2019a) and extreme temperatures lead to significant reductions in health through various channels such as inducing cardiovascular and respiratory diseases (Curriero et al. 2002; Zivin and Shrader 2016). Climate change also creates mental health challenges. A growing number of studies point out the link between mental health and environmental factors through biological mechanisms. Human emotions such as happiness are influenced by daily weather (Baylis 2020).

From the perspective of macro–health evaluation, we find consistent conclusions in the literature where mortality and morbidity are used to measure the health level (Curriero et al. 2002; IPCC 2007; Yang et al. 2019a). The body's heat regulatory function enables us to cope with exposure to high and low temperatures. However, this adaptation increases the stress on many organs, and when the human body experiences excessive temperature, health will be impaired (Deschênes 2014). For physical health, heat exhaustion and heat stroke are the most serious illnesses caused directly by extreme heat. The body may overheat, leading to prostration, dizziness, and muscle cramps (Bouchama and Knochel 2002; Qu and Xiao 2019). In cold weather, the direct health impact of hypothermia is more likely to happen, and exposure to cold indirectly leads to frostbite, pneumonia, and influenza (Qu and Xiao 2019). When it comes to anomalous cold events, such as heavy snow or frost, people might fall, especially the elderly (Hajat et al. 2016). Exposure to cold and heat indirectly increases the risk of cardiovascular and respiratory disease. Studies have shown that every 1°C increase above 29°C leads to about 3% more adult hospitalizations due to respiratory disease; the incidence of cardiovascular disease also increases in many cases (Michelozzi et al. 2009; Lin et al. 2009). In addition, for infectious diseases such as malaria, enteric fever, and diarrhea, extreme heat also

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DOI: 10.1175/WCAS-D-21-0038.1

increases the risk (Chowdhury et al. 2018). The Lancet health report (Watts et al. 2015) shows the complex mechanisms of rising temperatures and changes in precipitation patterns alter the viable distribution of disease vectors such as mosquitoes carrying dengue or malaria, which increases the incidence of these infectious diseases. On the other hand, due to the role of certain neurotransmitters (such as biogenic amines) in both emotional and thermal regulation, mental health might also be affected adversely (Iversen 1982). There is also a link between hot temperatures and anxiety, aggression, and suicide risk based on previous studies (Maes et al. 1994; Anderson and Anderson 1998; Hansen et al. 2008).

Our research addresses three gaps in the existing literature. First, most studies have focused on the extreme heat effects (e.g., heat waves) on human health under global warming. Only a few studies consider the role of extreme cold events (Hajat et al. 2006; Yang et al. 2019a). The relationship between extreme cold temperatures and human health is not well explored. Second, previous studies focus on mortality and morbidity indicators and largely ignore the assessment of human daily health status, partly due to the lack of availability for credible and large-scale empirical data. In addition, as mental illness has become the major driver of the global burden of disease (Murray et al. 2015), many psychological mechanisms make an epidemiological linkage between environmental factors and mental health biologically plausible (Xue et al. 2019). More research is needed on the relationship between mental health and external environmental factors. Third, most studies are carried out in developed countries, and little research is conducted in developing countries with substantial regional differences. Developing countries have lower income levels, less access to health care, and more difficult living conditions. The response patterns to extreme temperature events in developing countries may differ significantly from developed countries. As a member of the developing countries, China has a huge population covering a wide region with substantial regional climate differences, which is suitable to investigate the complicated relationship between humans and the environment.

We use both physical and mental health indicators based on the Chinese Family Panel Studies (CFPS) national survey data from 2010 to 2016. The CFPS survey includes basic sociodemographic indicators such as age, gender, and income, allowing heterogeneous analyses across subpopulations. After matching the samples with the climate data from 839 meteorological stations in China spatially and temporally, we obtained 98 423 individual-level observations. We find that the relationship between temperature and overall health, physical health, and mental health all exhibited an inverted U-shaped curve, which suggests that poorer health conditions were more likely to occur on days with very high or very low temperatures. We also explored the impact of 10 extreme weather indices such as heating degree-days, warm nights, and cool days on residents' health. In addition, we investigated the impact of extreme weather among different gender, age, and income categories. Our results reveal that women and low-income households are more likely to be influenced by extreme cold, while men, the elderly, and high-income households are more sensitive to extreme heat.

2. Data

a. Data sources

We use the most comprehensive individual health and climate data available in China based on a national-scale survey and the meteorological networks. The key dependent variable, residents' health status, comes from the CFPS project hosted by the Institute of Social Science Survey at Peking University. The survey has a wide range of sociodemographic indicators and extensive geographical coverages (Yao 2021). The CFPS survey is conducted every two years since 2010 and collects information on individuals, families, and communities about economic activities, social attitudes, health, and other variables for more than 100 000 residents in 162 counties in 25 provincial regions. The survey also records residents' geographical location and time of the interview, providing gateways to match health status and other time-varying information related to temperature. Since personal health status is a complicated measure influenced by the individual's physiological state, living habits, and social environment, we include various indicators such as physical health, mental health, and a wide array of demographic variables in the years 2010, 2012, 2014, and 2016. Because of the complexity and wide coverage of the investigation, the length of the survey may last for more than a year. As a result, our final dataset also includes individual samples collected in 2011, 2013, and 2015.

Temperature and precipitation data are compiled from the China Meteorological Science Data Sharing Service Network, which contains daily data from 839 basic meteorological stations in China, including pressure, temperature, precipitation, relative humidity, and other indicators since January 1951. Stringent data quality controls in the network ensure high availability and accuracy rates. Studies have shown that $PM_{2.5}$ contributed to respiratory and heart diseases (Song et al. 2017) because fine particles can cross the blood-brain barrier and damage the neurological system (Jia et al. 2018). We collected the $PM_{2.5}$ data from the global surface $PM_{2.5}$ datasets established by the Atmospheric Composition Analysis Group and use the original value in the regression model to control the influence of air pollution (https://sites.wustl.edu/acag/datasets/surface-pm2-5/).

Figure 1 details the data assembling and matching process. We extracted 143 358 CFPS observations collected between 2010 and 2017. To create a panel dataset, we only keep observations that are included in the 162 counties from the 2010 survey, resulting in 134 425 samples. We further match the weather data to the individual respondent and exclude observations that cannot be matched. We excluded 33 650 observations with missing individual demographic characteristics. We are able to identify 98 423 individual-level observations for our research.

b. Variable descriptions

1) Health

We focus on the effects of temperature on residents' overall health, physical health, and mental health. We use self-reported data in the CFPS questionnaire to measure the residents' daily health levels. For physical health indicators, CFPS

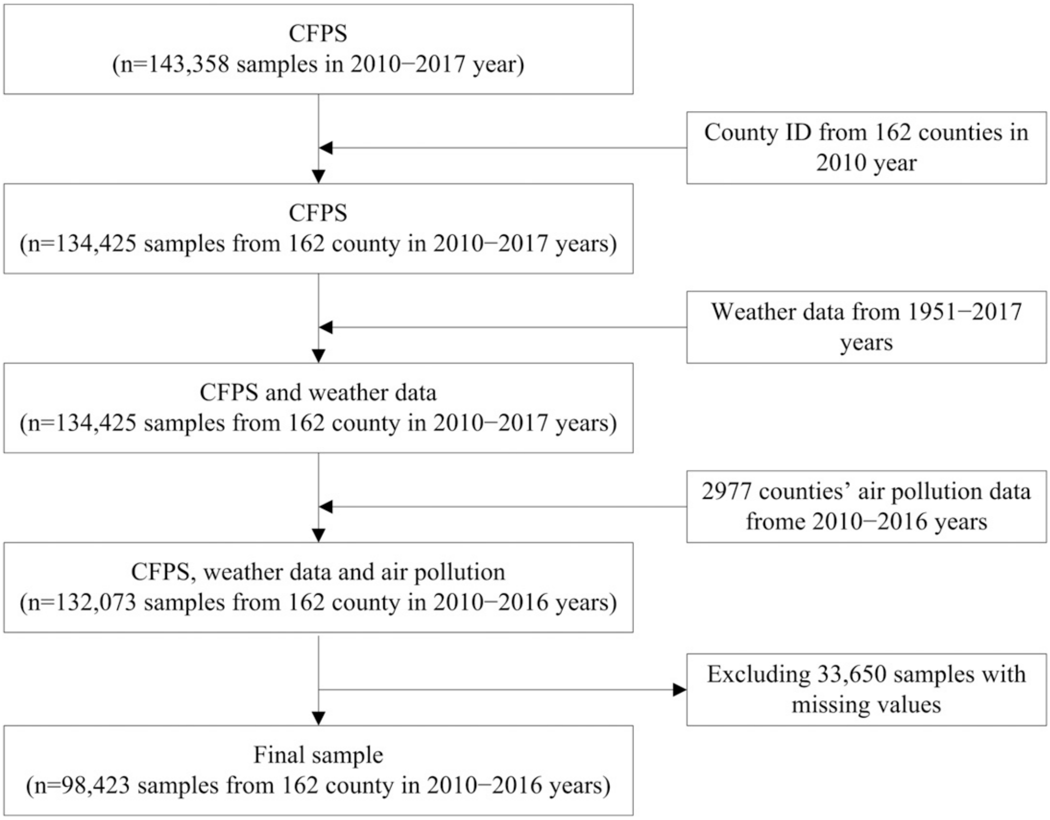

FIG. 1. Data assembly and matching flowchart.

asks respondents to evaluate their health status at the time of the interview by asking "What do you think of your health?" In comparison with other health indicators, the self-assessment method of health is more comprehensive and may reflect the diagnosis of diseases and early onset diseases that may be missed by doctors. The self-assessment data also account for the personal feelings about physical conditions in daily life and the personal understanding of family history (Idler and Benyamini 1997; Jylhä et al. 2006), which has been successful in predicting mortality and disability rates with good reliability and validity (DeSalvo et al. 2005; Qi 2014; Halliday et al. 2021). To standardize the subjective evaluation, examples and references were provided during the interview to differentiate the varying cut points applied by respondents.

In the 2010 questionnaires, the physical health options are healthy, fair, relatively unhealthy, unhealthy, and very unhealthy. In the 2012, 2014, and 2016 questionnaires, the options are changed to extremely healthy, very healthy, relatively healthy, fair, and unhealthy. In our study, we assign health indicators to corresponding quantitative values each year to measure physical health. We use a score of 3 to represent "healthy," which corresponds to the options of healthy in 2010, extremely healthy and very healthy options from the 2012 to 2016 questionnaires, a score of 2 to represent "fairly healthy," which corresponds to the options of the fair in 2010, relatively healthy and fair options from the 2012 to 2016 questionnaires, and a score of 1 to represent "unhealthy," which corresponds to the options of relatively unhealthy, unhealthy, and very unhealthy in 2010, unhealthy options from the 2012 to 2016 questionnaires.

Biological mechanisms for maintaining body temperature suggest that mental health may be affected by ambient temperature (Iversen 1982). Following Zhang et al. (2017), we chose the frequency of respondents' depression during a given period to measure depression. The frequency of depression measures short-term hedonic unhappiness status and is more directly related to the immediate environment and emotional state in daily life when compared with the life satisfaction indicators (Stone and Mackie 2014). A more frequent occurrence of depression reflects lower mental health status. In the 2010 and 2014 questionnaires, the options to measure frequency are "almost every day," "often," "half the time," "sometimes," and "never." In 2012 and 2016, the options are changed to almost none (less than a day), sometimes (1–2 days), often (3–4 days), and most of the time (5–7 days).

Similar to the classification of physical health, we assign different scores to individual mental health status. The questionnaires in 2010 and 2014 ask the frequency of depression in the most recent month and the questionnaires in 2012 and 2016 investigate the frequency in the most recent week. We divide the options according to the actual proportion of depressed days as below. We use 3 to represent "healthy," which corresponds to the option of never in 2010 and 2014, and almost none (less than a day) option from the 2012 and 2016 questionnaires. We use 2 to represent "fairly healthy," which

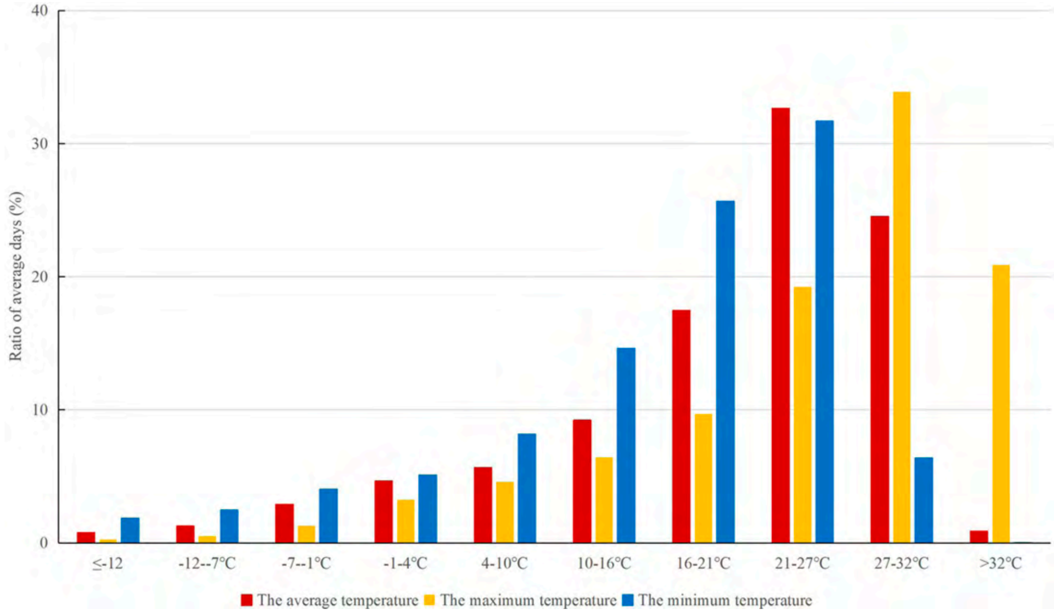

FIG. 2. Temperature distribution (2010–16).

corresponds to the options of often, half the time, sometimes, in 2010 and 2014, and sometimes (1 to 2 days) option from the 2012 and 2016 questionnaires. We use 1 to represent ''unhealthy,'' which corresponds to the option of almost every day in 2010 and 2014, and options often (3 to 4 days), and most of the time (5 to 7 days) from the 2012 and 2016 questionnaires.

The scores of physical health and mental health are combined to represent the overall health level of the respondents. Therefore, the scores are in the range of 2–6. A higher score indicates a healthier status. To test the robustness of the results, we used principal component analysis (PCA) to measure the overall health status. Our results are consistent across different categorizations of health status.

2) TEMPERATURE

We match individual responses and weather stations to ensure that temperature data in different regions can be accurately linked with individual response data. We use data from the weather stations that are nearest to the respondent's county to analyze the effects of temperature on the health status.

The weather measurements include the maximum, minimum, and average temperatures on each day (Fig. 2). To incorporate potential lagged effects, we calculate the average of these three temperature indicators for the month prior to each interview (the monthly average of the daily average temperature, the monthly average of the daily maximum temperature, and the monthly average of the daily minimum

TABLE 1. Temperature indicators. The 10th and 90th percentiles of daily minimum temperature from 2010 to 2016 are −10.6° and 23.0°C, respectively, and the 10th and 90th percentiles of daily maximum temperature from 2010 to 2016 are 1.2° and 32.3°C, respectively.

Name	Definition	Unit
	Cold temperature	
Cold temperature frequency	The day frequency index of temperature lower than the balance point temperature	%
Heating degree days	The cumulative heating degree required when the temperature is below the balance point	°C
Cool nights	(Daily min temperature < 10th percentile)/the no. of days per month	%
Cool days	(Daily max temperature < 10th percentile)/the no. of days per month	%
Cold-spell duration indicator	(Daily min temperature < 10th percentile for ≥2 consecutive days)/the no. of days per month	%
	Hot temperature	
Hot temperature frequency	The day frequency index of temperature higher than the balance point temperature	%
Cooling degree days	The cumulative cooling degree required when the temperature is above the balance point	°C
Warm nights	(Daily min temperature > 90th percentile)/the no. of days per month	%
Warm days	(Daily max temperature > 90th percentile)/the no. of days per month	%
Warm-spell duration indicator	(Daily max temperature > 90th percentile for ≥2 consecutive days)/the no. of days per month	%

temperature). Moreover, two categories of extreme cold and extreme hot indicators are constructed to explore the effect of extreme weather on human health based on a series of temperature indicators. The cold temperature category includes the cold temperature frequency, heating degree-days, cool nights (TN10p), cool days (TX10p), and cold-spell duration indicator (CSDI), and the hot temperature category includes the hot temperature frequency, cooling degree-days, warm nights (TN90p), warm days (TX90p), and warm-spell duration indicators (WSDI). Detailed definitions of each indicator are shown in Table 1.

To further analyze the health effect of extreme heat and cold, we divide the temperatures by Fahrenheit degrees into nine segments according to a 12.22°C (or 10°F) interval in the range from −12.11°C (or 10°F) to 32.22°C (or 90°F). Each temperature critical point (−12.11°, −6.67°, . . . , 26.67°, 32.22°C) is designated as a balance point temperature. We choose the daily temperature frequency index to calculate the proportion scale in which the temperature was higher or lower than the balance point temperature. For example, for the balance point temperature in the heat environment (e.g., 90°F), we calculate the monthly frequency in which the daily average temperature exceeds 90°F in the month before being interviewed. For the balance point temperature in the cold environment (e.g., 10°F), we calculate the monthly frequency in which the daily average temperature is below 10°F. As the balance point temperatures become more extreme, the frequency of days in the corresponding range will become lower, which implies a more extreme temperature on either end of the spectrum.

In addition, we use the cooling degree-days (CDD) and heating degree-days (HDD) defined by European Environment Agency to project climate change and its impacts on environmental, social systems, and human health (European Environment Agency 2020). CDD is the sum of cumulative degrees above the balance point temperature over a period of time; the corresponding HDD reflects the cumulative degrees of the daily average temperature below the balance point temperature. These indicators have been frequently used to estimate energy consumption (Ahmed et al. 2012; Shen et al. 2017; Alola et al. 2019; Yang et al. 2019b).

We also consider six indicators produced by the World Meteorological Organization (WMO), such as warm nights, cool days, and warm-spell duration indicators to measure extreme temperature. The nights and days indicators are constructed based on the observation data with cutoff points, while the warm-spell duration indicator and cold-spell duration indicator consider spatial and temporal heterogeneity. As proxy indices of extreme temperature, these indicators were widely used in the literature (Alexander et al. 2006; New et al. 2006; Choi et al. 2009; Zhou and Ren 2010).

3) OTHER CONTROL VARIABLES

We control for sociodemographic and health behavior variables, including age, gender, marital status, rural–urban residence, income, educational level, smoking, drinking, and physical exercise in regression models (Xu and Xie 2017). We use dummy variables to represent gender, marriage, and rural–urban residential settlements, as well as personal behavioral patterns such as smoking and drinking behavior according to reported frequency. We also take into account the effects of average precipitation and average $PM_{2.5}$ on health.

TABLE 2. Statistical descriptions (for the entire sample, $N = 98\,423$).

Variable	Mean	Std dev
Avg temperature (°C)	23.712	5.324
Max temperature (°C)	28.663	5.065
Min temperature (°C)	19.857	5.737
Avg precipitation (mm)	4.996	3.677
Fine particulate matter ($PM_{2.5}$; $\mu g\ m^{-3}$)	52.608	26.316
Overall health	4.136	1.103
Physical health	2.176	0.703
Mental health	1.960	0.796
Per capita annual household income (CNY)	12,064	20,881
	N	%
Sex		
Male	48 022	48.791
Female	50 401	51.209
Age		
16–30	18 231	18.523
30–40	14 948	15.188
40–50	22 256	22.613
50–60	19 570	19.884
60–70	15 458	15.706
>70	9030	9.175
Marital status		
Married	80 107	81.391
Unmarried	18 316	18.609
Education		
No education/primary school	50 732	51.545
Middle school/high school	41 469	42.133
Junior college and above	7292	7.409
Smoking status		
Current smoker	28 747	29.208
Nonsmoker	69 676	70.792
Drinker status		
Frequent drinker	15 330	15.576
Nondrinker	83 093	84.424
Location		
Urban	46 107	46.846
Rural	52 316	53.154

3. Empirical strategy

To explore the impact of temperature on the residents' health status, we specify the following econometric model:

$$H_{ijt} = \alpha_0 + \alpha_1 \times \mathrm{Temp}_{jt} + \alpha_2 \times \mathrm{Temp}_{jt}^2 + \alpha_3 \times \ln Y_{ijy} + \alpha_4 \times \mathrm{CV}_{ijt} + \eta_m + \gamma_i + \eta_y \times \gamma_r + \varepsilon_{ijt}, \quad (1)$$

where i, j, and t represent resident i in location j at month t, respectively; H_{ijt} denotes the health status for resident i at time t and location j; Temp_{jt} represents three temperature indices,

TABLE 3. Nonlinear relationship between temperature and health (the dependent variable is the health score). Significance levels $p < 0.01$, $p < 0.05$, and $p < 0.1$ are indicated by three asterisks, two asterisks, and one asterisk, respectively; robust standard errors are in parentheses; $N = 98\,423$.

Variable	Model 1	Model 2	Model 3
Square of the avg temperature	−0.000 254***		
	(0.000 085)		
Avg temperature	0.009 495***		
	(0.003 589)		
Square of the max temperature		−0.000 240***	
		(0.000 092)	
Max temperature		0.010 054**	
		(0.004 641)	
Square of the min temperature			−0.000 252***
			(0.000 078)
Min temperature			0.010 864***
			(0.002 984)
Log of per capita annual household income	0.007 863**	0.007 825**	0.007 891**
	(0.003 682)	(0.003 682)	(0.003 682)
Individual characteristics (time varying)	Yes	Yes	Yes
Weather controls and air pollution	Yes	Yes	Yes
Individual fixed effect	Yes	Yes	Yes
Month fixed effect	Yes	Yes	Yes
Region-by-year fixed effect	Yes	Yes	Yes
R squared	0.4541	0.4541	0.4542

including the daily average temperature, daily maximum temperature, and daily minimum temperature recorded by the nearest weather station; $\ln Y_{ijy}$ is the logarithm of household income in year y (we use this logarithmic transformation to minimize the skewness of the income distribution; Jorgenson 2009); and CV_{ijt} is the set of the other, time-varying control variables, including the average precipitation and fine particulate matter. The regression coefficient vectors of temperature, temperature squared, the logarithm of income, and other control variables are respectively denoted by α_1, $\alpha_{2,}$ $\alpha_{3,}$ and $\alpha_{4,}$ and α_0 is the intercept term; η_m is the month-of-the-year fixed effects to control for any policies or emergencies that appear in different months; γ_i represents the individual fixed effects and control for all individual

TABLE 4. Nonlinear relationship between temperature and health by symptom. Significance levels $p < 0.01$, $p < 0.05$, and $p < 0.1$ are indicated by three asterisks, two asterisks, and one asterisk, respectively; robust standard errors are in parentheses; $N = 98\,423$.

	Dependent variable: the physical health score			Dependent variable: the mental health score		
Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Square of the avg temperature	−0.000 087*			−0.000 168**		
	(0.000 052)			(0.000 065)		
Avg temperature	0.004 708**			0.004 787*		
	(0.002 201)			(0.002 693)		
Square of the max temperature		−0.000 074			−0.000 167**	
		(0.000 057)			(0.000 069)	
Max temperature		0.003 240			0.006 814**	
		(0.002 846)			(0.003 471)	
Square of the min temperature			−0.000 095**			−0.000 157***
			(0.000 047)			(0.000 059)
Min temperature			0.006 113***			0.004 751**
			(0.001 847)			(0.002 231)
Log of per capita annual household income	0.007 994***	0.007 974***	0.008 014***	−0.000 131	−0.000 149	−0.000 123
	(0.002 400)	(0.002 401)	(0.002 400)	(0.002 70)	(0.002 701)	(0.002 702)
Individual characteristics (time varying)	Yes	Yes	Yes	Yes	Yes	Yes
Weather controls and air pollution	Yes	Yes	Yes	Yes	Yes	Yes
Individual fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Month fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Region-by-year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
R squared	0.0501	0.0500	0.0502	0.5358	0.5358	0.5358

TABLE 5. Nonlinear relationship between temperature and health: robustness checks (the dependent variable is the health score). Significance levels $p < 0.01$, $p < 0.05$, and $p < 0.1$ are indicated by three asterisks, two asterisks, and one asterisk, respectively; robust standard errors are in parentheses; the health score: PCA = (0.5395 × the physical health score) + (0.4605 × the mental health score); the average temperature of distance aggregation = [(shortest distance × the average temperature of shortest distance) + (second shortest distance × the average temperature of the second shortest distance)]/(shortest distance + second shortest distance).

				Radius		
Variable	Baseline: model 1	Tobit: model 2	Health score PCA: model 3	Distance < 60 km: model 4	Second shortest distance: model 5	Distance aggregation: model 6
Square of the avg temperature	−0.000 254***	−0.000 066	−0.000 124***	−0.000 210**		
	(0.000 085)	(0.000 059)	(0.000 042)	(0.000 087)		
Avg temperature	0.009 495***	0.005 368**	0.004 744***	0.008 188**		
	(0.003 589)	(0.002 528)	(0.001 773)	(0.003 648)		
Square of the avg temperature of the second shortest distance					−0.000 229***	
					(0.000 081)	
Avg temperature of the second shortest distance					0.007 156**	
					(0.003 442)	
Square of the avg temperature of distance aggregation						−0.000 229***
						(0.000 084)
Avg temperature of distance aggregation						0.007 756**
						(0.003 502)
Log of per capita annual household income	0.007 863**	0.014 962***	0.004 252**	0.008 473**	0.007 302**	0.007 359**
	(0.003 682)	(0.002 560)	(0.001 830)	(0.003 811)	(0.003 701)	(0.003 701)
Individual characteristics (time varying)	Yes	Yes	Yes	Yes	Yes	Yes
Weather controls; air pollution	Yes	Yes	Yes	Yes	Yes	Yes
Individual fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Month fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Region-by-year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
R squared	0.4541		0.4280	0.4519	0.4542	0.4543

characteristics that do not vary over time; and $\eta_y \times \gamma_r$ is the region-by-year fixed effects to control for time-varying factors that differ across regions, which include the eastern, middle, and western regions according to National Bureau of Statistics of China. The ε_{ijt} represents the error term.

To further analyze the health effects of extreme temperatures, we constructed the following model:

$$H_{ijt} = \beta_0 + \beta_1 \times \mathrm{ET}_{ji} + \beta_2 \times \ln Y_{ijy} + \beta_3 \times \mathrm{CV}_{ijt} + \eta_m + \gamma_i + \eta_y \times \gamma_r + \varepsilon_{ijt}, \quad (2)$$

where the extreme index ET_{ji} reflects the extreme cold and heat indexes such as cold temperature frequency, heating degree-days, cool nights, cool days, cold-spell duration indicator, hot temperature frequency, cooling degree-days, warm nights, warm days, and warm-spell duration indicator; β_1 represents its regression coefficient. Other variables are defined similarly as in Eq. (1). We also apply the hierarchical regression method to test the heterogeneity of control variables.

4. Results

a. Summary statistics

Table 2 reports the summary statistics of our sample. Based on the general climate data statistics, the average temperature of all the counties included in our sample is 23.71°C (standard deviation SD = 5.32°C), which varies from −25.08° to 31.37°C. We also calculate that the means of the daily maximum and minimum temperatures are 28.66°C (SD = 5.07°C) and 19.86°C (SD = 5.74°C), respectively. The average values of precipitation and $PM_{2.5}$ in the region are 5.00 mm (SD = 3.68 mm) and 52.61 μg m^{-3} (SD = 26.32 μg m^{-3}), respectively.

The mean value of the aggregated individual health index is 4.14 (SD = 1.10). When divided into physical health and mental health, the means of individual physical and mental health are 2.18 (SD = 0.70) and 1.96 (SD = 0.80), respectively. The subjects in the CFPS survey range from 16 to 116 years old. The average age of the respondents is around 46.90 yr (SD = 16.52 yr). Nearly 81.39% are married, and 51.21% of the population are women. Most of the residents do not have a college diploma (junior college and above accounted for 7.41%), the families earn an annual income per capita of CNY 12,064 (SD = 20,881, around USD 1,743), and 46.85% of them live in the urban areas.[1] From the lifestyle index data, we find that, among all the respondents, about 29.21% and 15.58% of the population have frequent smoking and drinking habits, respectively

[1] The definition of city is based on the CFPS data, including municipalities, prefecture-level cities, and county-level cities.

TABLE 6. Effect of cold and hot temperature on health: cold temperature and hot temperature (the dependent variable is the health score). Significance levels $p < 0.01$, $p < 0.05$, and $p < 0.1$ are indicated by three asterisks, two asterisks, and one asterisk, respectively; robust standard errors are in parentheses; $N = 98\,423$.

	Cold temperature frequency						Hot temperature frequency		
Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9
Proportion of days with temperature < −12.22°C	−0.289 14 (0.192 074)								
Proportion of days with temperature < −6.67°C		−0.137 177 (0.114 086)							
Proportion of days with temperature < −1.11°C			−0.201 026*** (0.073 862)						
Proportion of days with temperature < 4.44°C				−0.234 186*** (0.065 820)					
Proportion of days with temperature < 10°C					−0.141 932** (0.055 192)				
Proportion of days with temperature < 15.56°C						0.042 821 (0.039 335)			
Proportion of days with temperature < 21.11°C							0.066 589** (0.026 332)		
Proportion of days with temperature < 26.67°C								−0.085 152*** (0.022 697)	
Proportion of days with temperature < 32.22°C									−0.137 401 (0.088 521)
Log of per capita annual household income	0.007 736** (0.003 683)	0.007 738** (0.003 683)	0.007 774** (0.003 682)	0.007 809** (0.003 682)	0.007 739** (0.003 682)	0.007 662** (0.003 683)	0.007 747** (0.003 683)	0.007 865** (0.003 683)	0.007 803** (0.003 683)
Individual characteristics (time varying)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Weather controls; air pollution	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region-by-year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R squared	0.4540	0.4540	0.4541	0.4541	0.4541	0.4540	0.4541	0.4541	0.4540

TABLE 7. Effect of cold and hot temperature on health: HDDs and CDDs (the dependent variable is the health score). Significance levels $p < 0.01$, $p < 0.05$, and $p < 0.1$ are indicated by three asterisks, two asterisks, and one asterisk, respectively; robust standard errors are in parentheses; $N = 98\,423$.

	HDDs						CDDs		
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9
HDDs based on −12.22°C	−0.061 652** (0.027 591)								
HDDs based on −6.67°C		−0.029 521* (0.017 449)							
HDDs based on −1.11°C			−0.040 407*** (0.012 314)						
HDDs based on 4.44°C				−0.043 848*** (0.011 014)					
HDDs based on 10°C					−0.014 427* (0.008 164)				
HDDs based on 15.56°C						−0.000 823 (0.006 472)			
CDDs based on 21.11°C							0.009 947 (0.006 98)		
CDDs based on 26.67°C								−0.005 919 (0.004 747)	
CDDs based on 32.22°C									−0.015 533 (0.010 599)
Log of per capita annual household income	0.007 747** (0.003 683)	0.007 744** (0.003 682)	0.007 743** (0.003 681)	0.007 741** (0.003 682)	0.007 691** (0.003 683)	0.007 718** (0.003 683)	0.007 758** (0.003 67)	0.007 751** (0.003 683)	0.007 819** (0.003 684)
Individual characteristics (time varying)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Weather controls and air pollution	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region-by-year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R squared	0.4540	0.4540	0.4541	0.4541	0.4540	0.4540	0.4540	0.4540	0.4540

TABLE 8. Effect of cold and hot temperature on health: extreme cold and extreme heat (the dependent variable is the health score). Significance levels $p < 0.01$, $p < 0.05$, and $p < 0.1$ are indicated by three asterisks, two asterisks, and one asterisk, respectively; robust standard errors are in parentheses; $N = 98\,423$.

	Extreme cold			Extreme heat		
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Cool nights	−0.231 001** (0.105 118)					
Cool days		−0.131 832 (0.092 571)				
CSDI			−0.228 669** (0.108 269)			
Warm nights				−0.075 760*** (0.023 758)		
Warm days					−0.030 624 (0.024 709)	
WSDI						−0.034 923 (0.023 937)
Log of income	0.007 777** (0.003 682)	0.007 731** (0.003 682)	0.007 763** (0.003 682)	0.007 877** (0.003 683)	0.007 758** (0.003 683)	0.007 779** (0.003 682)
Individual characteristics (time varying)	Yes	Yes	Yes	Yes	Yes	Yes
Weather controls and air pollution	Yes	Yes	Yes	Yes	Yes	Yes
Individual fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Month fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Region-by-year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
R squared	0.4540	0.4540	0.4540	0.4541	0.4540	0.4540

b. *Overall regression results analysis*

Table 3 presents the regression results for estimating the overall effect of temperature on human health. The effects of average temperature, maximum temperature, and minimum temperature on health were shown in sequence (Table 3, models 1–3). We find that the influence of temperature on health presents a clear inverted U-shaped curve across different model specifications, indicating that both hot and cold weather produce negative effects on human health, while a moderate temperature is best for health. This result is consistent with our prior expectations (e.g., Yang et al. 2019a). The coefficient of the square of the average temperature and the average temperature are −0.000 254 and 0.009 495 in Table 3, model 1, respectively. We also calculate the inflection point of the curve. When the average temperature is less than 18.69°C, a higher temperature leads to more health benefits. When the average temperature is higher than 18.69°C, the increase in temperature leads to negative effects on health (Table 3, model 1). We classify nine balance point temperatures into two ranges, cold and hot temperatures, based on the 18.69°C benchmark.

The impact of temperature on physical health and mental health are investigated separately in Table 4. Our regression results are consistent with the results of overall health, and we observed an inverted U-shaped relationship between the temperature and both physical and mental health. Our results show that the when the physical health is used as the dependent variable, the R square is smaller relative to the specification when mental health is used as the dependent variable, suggesting the current control variables better explain the variations for mental health. (In the appendix, Tables A1 and A2 present the coefficient estimates for the full set of control variables based on the specifications used in Tables 3 and 4, respectively).

c. *Robustness checks*

Table 5 presents results from additional robustness tests. The total health measurement scale ranged between 2 and 6, representing a limited dependent variable. We use the Tobit model and PCA method for robust analysis. Results are shown in model 2–3 of Table 5. The results are consistent with regressions in Tables 3 and 4, which confirm the nonlinear relationship between temperature and health.

We also analyze alternative methods of matching meteorological station data to test the robustness of our results. We detect a nonlinear, quadratic relationship using alternative matching methods (Table 5, models 4–6). In Table 5, model 1, we match each respondent to the nearest meteorological station to link meteorological data and the individual. To address potential measurement errors and attenuation effects, we defined a cutoff radius of 60 km and eliminated the sample individuals who did not meet the conditions (Table 5, model 4). Alternatively, we used the weather data from the second nearest weather station and a temperature–distance-weighted index to measure this regression relationship (Table 5, models 5 and 6). We find alternative distance calculations have little influence on our main conclusions.

d. *Health effects of hot and cold temperature*

In this section, we construct a series of temperature indicators and evaluate if extreme hot and cold weather events have a more pronounced negative effect on health. Our main results are presented in Tables 6–8 and Fig. 3. In Table 6, the

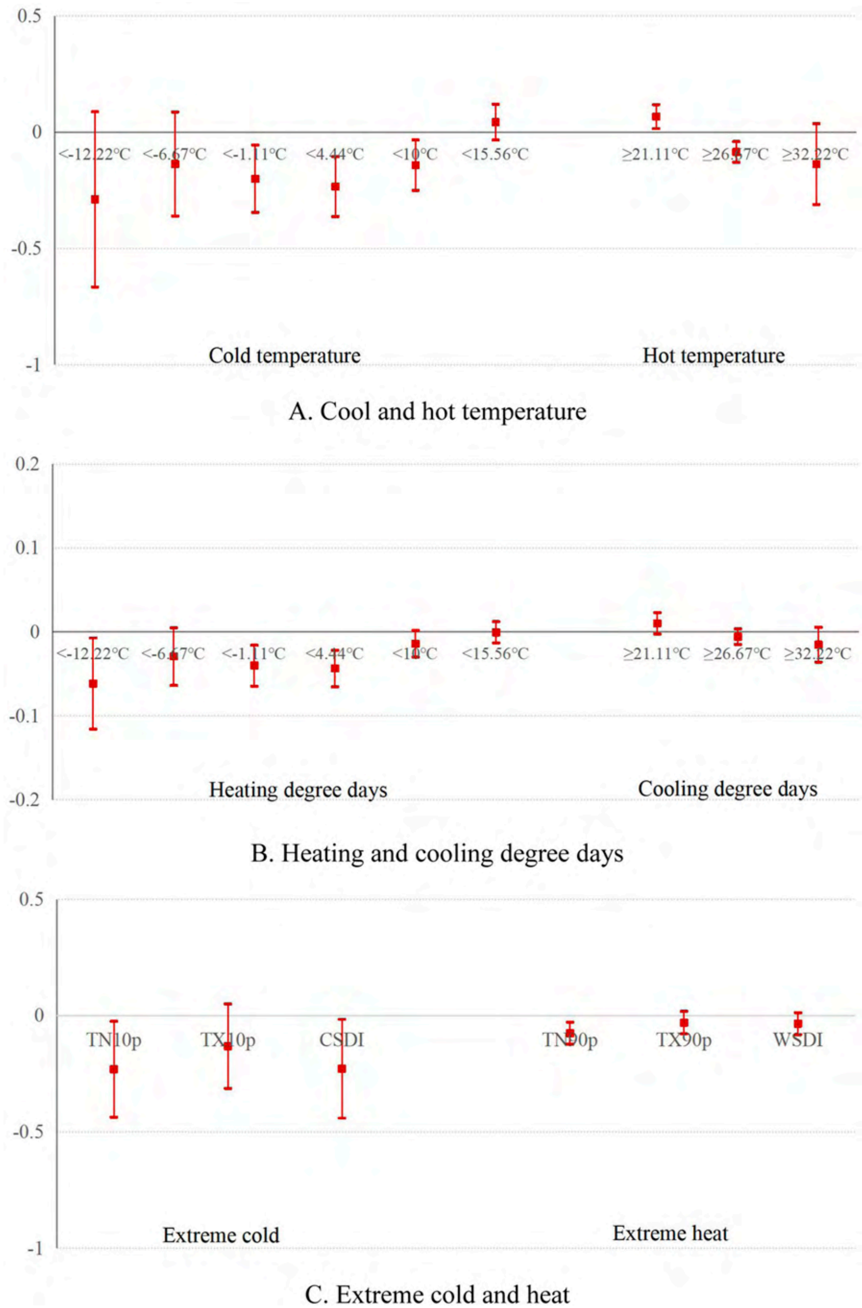

FIG. 3. Effect of cold and hot temperature on health. The vertical axis represents the change in the health score. The vertical lines show the 95% confidence interval.

temperature frequency index is calculated as the proportion of days with temperatures in the designated range. Results show that both hot and cold temperatures will contribute to negative health effects. The negative impact gradually deepened as the temperature rises or drops farther. When the temperature falls below −12.22° or −6.67°C threshold, and if the cold duration increases by 1 percentage point, the health score will decrease by 0.29% or 0.14%, respectively (models 1 and 2 in Table 6). When the threshold is 26.67°C, a 1 percentage increase in the duration only decreases the health score by 0.09% (model 8 in Table 6). When the temperature rises above the 32.22°C threshold, a 1 percentage increase in the duration will lead the health score to decrease by 0.14% (model 9 in Table 6). Based on the method proposed by Joyce et al. (1989), and Chen and Shi (2013), we use differential transformation to evaluate the money metric value of temperature by calculating the average marginal rate of substitution between daily temperature and household per capita

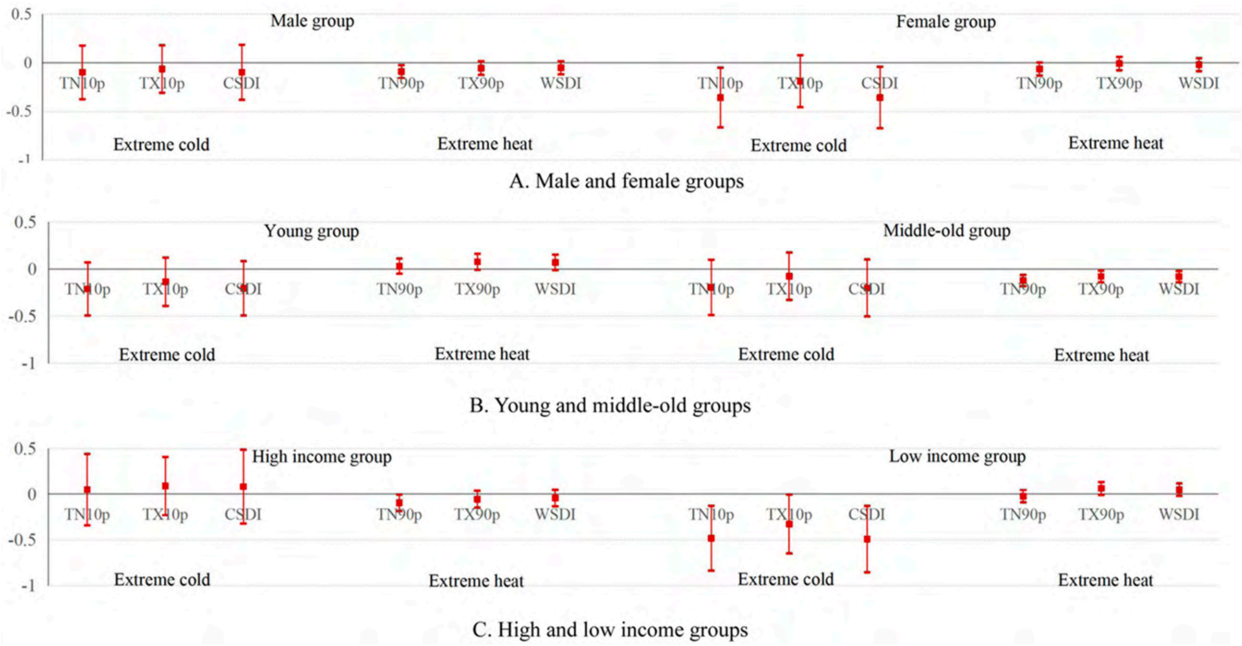

FIG. 4. Effect of extreme cold and heat on health for different subgroups. The vertical axis represents the change in the health score. The vertical lines show the 95% confidence interval. The young group consists of people age 16–40, and the middle-old group consists of people over age 40. We calculate the average value (CNY 12,064) of the households' per capita annual income and subsequently classify residents with higher-than-average incomes as the high-income group and those with lower-than-average incomes as the low-income group.

income, also known as "willingness to pay" (WTP).[2] According to the formula, when the temperature falls below −12.22° or −6.67°C, and rises above 26.67° or 32.22°C, the corresponding WTP are CNY 4,525.91 (or USD 654), CNY 2,146.68 (or USD 310), CNY 1,311.02 (or USD 189), and CNY 2,132.27 (or USD 308), respectively, if the temperature becomes less extreme by 1%. Figure 3 also shows that the negative effect estimates for cold temperatures are much larger than for hot temperatures, but less precisely estimated, which is consistent with results in Anderson and Bell (2009) and Yang et al. (2019a) where they find that the extreme cold temperatures have a larger impact on mortality than does extreme heat. Based on Fig. 2, the distribution of temperature is heavily right skewed, and we have fewer observations for cold temperature (e.g., below 0°C), which may lead to relatively large standard errors for cold temperature.

Previous studies have shown that temperature has a cumulative effect on health (Huang et al. 2015; Liang et al. 2007). We use HDD and CDD indicators based on the European Environment Agency (2020) to evaluate climate change and its corresponding impacts on environmental and social systems, as well as human health. Based on Table 7, when the temperature is lower than −12.22°C, a 1°C increase in the monthly accumulation of temperature, which means an increase of one unit degree in the HDD value will lower the health score by 0.06%, and the WTP index is CNY 963.67 (or USD 139; model 1 in Table 7). When the temperature is lower than −6.67°C, the degree of unit health affected is −0.03%, and the corresponding WTP index is CNY 461.61 (or USD 67; model 2 in Table 7). When the temperature threshold is higher than 26.67°C, the unit health effect is −0.006%, which implies CNY 240.56 willingness to pay (or USD 35; model 8 in Table 7). When the temperature is higher than 32.22°C, a one unit in the CDD value will decrease the health score by 0.016%, which implies CNY 92.47 willingness to pay (or USD 13.38; model 9 in Table 7). The results in HDD also suggest that both extreme low temperatures create greater adverse burdens on human health. Changes in extreme cold indicators are negatively correlated with the health status of residents.

Table 8 presents the regional adaptation patterns using the temperature threshold based on WMO extreme weather indicators. The regression results reveal that for each 1% increase in TN10p, TX10p, CSDI, TN90p, TX90p, and WSDI, the health score decreased by 0.231%, 0.132%, 0.229%, 0.076%, 0.031%, and 0.035%, and the WTP indices are CNY 3,586.80, CNY 2,064.90, CNY 3,566.91, CNY 1,164.64, CNY 478.00, and CNY 543.63, respectively (models 1–6 in Table 8). The absolute magnitude of the parameters related to cold

[2] With respect to Eq. (2), we take the total derivative of health for a given level (i.e., let $dH = 0$), and we can calculate the WTP as the average marginal rate of substitution between temperature and per capita household income, $\partial Yijt/\partial ETji \mid (dH_{ijt} = 0) = -Y_{ijt} \times \beta_1/\beta_2$.

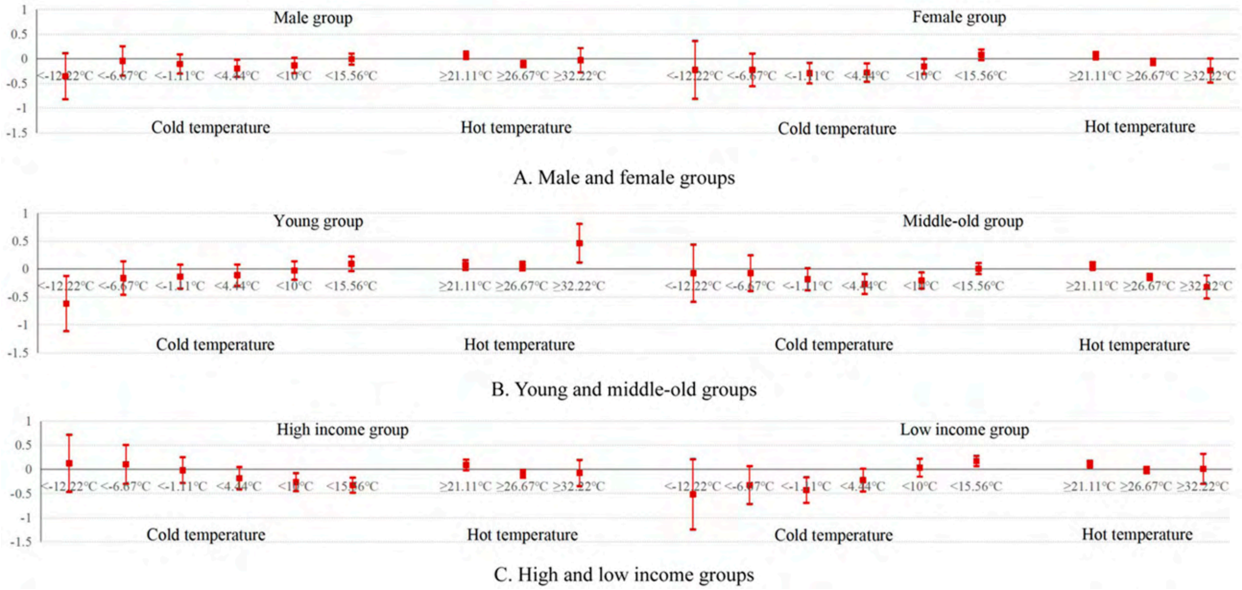

FIG. 5. As in Fig. 4, but for cold and hot temperature.

weather is larger than their warm weather counterparts, indicating that the extremely cold weather has a greater impact on human health.

e. Regression results in different subgroups

Based on the hierarchical regression method, we further estimated the differences in temperature and health among subgroups at the sociodemographic level. When using the six WMO extreme temperature indicators for regression, we find that subgroups of sex, age, and low income show the same results as the general population, with greater health impacts in extreme cold environments, while only the high-income population experience little effects when measured against the cold indicators. Figure 4a reveals that men are more sensitive to high temperatures, and women are more vulnerable in cold temperatures. We further divide the population into youth and middle-elderly groups using 40 as the cutoff point, referring to Zhang et al. (2017), which suggests that a person's health, immunity, and various aspects of metabolism decline after the age of 40 in general. Many studies have shown that the elderly are more vulnerable to extreme weather (Zeng et al. 2010; Kinay et al. 2019). Our results show that middle or old people are more sensitive to extreme heat (Fig. 4b). When the population is categorized by

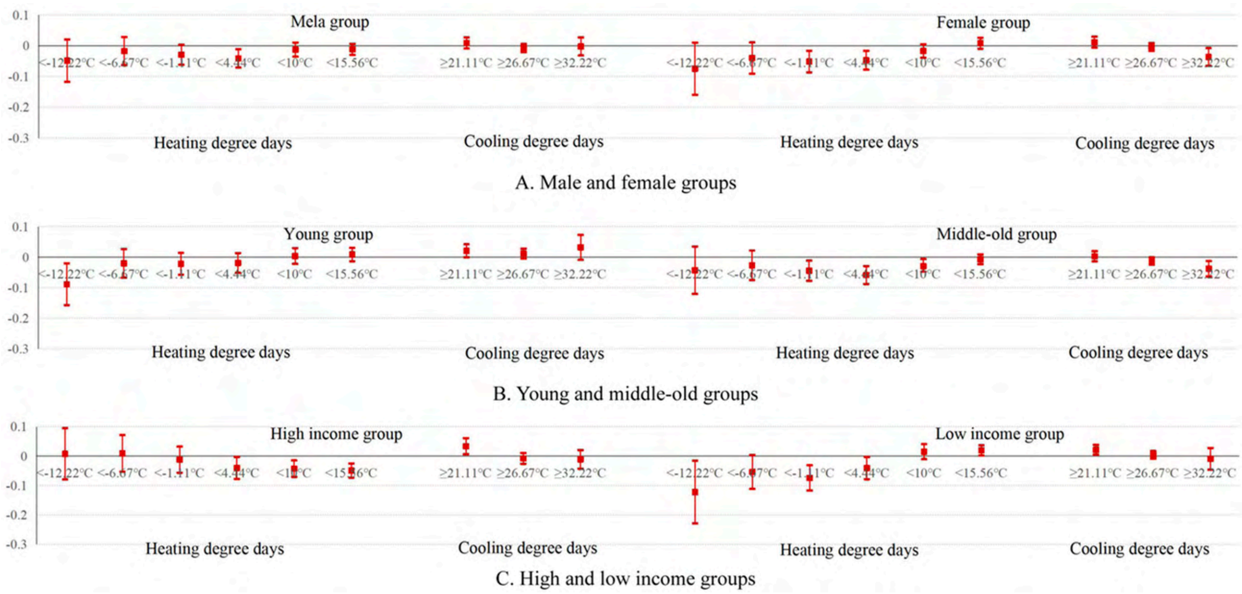

FIG. 6. As in Fig. 4, but for HDDs and CDDs.

TABLE A1. Nonlinear relationship between temperature and health (the dependent variable is the health score). Significance levels $p < 0.01$, $p < 0.05$, and $p < 0.1$ are indicated by three asterisks, two asterisks, and one asterisk, respectively; robust standard errors are in parentheses; $N = 98\,423$.

Variable	Model 1	Model 2	Model 3
Square of the avg temperature	−0.000 254***		
	(0.000 085)		
Avg temperature	0.009 495***		
	(0.003 589)		
Square of the max temperature		−0.000 240***	
		(0.000 092)	
Max temperature		0.010 054**	
		(0.004 641)	
Square of the min temperature			−0.000 252***
			(0.000 078)
Min temperature			0.010 864***
			(0.002 984)
Avg precipitation	0.004 838***	0.004 481***	0.005 048***
	(0.001 145)	(0.001 195)	(0.001 113)
Log of $PM_{2.5}$	−0.050 865	−0.050 765	−0.053 118
	(0.033 735)	(0.033 736)	(0.033 761)
Log of per capita annual household income	0.007 863**	0.007 825**	0.007 891**
	(0.003 682)	(0.003 682)	(0.003 682)
Male	0.041 868	0.042 733	0.041 814
	(0.161 854)	(0.161 769)	(0.161 894)
$30 \leq$ age < 40	−0.025 387	−0.025 780	−0.024 948
	(0.023 355)	(0.023 352)	(0.023 354)
$40 \leq$ age < 50	−0.025 710	−0.026 027	−0.025 311
	(0.031 825)	(0.031 825)	(0.031 822)
$50 \leq$ age < 60	−0.032 552	−0.032 959	−0.031 883
	(0.038 839)	(0.038 838)	(0.038 836)
$60 \leq$ age < 70	−0.034 988	−0.035 492	−0.034 222
	(0.046 222)	(0.046 221)	(0.046 221)
Age ≥ 70	−0.030 481	−0.031 001	−0.029 840
	(0.056 531)	(0.056 530)	(0.056 529)
Married	−0.080 724***	0.080 788***	−0.080 808***
	(0.021 677)	(0.021 674)	(0.021 678)
Middle school/high school	0.090 554***	0.090 821***	0.090 302***
	(0.031 001)	(0.031 004)	(0.030 992)
Junior college and above	0.043 171	0.043 148	0.043 087
	(0.044 204)	(0.044 213)	(0.044 197)
Current smoker	0.036 022**	0.035 920**	0.036 034**
	(0.017 400)	(0.017 402)	(0.017 399)
Frequent drinker	0.041 105***	0.041 032***	0.041 076***
	(0.013 649)	(0.013 649)	(0.013 648)
Urban	−0.026 594	−0.026 323	−0.027 207
	(0.022 926)	(0.022 931)	(0.022 915)
Individual fixed effect	Yes	Yes	Yes
Month fixed effect	Yes	Yes	Yes
Region-by-year fixed effect	Yes	Yes	Yes
R squared	0.4541	0.4541	0.4542

economic income,[3] wealthy people are more susceptible to extreme heat. However, under an extreme cold environment, the low-income groups will be more adversely affected (Fig. 4c).

We further test the robustness of the results of the above subgroups by using temperature frequency indicators, and the HDD and CDD indicators. The results are consistent with the main conclusions and are displayed in Figs. 5 and 6).

5. Discussion

Based on the observations of nearly 100 000 Chinese residents, our research is the first to study the relationship between

[3] We calculate the average value (CNY 12,064) of the households' per capita annual income and subsequently classify residents with higher-than-average incomes as the high-income group and those with lower-than-average incomes as the low-income group.

temperature and physical and mental health based on self-reported data at an individual level. We also investigate the heterogeneous effects of sociodemographic factors, including gender, age, and income types, on the health effects of temperature.

We confirm the regression relationship between daily health level and the temperature is an inverted U curve under various model specifications. The inflection point of the average temperature on health was estimated at 18.69°C (or 62.62°F), an average indicator based on a large sample from China. The effect of temperature on health could vary across geography or climatic baselines (Deschênes 2014). As the temperature moves away from the inflection point, the health of residents will be more adversely affected.

Due to different latitudes and impacts of climate change, the population's adaptability to temperature varies. Our results suggest that extreme cold days have a greater impact on overall health. Previous studies suggested that temporary warming can make people more sensitive to intense cold waves (Qu and Xiao 2019). As the global warming trend continues, people can initiate a more gradual increase in thermal adaptation, while adaptation to extreme cold weather may be more difficult.

Six extreme temperature indicators produced by WMO are used as the main temperature explanatory variables to determine the influence of health heterogeneity under different population characteristics. Existing studies have found females were more vulnerable to the impact of temperature variation than men (Stafoggia et al. 2006; Ishigami et al. 2008; Yu et al. 2010; Gao et al. 2019), while others have not found differences between genders (Basu and Ostro 2008; Stafoggia et al. 2008). Our study finds that men and women show different responses to cold and heat. Women exhibit a stronger response to cold, while men are more sensitive to heat. Lan et al. (2008) investigated the gender difference in thermal comfort in China and found that females are more sensitive to the cool environment according to the analysis of skin temperature and the relationship between bodily state and sensation.[4] Previous conclusions indicate that the temperature-related health effects are more pronounced in the middle-aged and elderly (Anderson and Bell 2009; Hajat et al. 2006; Ishigami et al. 2008). We find that the middle and old age groups will be affected by extreme cold and heat, and the influence was more significant under extreme heat. For this group, preexisting disorders create difficulty in thermoregulation (Stafoggia et al. 2008). The elderly are less resistant to heat, which might be caused by poor aerobic fitness, differences in body composition, and chronic health conditions (Pandolf 1997). On the psychological level, Hayes and Poland (2018) summarized that while the mental health implications of climate change can affect all age groups, these impacts tend to be greatest among individuals who are the most vulnerable, such as seniors.

We also find significant differences between incomes. The health of low-income groups is more affected by cold weather conditions, while high-income groups are significantly more affected by extreme heat, though the impact of very low temperatures is not precisely estimated for the high-income group. Our results depart slightly from previous studies. Yu et al. (2020) suggested that people with higher socioeconomic status have more ability to resist external heat pressure. Yang et al. (2019a) concluded that extreme temperatures have a greater influence on the mortality rate in regions with low economic development, due to the lack of prevention and adaptation measures, such as air conditioning and medical facilities. In the case of extreme heat, our results show that the rich are slightly more affected than the poor. The vast majority of wealthy people live in urban areas in China, where there might be a more serious heat island effect (Hua et al. 2008), which brings a more severe and lasting negative effect to local people.

6. Conclusions

We establish the relationship between temperature and respondents' physical and mental health conditions based on individual-level survey and climate data in China. Our study also uncovers the effects of extreme temperatures among subgroups of populations. Our analyses contribute to the growing empirical results with regard to the climate effects on gender (Yu et al. 2010). Our data do not include individuals younger than 16. Existing literature suggests that young children are particularly vulnerable to heat-related deaths, and extreme heat and cold will primarily burden children with infectious diseases (Xu et al. 2012). Climate-related impacts on children are important for further studies.

Our research results have important implications for climate change mitigation policies. We find significant effects of extreme temperatures on the daily health of respondents. For example, low-income groups are more vulnerable to extremely cold weather, and the government or agencies can actively help low-income groups install and improve heating equipment, increase the proportion of renewable and clean energy heating, and optimize operating subsidy policies.

Acknowledgments. The authors are grateful for financial support from the National Natural Science Foundation of China (NSFC) (71704009; 72074021), the Joint Development Program of Beijing Municipal Commission of Education, the Science and Technology Research Project of Hubei Provincial Department of Education (Q20201104), and the Fundamental Research Funds for the Central Universities (FRF-BR-20-04A). We acknowledge the China Family Panel Studies team for providing data and the training of using the dataset.

Data availability statement. Data generated for this project are openly available online (http://isss.pku.edu.cn/cfps/download/login).

[4] The reason for reference may be that men are more muscular and have a faster metabolism, leading to a higher body surface temperature. And there are also medical explanations saying that this is related to the structure of the male and female reproductive systems.

TABLE A2. Nonlinear relationship between temperature and health: by symptom. Significance levels $p < 0.01$, $p < 0.05$, and $p < 0.1$ are indicated by three asterisks, two asterisks, and one asterisk, respectively; robust standard errors are in parentheses; $N = 98\,423$.

	Dependent variable: the physical health score			Dependent variable: the mental health score		
Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Square of the avg temperature	−0.000 087*			−0.000 168**		
	(0.000 052)				(0.000 065)	
Avg temperature	0.004 708**			0.004 787*		
	(0.002 201)			(0.002 693)		
Square of the max temperature		−0.000 074			−0.000 167**	
		(0.000 057)			(0.000 069)	
Max temperature		0.003 240			0.006 814**	
		(0.002 846)			(0.003 471)	
Square of the min temperature			−0.000 095**			−0.000 157***
			(0.000 047)			(0.000 059)
Min temperature			0.006 113***			0.004 751**
			(0.001 847)			(0.002 231)
Avg precipitation	0.001 779**	0.001 587**	0.001 741**	0.003 059***	0.002 893***	0.003 307***
	(0.000 743)	(0.000 775)	(0.000 721)	(0.000 847)	(0.000 890)	(0.000 821)
Log of $PM_{2.5}$	−0.018 542	−0.018 206	−0.020 141	−0.032 323	−0.032 559	−0.032 977
	(0.022 037)	(0.022 038)	(0.022 044)	(0.025 531)	(0.025 525)	(0.025 557)
Log of per capita annual household income	0.007 994***	0.007 974***	0.008 014***	−0.000 131	−0.000 149	−0.000 123
	(0.002 400)	(0.002 401)	(0.002 400)	(0.002 70)	(0.002 701)	(0.002 702)
Male	0.067 774	0.068 238	0.067 944	−0.025 906	−0.025 505	−0.026 131
	(0.109 576)	(0.109 507)	(0.109 612)	(0.100 108)	(0.100 076)	(0.100 08)
30 ≤ age < 40	−0.028 566*	−0.028 847*	−0.028 382*	0.003 179	0.003 068	0.003 434
	(0.015 939)	(0.015 938)	(0.015 938)	(0.016 928)	(0.016 926)	(0.016 927)
40 ≤ age < 50	−0.014 341	−0.014 647	−0.014 183	−0.011 369	−0.011 380	−0.011 128
	(0.021 686)	(0.021 687)	(0.021 683)	(0.022 730)	(0.022 730)	(0.022 730)
50 ≤ age < 60	−0.016 276	−0.016 704	−0.015 972	−0.016 276	−0.016 255	−0.015 911
	(0.026 255)	(0.026 254)	(0.026 253)	(0.027 814)	(0.027 813)	(0.027 813)
60 ≤ age < 70	−0.002 183	−0.002 660	−0.001 781	−0.032 805	−0.032 832	−0.032 441
	(0.031 216)	(0.031 215)	(0.031 213)	(0.033 189)	(0.033 189)	(0.033 190)
Age ≥ 70	0.019 212	0.018 757	0.019 542	−0.049 693	−0.049 758	−0.049 382
	(0.038 085)	(0.038 09)	(0.038 081)	(0.040 557)	(0.040 555)	(0.040 558)
Married	−0.019 737	−0.019 756	−0.019 805	−0.060 987***	−0.061 032***	−0.061 002***
	(0.014 641)	(0.014 642)	(0.014 638)	(0.016 147)	(0.016 145)	(0.016 149)
Middle school/high school	0.013 408	0.013 576	0.013 241	0.077 146***	0.077 246***	0.077 061***
	(0.020 947)	(0.020 951)	(0.02 0940)	(0.022 280)	(0.022 281)	(0.022 278)
Junior college and above	0.009 632	0.009 660	0.009 629	0.033 540	0.033 489	0.033 458
	(0.030 124)	(0.030 129)	(0.030 119)	(0.031 254)	(0.031 262)	(0.031 254)

TABLE A2. (*Continued*)

Variable	Dependent variable: the physical health score			Dependent variable: the mental health score		
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Current smoker	0.049 210***	0.049 213***	0.049 203***	−0.013 188	−0.013 292	−0.013 169
	(0.011 742)	(0.011 741)	(0.011 742)	(0.012 220)	(0.012 222)	(0.012 219)
Frequent drinker	0.058 747***	0.058 726***	0.058 701***	−0.017 642*	−0.017 694*	−0.017 625*
	(0.009 123)	(0.009 124)	(0.009 123)	(0.010 052)	(0.010 052)	(0.010 052)
Urban	−0.021 038	−0.020 589	−0.021 422	−0.005 556	−0.005 734	−0.005 784
	(0.015 564)	(0.015 568)	(0.015 563)	(0.016 810)	(0.016 808)	(0.016 809)
Individual fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Month fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Region-by-year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
R squared	0.0501	0.0500	0.0502	0.5358	0.5358	0.5358

APPENDIX

Full Set of Control Variables

Tables A1 and A2 present the coefficient estimates for the full set of control variables based on the specifications used in Tables 3 and 4, respectively.

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