Journal of Environmental Economics and Management 96 (2019) 195–212

Contents lists available at ScienceDirect

Journal of Environmental Economics and Management

journal homepage: www.elsevier.com/locate/jeem

Temperature effects on mortality and household adaptation: Evidence from China

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A R T I C L E I N F O

Article history:
Received 23 May 2018
Received in revised form 16 April 2019
Accepted 31 May 2019
Available online 7 June 2019

JEL classification:
I12
Q41
Q52
Q54
Q56

Keywords:
Climate change
Temperature
Mortality
Adaptation
Energy

A B S T R A C T

This paper examines the effects of extreme temperatures on mortality rates, using random year-to-year variation in temperature based on county-level panel data from China. The analysis finds a robust, U-shaped relationship between temperature and mortality rates, indicating that extremely cold or hot temperatures lead to excess deaths. The heat-related (cold-related) effect is 3.5 times (3.2 times) as large as previous findings that used U.S. data, and it is especially large for the elderly population, mainly due to excess deaths caused by cardiovascular diseases. Applying these results to climate change predictions from Hadley Centre Global Environmental Model shows that by 2061–2080 the annual mortality rate is likely to increase by 14.2% if global greenhouse gas emissions continue to rise throughout the 21st century, the estimated health cost of which is around 0.98 trillion Chinese Yuan per year. The paper also explores households' adaptation behaviors to extreme temperatures. It finds that although urban households adaptively increase energy consumption when they are exposed to cold temperatures and purchase more air conditioners on hot and cold days, rural households are unresponsive to temperature fluctuations. This finding implies that rural people may be more resource constrained and suffer more when extreme temperatures occur.

1. Introduction

The last century witnessed an increase in average temperature and extreme weather events, such as the frequency of heat waves (IPCC, 2013). It has been suggested that climate change "is the biggest global health threat of the 21st century" and "threatens to undermine the last half century of gains in development and global health" (Costello et al., 2009; Watts et al., 2015).[1] Although many studies have examined climate impacts on human health,[2] there has been little such research in developing countries (Deschênes, 2014).

Households in developing countries generally have limited income and resources with which to adapt to an increasingly severe climate. Therefore, it is important to understand the differences in how climate change influences human health in

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[1] The current literature documents a wide array of effects of temperature on human welfare, including decreased agricultural output (Schlenker et al., 2006; Deschênes and Greenstone, 2007; Fisher et al., 2012; Chen et al., 2016; Zhang et al., 2017a, b) and manufacturing output (Zhang et al., 2018; Chen and Yang, 2019), decreased labor productivity (Hsiang, 2010; Graff Zivin and Neidell, 2014), increased absenteeism (Somanathan et al., 2015), and reduced economic growth in poor countries (Dell et al., 2012).

[2] See Deschênes and Moretti (2009), Deschênes and Greenstone (2011), Barreca (2012), and Barreca et al. (2016), for example.

https://doi.org/10.1016/j.jeem.2019.05.004
0095-0696/

developing countries compared to developed countries and determine whether it is possible for households in developing countries to take effective actions to adapt. To address these issues, this study investigates the effects of weather, mainly measured by temperature, on the mortality rates of the Chinese population, as well as people's response to extreme temperatures, by focusing on the behavioral differences between rural and urban residents. The paper presents evidence of large distributional effects of weather change, not only across countries, but also within countries, between rural and urban areas.

Exposure to temperatures outside a certain range can pose a danger to human health and result in premature death, as the body has to work harder to maintain its stable core temperature.[3] Extensive public health and epidemiology literature has studied the effect of extreme temperatures on human health by analyzing daily mortality counts (often for one city) in a Poisson regression framework. Most studies find a U-shaped relationship between temperature and mortality counts. That is, extremely high or extremely low temperature results in increased deaths.[4] However, due to the short exposure window, the results found in these studies with daily data may be confounded by "harvesting" or delayed effects.[5] Moreover, the outcome variable in these studies is the mortality count instead of the mortality rate, which can lead to severe endogeneity problems caused by migration if the total population is not controlled in the regression.[6]

In contrast, recent economic studies on the health effects of weather change generally apply fixed-effect analysis based on monthly or annual mortality rates (rather than mortality counts) across larger geographical areas and over a longer time frame, allowing for richer variation in weather and a longer exposure window.[7] To account for the nonlinearity of the temperature-mortality relationship, these studies often model temperature through temperature-day bins.[8] This approach discretizes the daily temperature distribution and allows each temperature bin to have different impacts on mortality. However, the existing economic studies on the health effects of climate change, including Deschênes and Greenstone (2011), Barreca (2012), and Barreca et al. (2016), mainly use data from the United States. They consistently find a U-shaped relationship between temperature and mortality rate.[9]

As far as we know, Burgess et al. (2014) is the only paper that uses data from a developing country, India, to study this issue. We add to this literature with the study on the world's largest developing country, China, which accounts for more than 18% of the world's population. Moreover, as the largest carbon emitter in the world, the Chinese government is undertaking aggressive policies to reduce carbon emissions, such as providing lavish subsidies for renewable energie (around 100 billion Chinese Yuan (CNY) per year) and establishing a national carbon trade market. This will be the world's largest carbon trade market. Understanding the effects of temperature change on human health in China is essential for cost-benefit analysis of such climate policies.

Following the temperature-day bins approach in this literature, we investigate the impacts of extreme temperatures on human health in China. Our analysis is based on a county-level panel of annual mortality rates during 2004–2012. The data are from the National Disease Surveillance Points (DSP) system, and daily weather outcomes are from the China Meteorological Data Sharing Service (CMDSS) system. We model temperature distribution through certain bins and when estimating the relationship between temperature and mortality rate, we also control for other weather variables, including precipitation and specific humidity, in addition to other commonly used control variables.

Our results show that there is a statistically significant and robust U-shaped relationship between mortality and daily temperature, indicating that extremely high or low temperatures are associated with excess mortality rates. For example, we find that an additional day with a mean temperature exceeding 90 °F (relative to a day in the 50°F-60 °F range) would lead to an increase of 0.6% in the annual mortality rate, which is equivalent to 3.31 more annual deaths per 100,000 persons. Similarly, an additional day with a mean temperature below 10 °F would lead to an increase of 0.4% in the annual mortality rate, which is equivalent to 2.20 more annual deaths per 100,000 persons. The annual deaths per 100,000 persons due to heat-related effects (cold-related effects) are almost 3.5 times (3.2 times) as large as those suggested by Deschênes and

[3] The human body is capable of maintaining a constant core temperature through heat generation and dissipation. For example, it responds to hot ambient temperature with skin vasodilation and sweating and to cold temperature with skin vasoconstriction and shivering.

[4] Braga et al. (2001) carry out time-series analysis of data on 12 U.S. cities and conclude that high and low temperatures are associated with increased deaths in cold cities. Gouveia et al. (2003) investigate the impact of temperature on mortality counts in São Paulo, Brazil, finding a U-shaped pattern of the temperature-mortality relationship. Deschênes (2014) summarizes related research. There are also many similar studies for China. For example, Yang et al. (2013) find that an average of 12 excess deaths per day occurred during the heat wave in 2005 in Guangzhou. Sun et al. (2014) report that the 2013 heat wave caused 167 excess deaths in Pudong New Area. Wang et al. (2015), Ma et al. (2014), Zeng et al. (2016), Zhang et al. (2016), Han et al. (2017), and Y. Zhang et al. (2017) find a U-shaped relationship between temperature and mortality count.

[5] Deschênes and Moretti (2009) find that the effects caused by hot temperatures are associated with short-term displacement (a short-term forward shift in the mortality rate), mainly resulting from premature deaths among persons who are already in poor health status, which is called the "harvesting" effect. Another possibility is that the effect may take time to reveal itself, which is called a delayed effect.

[6] The mortality count is the total number of deaths in a certain period, and the mortality rate is calculated by dividing the total mortality count by the size of the population at the beginning of the same time period.

[7] More discussion on the methodological differences between these public health studies and economic studies can be found in Deschênes (2014).

[8] The approach first divides temperature into several bins and then uses the number of days in a month or year when the daily mean temperature of the sample city is in a given temperature bin as explanatory variables.

[9] Deschênes and Greenstone (2011) investigate the relationship between temperature and mortality using annual county-level mortality rates from 1968 to 2002 in the United States and find a U-shaped pattern. Barreca (2012) uses monthly county-level mortality rate data from 1973 to 2002 in the United States to investigate the effect of temperature on mortality when controlling for humidity. The study shows that both the temperature-related mortality and humidity-related mortality relationships are U-shaped. Barreca et al. (2016) examine the impact of climate change on mortality by using monthly state-level data from 1900 to 2004 in the United States. They find a sharp decline in the mortality impact of high temperature after 1960.

Greenstone (2011). Age and cause-specific estimates show that the heat and cold effects are the largest for the elderly, mainly through excess deaths caused by cardiovascular diseases. Coupled with the climate change model, Hadley Centre Global Environmental Model, version 2, Earth System (HadGEM2-ES), we predict that by 2061–2080, the annual mortality rate in China will increase by 14.2% if global greenhouse gas emissions continue to rise throughout the 21st century under Representative Concentration Pathway (RCP) 8.5, which could cost 0.98 trillion CNY per year in health losses.

Taking advantage of the rich information in the data, we further investigate households' adaptation behaviors in response to extreme temperatures. The literature suggests that households respond to extreme temperatures by using adaptation strategies, including change in energy consumption (Deschênes and Greenstone, 2011; Barreca, 2012; Li et al., 2019), outdoor activities (Graff Zivin and Neidell, 2014), geographical mobility (Deschênes and Moretti, 2009), and air conditioning (AC) adoption (Barreca et al., 2016; Heutel et al., 2017). Among these behaviors, AC usage seems to play a vital role in adaptation. Barreca et al. (2016) conclude that, in the United States, almost the entire decline in heat-related fatalities since 1960 can be explained by the diffusion of residential AC. Heutel et al. (2017) also report that residential AC adoption can explain nearly all the regional differences in heat-related deaths in the United States. As stated in Deschênes (2014), AC is "the form of adaptation to climate change that is by far the most cited in both the broad policy and academic literature," because it can regulate the ambient indoor temperature directly. However, due to the unavailability of data on AC usage and ownership, previous studies only drew inferences from residential energy consumption.[10]

In this paper, we study residential energy consumption and AC purchases and investigate the behavioral difference between urban and rural residents. Auffhammer (2014) studies the impact of temperature on AC adoption using provincial data in China, but the study only focuses on urban areas. Moreover, it uses average monthly temperature instead of daily temperature, so that temperature can only enter the regressions linearly. In this paper, we not only allow nonlinearity of the relationship between temperature and AC adoption, but also consider the difference between urban and rural areas. We further use both provincial data and household survey data to examine the temperature–AC adoption relationship in China. Our results show that households take adaptive measures in response to uncomfortable weather by consuming more energy and purchasing more AC. However, these adaptive behaviors exist only among urban residents; rural residents do not respond at all. Because rural residents tend to be poorer, it is quite possible that temperature change will have a larger impact on mortality rates in rural areas.

We believe this paper contributes to the literature in at least three aspects. First, it is one of the few economic studies that use data from developing countries to investigate the health effects of temperature change. Considering the large size of China's population and carbon emissions, the study has important policy implications, especially given our results showing that the health impact of extreme temperatures on Chinese residents is much larger than that on residents living in developed countries, represented by the United States. Second, studying the impact of temperatures on the purchase of AC contributes to the existing literature that investigates adaptive behaviors to weather change. Third, we study the adaptation strategies in urban and rural areas separately. In most developing countries, the inequality between urban and rural areas is prominent. Examining the difference in adaptation measures between urban and rural households helps us understand the distributional effects of temperature change and therefore provides a reference for policy makers to make relevant public investments in the right places.

The paper proceeds as follows. Section 2 describes the data sources in detail. Section 3 investigates the temperature-mortality relationship. Section 4 studies how people adapt to temperature shocks. Section 5 concludes the paper.

2. Data sources

Our exploration of the temperature-mortality relationship uses the most comprehensive set of mortality data available in China and detailed daily weather outcomes. To estimate the relationship between temperature and households' adaptation behavior, we use provincial data on residential energy consumption and AC ownership.[11] To project the cost of climate change on mortality rates in China, we employ the publicly available WorldClim-Global Climate Data.[12] This section describes the data sources.

2.1. Mortality data

The mortality data come from China's DSPs. The network of DSPs was founded in 1978, with only two counties at the beginning. In 1990, a new sample consisting of 145 counties was selected by stratified cluster random sampling from 31 provinces (autonomous regions and municipalities), which aimed to cover a nationally representative sample of China's population. After an adjustment in 2003, the DSP system currently covers 161 counties.

[10] Barreca et al. (2016) construct data on AC ownership for 1960–2004 by using linear interpolation based on the 1960, 1970, and 1980 U.S. Census of Population. Heutel et al. (2017) compute the AC penetration rate using machine learning. Some papers find a significant impact of temperature on AC market saturation (Mendelsohn, 2003; Sailor and Pavlova, 2003), but their analyses are focused on data from a single year or only several cities.

[11] As a robustness check, we also use Urban Household Survey data to confirm the impact of temperature on the AC purchases of urban households. The results are available upon request.

[12] We thank an anonymous referee for suggestions on the projection.

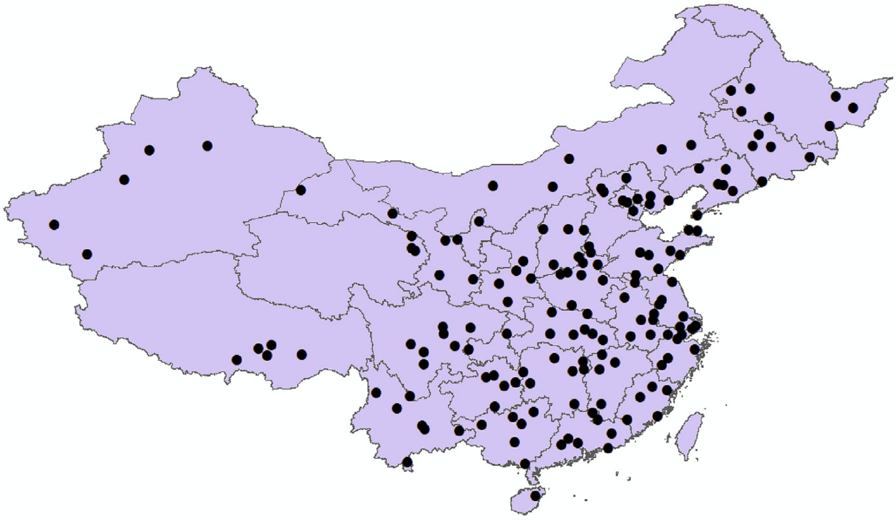

Fig. 1. Distribution of disease surveillance points.

Our analysis is based on data from 2004 to 2012. The DSPs includes 158 counties in 2004 and 2005 and 161 counties after 2006. We chose the 158 counties that have information for all the years and thus have a panel of 158 sites from 2004 to 2012 at the county level. The population of these 158 counties was about 80 million in 2010, accounting for 6% of China's total population. Fig. 1 shows the distribution of these 158 surveillance points, from which we can see that they are distributed across the country and cover all 31 provinces in mainland China. The primary data consist of annual deaths by age, sex, and cause of death, as well as the total population at the beginning of the year by age and sex, from which we can calculate the mortality rate.

2.2. Daily weather data

The weather data come from CMDSS, which contains daily mean temperature, precipitation, average relative humidity, and atmospheric pressure from 820 weather stations in China. The quality of the data set is well controlled, with a missing rate of less than 1%, and the accuracy of the data is close to 100%.[13] Following Deschênes and Greenstone (2011), we first develop a selection rule to select the weather stations that report the weather data for a minimum number of days within a year.[14] Then we construct the county-level weather variables by taking an inverse-distance weighted average of all the valid measurements from stations located within a 50-mile (80-km) radius of the county centroid, where the inverse of the squared distance is used for the weights, so that less distant stations are given greater weight.[15]

2.3. Climate change prediction data

Climate predictions are from WorldClim-Global Climate Data, which provides the climate projections based on the most recent global climate models that are used in the Fifth Assessment Intergovernmental Panel on Climate Change (IPCC) Report.[16] The temperature data from WorldClim are monthly average minimum and maximum temperatures for the medium term (2050, average for 2041–2060) and the long term (2070, average for 2061–2080) at four RCPs: RCP2.6, RCP4.5, RCP6.0, and RCP8.5. These four pathways are labeled after a possible range of radiative forcing values at the end of the 21st century relative to pre-industrial values (+2.6, +4.5, +6.0, and +8.5 W per square meter, respectively). They are also consistent with different greenhouse gas (GHG) concentration trajectories. For example, RCP2.6 assumes that global GHG emissions peak between 2010 and 2020. In RCP8.5, emissions are assumed to rise continuously throughout the 21st century.

[13] http://data.cma.cn/data/cdcdetail/dataCode/SURF_CLI_CHN_MUL_DAY_V3.0.html.

[14] First, we use interpolation to fill in the missing data where the number of consecutive missing days is less than three. As our key explanatory variables are 10°Fbins, such interpolation is a balance between the accuracy and integrity of the data. Then we drop approximately 20 station-years for which there are still missing values for our key variables (temperature, precipitation, and humidity).

[15] Except for one county whose nearest station is about 73 miles away and is included in the sample, all counties have weather stations located within 50 miles. In addition, some stations are on the top of mountains, with elevation obviously higher than the residential area. To increase accuracy, we further drop the observations of stations at elevation 500 km higher than all the other neighboring stations located within 50 miles of a county centroid.

[16] http://www.worldclim.org/.

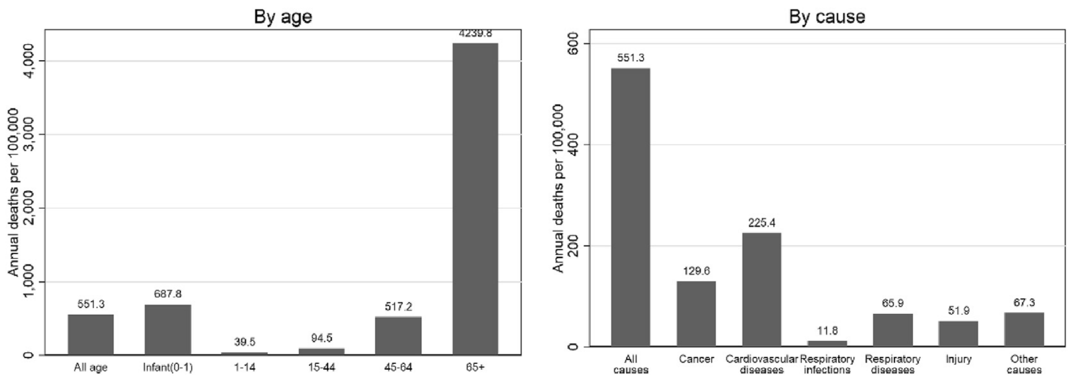

Fig. 2. Average mortality rate by age and cause. *Note:* The mortality rate is weighted by the population of corresponding age groups in a county-year.

We use the data projected by HadGEM2-ES at 2.5-min (of longitude/latitude degree) spatial resolution (about 4.5 km at the equator), from which we can obtain future temperature variables for all the counties in our sample. We focus our analysis on RCP2.6 and RCP8.5, because these two pathways represent two extremes of future GHG emissions. Similar to Hsiang et al. (2017) and Chen and Chen (2018), we use the following three-step process to generate county-level projections of daily mean temperature. First, based on the historical daily observations during 2004–2012, we construct monthly mean temperature and monthly probability distribution functions of daily mean temperature for all the counties in our sample. Second, we compute the projected changes in monthly mean temperature for each county, i.e., the differences between the projected monthly mean temperatures calculated from WorldClim data and the historical monthly mean temperatures obtained in the first step. Third, we construct each county's distributions of daily mean temperature in the medium and long terms for two forcing pathways, RCP2.6 and RCP8.5, by assuming that they mirror the temperature distributions obtained in the first step.

2.4. Residential energy consumption and penetration of AC

The energy consumption data are from the China Energy Statistical Yearbook. The provincial energy balance tables in the yearbook provide annual residential energy consumption, including raw coal, crude oil, natural gas, electricity, and so on. We convert the consumption of each energy type from the physical quantity into the coal equivalent level using conversion factors given by the yearbook. Then we aggregate the consumption of all types of energy to obtain total residential energy consumption measured in coal equivalent units. In this way, we obtain a panel of data on residential energy consumption, for urban and rural areas separately, in 30 provinces during 2004–2012.[17]

The AC data come from the National Bureau of Statistics (NBS) of China, which conducts household surveys in urban and rural areas through stratified random sampling every year. In the surveys, respondents are asked to record the number of durable consumer goods their household owns, including ACs.[18] NBS then aggregates the data at the province level. We obtained a panel of the number of ACs per 100 households for 30 provinces during 2004–2012, in urban and rural areas separately.

3. Impact of temperature on mortality

3.1. Empirical strategy and summary statistics

Following the common approach in the literature, we estimate the effects of temperature on mortality rates by fitting the following equation via weighted least squares:

$$\log(MORT_{ct}) = \sum_{j}\theta_1^{j}TEMP_{ct}^{j} + \sum_{j'}\theta_2^{j'}HUMD_{ct}^{j'} + \sum_{j''}\theta_3^{j''}PREC_{ct}^{j''} + \alpha X_{ct} + \lambda_c + \gamma_t + \varepsilon_{ct} \quad (1)$$

where $\log(MORT_{ct})$ denotes the log of the annual mortality rate of county c in year t. $TEMP_{ct}^{j}$ represents the number of days when the daily mean temperature is in the jth of the 10°F bins in county c and year t. Other weather outcomes include specific humidity and precipitation. We also control for the age structure of the population at the beginning of the year, which is represented by X_{ct}. λ_c and γ_t are county fixed effects and year fixed effects, respectively. The standard errors are clustered at the county level to allow the error terms within counties to be arbitrarily correlated over time.

[17] The data for Tibet are not available.

[18] The AC commonly used in China is a split AC system that can generate cool and hot air.

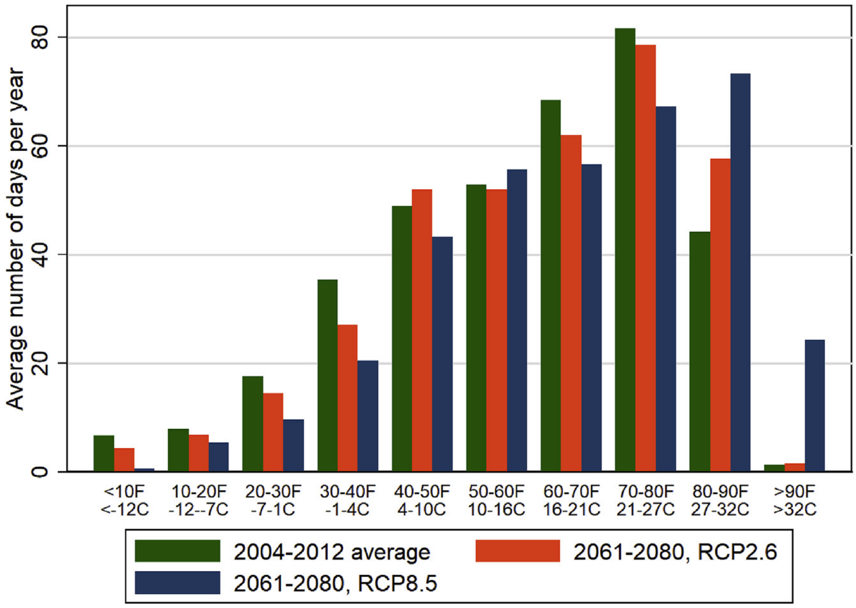

Fig. 3. Distribution of annual daily mean temperature and predicted distribution in 2061–2080 according to HadGEM2-ES. *Note:* The "2004–2012 average" bars represent the average number of days per year in each temperature bin for the 158 counties in our sample. The "2061–2080" bars represent the average number of days per year of these 158 counties in 2061–2080 projected by HadGEM-ES. All the bars are weighted by the average total population over 2004–2012 in each county.

3.1.1. Mortality rate

We estimate not only the impacts of temperature changes on the total population's mortality rate, but also the model by age and cause of death, to investigate the heterogeneity of temperature effects. We calculate the age-specific mortality rates for five age categories: younger than 1 (infants), 1–14, 15–44, 45–64, and 65 + years. As shown in Fig. 2, the average annual mortality rate is 551 deaths per 100,000 persons. Mortality rates vary largely across age groups. The average mortality rate is evidently higher for the elderly and infants than for other age groups: the average annual mortality rate is 4240 for the population ages 65 years or older and 688 for infants; it is 517 for the population between ages 45 and 64 years and below 100 for all others.

We consider five cause-specific mortality rates: cancer, cardiovascular disease (including cerebrovascular disease), respiratory infection, respiratory disease, and injury.[19] The all-cause mortality rate minus mortality rates caused by these five causes gives us the mortality rate by other causes, which include communicable diseases, nutritional deficiencies, congenital anomalies, and so on. Fig. 2 shows that cardiovascular disease and cancer are the two leading causes of death, accounting for 64% of total mortality. Together with respiratory infection, respiratory disease, and injury, the five causes contribute to 88% of total deaths.

3.1.2. Temperature

As too-high and too-low temperatures can harm human health, it is possible that the temperature-mortality relationship is nonlinear. Following previous studies, we use temperature-day bins to model such nonlinearities and threshold effects. Specifically, we divide temperature into ten 10°F bins, with less than 10°F and greater than 90°F at the extremes. The variable $TEMP^j_{ct}$ indicates the number of days when the county's daily average temperature is in the jth bin in year t. Since the number of days falling into these 10 bins sums to 365 (or 366) in each year, one bin should be dropped in the regression as a baseline group. The existing literature commonly uses the most comfortable temperature bin as the reference group. Therefore, we use the temperature bin $TEMP^6_{ct}$ (50°F-60°F), which has the lowest impact on the mortality rate, as the baseline group. In this way, the coefficient of $TEMP^j_{ct}$ indicates the impact on mortality rates of exchanging a day in the 50°F-60°F bin for a day in the jth bin.

Although the mortality rate and temperature are associated with natural geographic conditions, the county-specific dummies in our regression can absorb all time-invariant fixed effects. Hence, the estimates are identified from the unpredictable and presumably random year-to-year local variation in temperatures. Our identification strategy also relies on the assumption that the temperature effects do not vary within each bin and are the same for all counties, but we will also run

[19] Respiratory infections consist of respiratory tract infections and otitis media. Respiratory diseases consist of chronic obstructive pulmonary disease, asthma, and so on. Injury consists of traffic accidents, poisoning, fires, suicide and so on.

subsample regressions to see if the temperature effects vary across counties. For a robustness check, we also use an alternative temperature measure, temperature deviation from the local average, as the explanatory variable, to test the possibility that it is the temperature deviation instead of the absolute temperature level that matters.

Fig. 3 depicts the historical distribution of daily mean temperatures during 2004–2012 and predicted temperature distribution in 2061–2080. The green bars indicate the number of days in each temperature bin, calculated as the weighted average across county-by-year realizations, using the average total population of each county as the weight. The 70°F-80°F and 60°F-70°F bins have the greatest numbers of days, with the numbers of days in these two categories accounting for about 40% of the whole year. For exposure to low temperatures, the population on average is exposed to about 6.7 days per year with daily mean temperatures below 10°F and 7.9 days per year in the 10°F-20°F bin. For exposure to high temperatures, the average number of days with daily mean temperature greater than 90°F is 1.4, and the average number of days with daily mean temperature between 80°F and 90°F is 44.3.

The red and blue bars indicate the predicted average number of days in each temperature bin that the population in our sample counties is expected to encounter in 2061–2080 under the RCP2.6 and RCP8.5 scenarios, respectively. It is evident that the population is likely to be exposed to fewer cold days and more hot days in 2061–2080 relative to 2004–2012 under both pathways. The number of days with daily mean temperature in the 80°F-90°F bin (above 90°F) is expected to increase by 15.7 (almost zero) and 31.0 (24.1) days per year, respectively, under RCP2.6 and RCP8.5. As for extremely cold days, the predicted decreases in the number of days in the two coldest temperature bins are 3.4 and 8.5, respectively, for the two pathways, which is much smaller compared to the increase in extremely hot days.

3.1.3. Other weather outcomes

In the regression, we control for other weather outcomes, including specific humidity and precipitation, which are likely to be correlated with temperature. Barreca (2012) reports that extreme specific humidity is associated with excess deaths, and the temperature and humidity effects interact because high humidity impairs the body's ability to sweat and cool itself. Therefore, we also include specific humidity in our model.[20] We calculate specific humidity using data on temperature, atmospheric pressure, and relative humidity drawn from CMDSS via a meteorological formula. Then we divide specific humidity into 10 bins that are 2 g/kilogram, with 0–2 and greater than 18 at the extremes. $HUMD_{ct}^{j'}$ denotes the number of days in county c and year t when specific humidity is in the j'th bin. Precipitation is a common control in the literature, as droughts and floods can harm human health. $PREC_{ct}^{j''}$ indicates whether the annual rainfall in county c and year t is in the j''th of six 400-mm bins, ranging from less than 400 to more than 2000 mm.

3.1.4. Age structure

Following Barreca et al. (2016), we include the county's population shares in the five age groups, namely 0–1, 1–14, 15–44, 45–64, and 65 + years, to control for the age structure of the population. Notice that the age structure is constructed by using the population at the beginning of the year. As shown in Fig. 2, mortality rates vary largely across age groups. Moreover, as will be shown, the temperature effects on mortality differ substantially across age groups. We therefore control for age structure in our regressions when estimating the impacts of temperature on the total population.

3.1.5. Weighted least squares

As in the literature, we estimate equation (1) via weighted least squares estimation by using the population in a county-year as the weight. One reason for this approach is that this gives more meaningful results by revealing the effects on the average person instead of the average county. Another reason is that observations of mortality rates from counties with larger populations are more accurate, which means that the variance of the error term in equation (1) is not constant.

3.2. Main results

Table 1 presents the estimates of equation (1).[21] We start by regressing the vector of temperature variables on annual mortality rates without controlling for other weather outcomes. As shown in column (1), the temperature-mortality relationship is U-shaped. The mortality risk is lowest for temperatures between 50 °F and 60°F. When the daily mean temperature is below 50°F, the mortality rate increases as temperature decreases. For daily mean temperatures above 60°F, higher temperatures result in more deaths. For example, one additional day in the range >90°F (relative to temperatures between 50 °F and 60°F) would result in an increase of 0.6% in the annual mortality rate, which equals 3.31 annual deaths per 100,000 persons (the average mortality rate for the whole population is 551 per 100,000 persons). One additional day with temperatures below 10°F would increase the mortality rate by 0.3%, equivalent to 1.65 annual deaths per 100,000 persons.

Column (2) in Table 1 includes temperature and specific humidity in the regression, and column (3) adds precipitation as the control variable. Compared to the results presented in column (1), the changes in coefficients are almost negligible in the other two columns. Barreca (2012) shows that controlling for specific humidity results in diminished magnitude of the

[20] Barreca (2012) argues that specific humidity is a better option than relative humidity in regression analysis, because specific humidity is not determined by temperature.

[21] Suggested by an anonymous referee, we also estimate equation (1) without controlling for age structure. The main results are similar.

Table 1
Temperature effects on log mortality rate: Main results.

VARIABLES	(1)	(2)	(3)
	TEMP only	TEMP and HUMID	TEMP, HUMID and PREC
TEMP ≤ 10 F	0.003**	0.004**	0.004**
	(0.002)	(0.002)	(0.002)
TEMP = 10F–20F	0.003**	0.003*	0.003*
	(0.002)	(0.002)	(0.002)
TEMP = 20F–30F	0.002	0.002**	0.002**
	(0.001)	(0.001)	(0.001)
TEMP = 30F–40F	0.001	0.001**	0.001**
	(0.001)	(0.001)	(0.001)
TEMP = 40F–50F	0.002***	0.002***	0.002***
	(0.001)	(0.001)	(0.001)
TEMP = 60F–70F	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)
TEMP = 70F–80F	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)
TEMP = 80F–90F	0.002**	0.003**	0.003**
	(0.001)	(0.001)	(0.001)
TEMP = 90F+	0.006***	0.006***	0.006***
	(0.002)	(0.002)	(0.002)
Observations	1421	1421	1421
R-squared	0.677	0.680	0.682

Note: All regressions include controls for age structure, and county and year fixed effects. Regressions are weighted by the population in a county-year. Standard errors are clustered at the county level.
***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

coefficients for the low-temperature bins, due to the positive correlation between temperature and humidity. However, we find that the change in the coefficients of the temperature bins is quite small after controlling for humidity. One possible explanation is that although daily mean temperature and daily specific humidity are positively correlated, such correlation may not hold for our temperature-day bins and humidity-day bins after controlling for county and year fixed effects. To allow for the possibility that extremely high temperatures are more dangerous at high humidity levels, we also use the heat index as an alternative specification, and the results are still robust. The difference between our results and those of Barreca (2012) strengthens our belief in using Chinese data to explore how temperature effects on mortality differ across countries.

To understand the differences in temperature-mortality responses across countries, we compare our baseline results presented in column (3) in Table 1 to the U.S. results from Deschênes and Greenstone (2011). The two studies have some similar findings, such as the temperature-mortality relationship is U-shaped; the mortality rate is lowest in the 50°F-60 °F range; and the heat effect is greater than the cold effect. However, the temperature impacts are much larger in magnitude in our findings than in those of Deschênes and Greenstone (2011). According to our results, one additional day with mean temperature over 90°F leads to an increase of 0.6% in the mortality rate, which is about 3.31 more annual deaths per 100,000 persons, and one additional day with mean temperature below 10°F leads to an increase of 0.4% in the mortality rate, which is about 2.20 more annual deaths per 100,000 persons. In contrast, the excess deaths caused by one additional day in the two temperature bins are only 0.94 and 0.69, respectively, in Deschênes and Greenstone (2011). The findings imply that the health impacts of extreme temperatures are much larger in China than in the United States. This highlights that households and communities in developing countries such as China generally have limited resources to adapt to extreme weather, and the climate change will bring more challenges for these countries than for developed countries.

3.3. *Results by age group and cause of death*

Table 2 reports the regression results by age group. There are several important findings. First, exposure to extremely high temperatures statistically significantly increases mortality in all age groups except infants. The heat-related effect is largest for the old, both in absolute and percentage terms. Exposure to one additional day with temperature over 90°F would lead to an increase of 1% in the mortality rate for the elderly, equivalent to an increase of 42.40 annual deaths per 100,000 persons, while the percentage and absolute effects of these extremely hot temperatures on the whole population are only 0.6% and 3.31, respectively. Second, the effects of extremely cold temperatures are statistically significant for the population ages 1–14 and over 65. Although the percentage change in the mortality rate is higher for children ages 1–14, the elderly suffer a higher absolute increase in mortality rate due to the high mortality risk for the old. It is also notable that exposure to days with temperatures between 40 °F and 50°F is statistically significantly associated with excess mortality for all age groups. This may be because this temperature range is coincident with the change of seasons, in which the temperature fluctuates wildly, so that people are more likely to get sick. Like Deschênes and Greenstone (2011), we find that the coefficients of the two

Table 2
Temperature effects on log mortality rates: By age.

VARIABLES	(1)	(2)	(3)	(4)	(5)
	Infants (0–1)	Age 1-14	Age 15-44	Age 45-64	Age 65+
TEMP ≤ 10F	0.003	0.006**	0.000	0.001	0.004**
	(0.005)	(0.003)	(0.002)	(0.002)	(0.002)
TEMP = 10F–20F	0.005	0.006**	0.000	0.002	0.004**
	(0.005)	(0.003)	(0.002)	(0.002)	(0.002)
TEMP = 20F–30F	0.008*	0.008***	0.001	0.000	0.002
	(0.004)	(0.002)	(0.002)	(0.001)	(0.001)
TEMP = 30F–40F	0.001	0.005***	0.001	0.000	0.002**
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
TEMP = 40F–50F	0.005***	0.003**	0.002*	0.002*	0.002*
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
TEMP = 60F–70F	0.004*	−0.001	0.001	0.002**	0.001
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
TEMP = 70F–80F	0.005**	0.001	0.001	0.002*	0.003*
	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)
TEMP = 80F–90F	0.003	0.001	0.003	0.003*	0.005*
	(0.003)	(0.002)	(0.002)	(0.002)	(0.003)
TEMP = 90F+	0.000	0.008**	0.006*	0.006**	0.010**
	(0.007)	(0.004)	(0.003)	(0.003)	(0.004)
Observations	1421	1421	1421	1421	1421
R-squared	0.684	0.791	0.768	0.797	0.662

Note: All regressions include controls for specific humidity and precipitation and county and year fixed effects. Regressions are weighted by the population of the corresponding age group in a county-year. Standard errors are clustered at the county level.
***p < 0.01, **p < 0.05, *p < 0.1.

temperature bins at the endpoints are not statistically significant for infants, probably because infants are well protected from extreme temperatures.

Table 3 reports the effects of temperature on mortality rates by different causes. The table shows that heat and cold effects on mortality caused by cardiovascular disease are statistically significant. Although the percentage change in deaths caused by cardiovascular disease is not the largest, the absolute increase is the largest, given that deaths caused by cardiovascular disease account for about 40% of the total mortality. The heart plays an important role in the body's temperature regulating system. It has to work harder to maintain the body's core temperature when the ambient temperature is extremely high or low. Therefore, people with heart disease are especially vulnerable to extreme temperatures. The result is also consistent with the public health and epidemiology literature (Basu and Samet, 2002; Barnett, 2007; Yang et al., 2013).

Another interesting finding is that cold and hot temperatures lead to excessive deaths caused by cancer, and the effects of hot temperatures are especially large and statistically significant. Medical studies have shown that a cold environment can make cancer cells grow and spread faster in mice (Kokolus et al., 2013), and hot temperatures can affect mortality rates through influencing the mental state of patients or increasing the risk of cancer by increasing exposure to toxic chemicals or ultraviolet radiation. The result is consistent with Barreca (2012), who also finds that the heat-related impact on deaths from cancer is statistically significantly positive.[22]

The cold-related effects on respiratory infections are statistically significant. This is consistent with the health literature (Mourtzoukou and Falagas, 2007; Mäkinen et al., 2009), which find that cold temperature is associated with increased occurrence of respiratory tract infections. The heat-related effects on deaths caused by respiratory diseases are positive but statistically insignificant, contrary to the findings in epidemiological studies, such as Yang et al. (2013) and Sun et al. (2014). They use daily mortality counts in Guangzhou and Shanghai to study the health effects of heat waves and find statistically significant impact on deaths caused by respiratory disease. A possible explanation for this inconsistency is that we use annual mortality rates instead of daily data, which corrects for harvesting effects, thus leading to smaller estimated temperature effects. It is also notable that exposure to days with mean temperature above 90°F statistically significantly results in excess deaths caused by injury.[23] This is consistent with findings in the epidemiological literature, which reports that extremely hot weather places workers at increasing risk of heat-related injuries (Xiang et al., 2014).

Since as afore-discussed the elderly suffer the largest temperature effects on the absolute increase in mortality rates, we further run by-cause regressions for the elderly to identify the major causes of the temperature effects on this most affected population. The results are shown in Table 4, illustrating that the by-cause temperature impacts on the elderly have a similar

[22] This can be seen from Fig. 3 in Barreca (2012).

[23] Note that although the heat-related effect on injury is big in magnitude in terms of percentage change, the effect is small in terms of absolute change, which is consistent with our intuition. For example, exposure to one additional day with temperatures above 90 °F would result in 0.6%increase in mortality rate caused by injury, this is equivalent to only 0.31 excess death per 100,000 persons.

Table 3
Temperature effects on log mortality rates: By cause.

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
	Cancer	Cardiovascular	Respiratory infections	Respiratory disease	Injury	Other causes
TEMP ≤ 10 F	0.003	0.004**	0.011**	−0.001	0.000	0.003
	(0.002)	(0.002)	(0.005)	(0.004)	(0.002)	(0.003)
TEMP = 10F–20F	0.003	0.003	0.009*	−0.004	−0.001	0.003
	(0.002)	(0.002)	(0.005)	(0.003)	(0.002)	(0.002)
TEMP = 20F–30F	0.003*	0.002	0.006	−0.002	−0.001	0.003
	(0.001)	(0.001)	(0.004)	(0.002)	(0.002)	(0.002)
TEMP = 30F–40F	0.001	0.002**	−0.002	−0.001	0.001	0.001
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
TEMP = 40F–50F	0.002**	0.002***	0.001	−0.001	0.001	0.003***
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
TEMP = 60F–70F	0.002*	0.001	−0.001	−0.001	0.001	0.003**
	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)
TEMP = 70F–80F	0.002	0.002	−0.001	0.001	0.001	0.002
	(0.001)	(0.001)	(0.003)	(0.002)	(0.001)	(0.001)
TEMP = 80F–90F	0.003**	0.003*	0.001	0.002	0.002	0.001
	(0.001)	(0.001)	(0.004)	(0.002)	(0.002)	(0.002)
TEMP = 90F+	0.006**	0.005**	0.008	0.005	0.006**	0.008
	(0.003)	(0.002)	(0.007)	(0.003)	(0.003)	(0.005)
Observations	1416	1421	1383	1419	1418	1379
R-squared	0.793	0.787	0.785	0.847	0.867	0.747

Note: All regressions include controls for specific humidity and precipitation, age structure, and county and year fixed effects. Regressions are weighted by the population in a county-year. Standard errors are clustered at the county level.
***p < 0.01, **p < 0.05, *p < 0.1.

pattern as the impacts on the total population. Except for deaths caused by respiratory infections, the coefficients of the highest temperature bin are statistically significant for all other causes. Exposure to one additional day with temperatures above 90 °F would result in a 0.9% increase in the elderly's mortality rate caused by cardiovascular disease. The percentage increase in mortality rate caused by cardiovascular disease is not the largest among all the causes, but given that deaths caused by cardiovascular disease account for about 48% of all the deaths for the elderly, the absolute increase in deaths caused by cardiovascular diseases is the largest. Specifically, exposure to one additional day with temperatures above 90 °F would lead to 18.37 excess deaths caused by cardiovascular disease, which contributes to about 43% of the heat-related death on the elderly. Similarly, the cold-related effect on cardiovascular disease is the largest among all causes in the perspective of absolute increase of deaths. These findings warn us that special attention should be paid to the effects of temperature on cardiovascular disease, especially for the old. For example, the government could educate the elderly with heart disease to mitigate the effects of extreme temperatures through better preventive measures.

3.4. Robustness check and other results

Table 5 tests the robustness of the baseline estimates in column (3) in Table 1 with different specifications. To better compare our results, column (1) repeats the baseline regression. Following Zhang et al. (2018), column (2) constructs temperature bins using the daily heat index, which is also known as the "apparent temperature." High temperatures are especially dangerous when the humidity is also high, because high humidity reduces the evaporation rate, lowering the body's ability to cool itself by perspiration or sweating. We calculate the heat index as a combination of temperature and relative humidity, using the equations from the U.S. National Oceanic and Atmospheric Administration.[24] The regression results show a U-shaped relationship between the mortality rate and heat index. The coefficient of the 80°F-90°F bin becomes smaller and statistically insignificant, possibly because in the heat index formulation, a day with mean temperature between 80 °F and 90°F coupled with high relative humidity tends to be included in the above 90°F heat index category, causing the 80°F-90°F heat index bin to be less dangerous than the 80°F-90°F temperature bin. This finding is supported by the data, in which about 94% of the days with a daily heat index above 90°F have a daily mean temperature between 80°F and 90°F in our sample.

Column (3) in Table 5 uses weather variables in the current and previous years and reports the sum of the current and previous years' temperature coefficients, taking into consideration the dynamic effects of temperature.[25] Similar to Deschênes and Greenstone (2011), we find that the coefficients of the coldest and hottest temperature bins are larger than in the baseline regression, indicating the existence of delayed effects. Column (4) fits equation (1) through ordinary least

[24] https://www.wpc.ncep.noaa.gov/html/heatindex_equation.shtml.
[25] We estimate the equation, $\log(MORT_{ct}) = \sum_j \beta_1^j \Delta TEMP_{ct}^j + \sum_j \beta_2^j TEMP_{ct-1}^j + \beta X_{ct} + \lambda_c + \gamma_t + \varepsilon_{ct}$ with $\Delta TEMP_{ct}^j = TEMP_{ct}^j - TEMP_{ct-1}^j$, and report the estimation of β_2^j.

Table 4
Temperature effects on log mortality rates for the elderly: By cause.

VARIABLES	Cancer	Cardiovascular	Respiratory Infections	Respiratory Disease	Injury	Other Causes
TEMP ≤ 10 F	0.003	0.005**	0.013*	−0.001	0.001	0.006*
	(0.003)	(0.002)	(0.007)	(0.004)	(0.003)	(0.003)
TEMP = 10F−20F	0.004*	0.005**	0.010	−0.003	−0.002	0.005*
	(0.003)	(0.002)	(0.007)	(0.003)	(0.003)	(0.003)
TEMP = 20F−30F	0.002	0.002	0.006	−0.003	−0.002	0.002
	(0.002)	(0.001)	(0.005)	(0.002)	(0.002)	(0.003)
TEMP = 30F−40F	0.001	0.002**	−0.002	−0.001	0.001	0.002
	(0.001)	(0.001)	(0.003)	(0.001)	(0.002)	(0.001)
TEMP = 40F−50F	0.002	0.002	0.002	−0.001	0.002	0.003**
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
TEMP = 60F−70F	0.002	0.001	−0.001	−0.001	0.000	0.003***
	(0.001)	(0.001)	(0.003)	(0.001)	(0.002)	(0.001)
TEMP = 70F−80F	0.003	0.003*	0.001	0.003	0.001	0.003
	(0.002)	(0.002)	(0.004)	(0.002)	(0.002)	(0.002)
TEMP = 80F−90F	0.006*	0.005*	0.003	0.005*	0.005	0.005
	(0.003)	(0.003)	(0.006)	(0.003)	(0.004)	(0.003)
TEMP = 90F+	0.010**	0.009**	0.012	0.008*	0.012**	0.015**
	(0.004)	(0.004)	(0.009)	(0.005)	(0.005)	(0.007)
Observations	1414	1421	1360	1418	1405	1421
R-squared	0.739	0.764	0.729	0.847	0.844	0.727

Note: All regressions include controls for specific humidity and precipitation, and county and year fixed effects. Regressions are weighted by the population of the elderly in a county-year. Standard errors are clustered at the county level.
***p < 0.01, **p < 0.05, *p < 0.1.

Table 5
Temperature effects on log mortality rate: Alternative specifications.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Baseline	Heat Index	Including Lagged weather variables	Models without weighting (OLS)	Male	Female	Southern Counties	Northern Counties
TEMP ≤ 10 F	0.004**	0.004**	0.007**	0.004***	0.003**	0.004**		0.004**
	(0.002)	(0.002)	(0.003)	(0.001)	(0.002)	(0.002)		(0.002)
TEMP = 10F −20F	0.003*	0.003*	0.004	0.004**	0.004**	0.003*		0.004**
	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)		(0.002)
TEMP = 20F −30F	0.002**	0.003***	0.004**	0.002	0.002**	0.002**	0.000	0.003*
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.004)	(0.002)
TEMP = 30F −40F	0.001**	0.002**	0.003**	0.001**	0.002***	0.001*	0.000	0.002*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
TEMP = 40F −50F	0.002***	0.002**	0.002	0.002***	0.002***	0.002***	0.002***	0.002
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
TEMP = 60F −70F	0.001	0.001*	0.001	0.001	0.001	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
TEMP = 70F −80F	0.001	0.001	0.002	0.001	0.002**	0.001	0.001	0.000
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
TEMP = 80F −90F	0.003**	0.002	0.003	0.002*	0.003**	0.003**	0.004**	−0.001
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
TEMP = 90F+	0.006***	0.005***	0.010***	0.004**	0.006***	0.005**	0.005*	
	(0.002)	(0.002)	(0.004)	(0.002)	(0.002)	(0.002)	(0.003)	
Observations	1421	1421	1420	1421	1421	1421	738	683
R-squared	0.682	0.683	0.691	0.686	0.699	0.698	0.690	0.705

Note: Regressions are weighted by the corresponding population in a county-year. All regressions include other controls for specific humidity and precipitation, age structure, and county and year fixed effects. Column (2) uses separate sets of weather variables in the current and previous years and reports the sum of the current and previous years' temperature coefficients to account for dynamic effects. Column (7) combines the coldest three bins into one because the daily mean temperatures in southern counties hardly fall below 20°F. Column (8) combines the highest two bins into one because the daily mean temperatures in northern counties hardly fall below 90°F.Standard errors are clustered at the county level.
***p < 0.01, **p < 0.05, *p < 0.1.

squares, without using population as a weight. Although the heat effects are smaller in magnitude, the temperature-mortality relationship is still U-shaped. Since the unweighted method is inferior to the weighted regression, we use the weighted regression throughout the paper.

In columns (5) and (6) in Table 5, the model is estimated separately for males and females, respectively. The percentage change caused by extremely hot temperatures is larger for men than for women. Exposure to an additional day with mean temperature over 90°F leads to an increase of 0.6% in the male mortality rate and 0.5% in the female mortality rate.

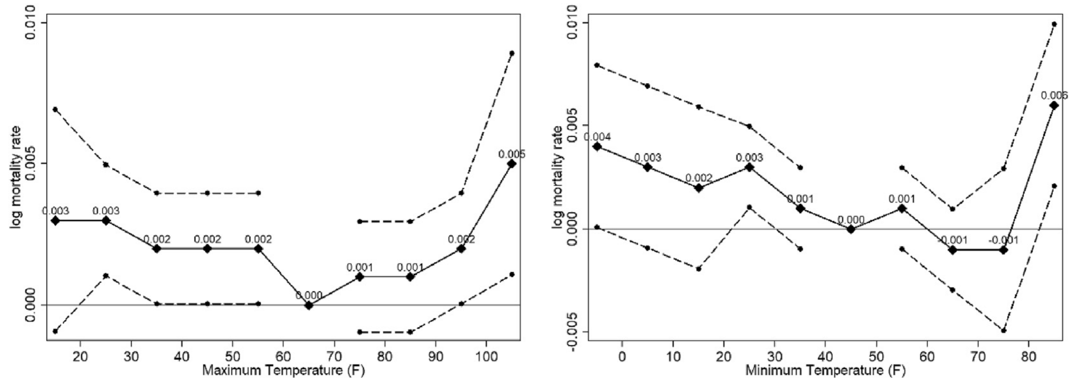

Fig. 4. Effects of temperature on log mortality rates: Using maximum and minimum temperatures. *Note:* The solid lines show the results from regressions using the daily maximum temperature or daily minimum temperature to form the temperature bins. The dashed lines indicate the 95% confidence intervals.

Considering that the average mortality rate for men (about 636 per 100,000 persons) is larger than that for women (about 463 per 100,000 persons), the absolute increase in the male mortality rate, 3.82 annual deaths per 100,0000 persons, is much larger than the increase in the female mortality rate, 2.31 annual deaths per 100,000 persons. That is, the heat-related effect is larger for men in both absolute number and percentage change in mortality rate. As for the cold-related effects, although the percent increase caused by the coldest bin is larger for females, the absolute increase in mortality for males is slightly larger. Exposure to a day with mean temperature below 10°F results in 0.3% increase in the male mortality rate (equivalent to 1.91 annual deaths per 100,000 persons) and 0.4% increase in the female mortality rate (equivalent to 1.85 annual deaths per 100,000 persons).

At first blush, it may seem that humans can adapt to local temperature, so that the population residing in hotter (colder) places is less vulnerable to extremely high (low) temperatures. However, previous studies have failed to reach a consistent conclusion on that. For example, Deschênes and Greenstone (2011) find that although there is great variation in the estimated effects of temperatures across regions, no evidence shows that the impacts are related to climate or baseline temperatures. In contrast, Barreca (2012) and Heutel et al. (2017) provide evidence that temperature effects vary systematically with current climate. To examine whether "adaptation" to hot or cold weather can mitigate the adverse effects of extreme temperatures on mortality, in columns (7) and (8) in Table 5, we separate the counties into two groups by whether they are in the north or south of the line formed by the Huai River and Qinling Mountain, the traditional geographical north-south divide of China. The south tends to be warmer and is more likely to suffer extremely hot temperatures than the north.[26] The results indicate that the heat-related effects are only statistically significant for the population living in the southern counties, and the cold-related effects are only statistically significant for the population living in the northern counties. These results do not seem to support the conventional view that heat-related effects are smaller in hot counties and cold-related effects are smaller in cold counties.

Fig. 4 shows the results from regressions that use the daily maximum temperature or daily minimum temperature instead of the daily mean temperature to explore the effects of peak temperatures within a day. Because the daily maximum temperature is higher than the daily mean temperature, we shift our original 10 temperature bins to the right by 10 °F in the maximum temperature framework, with less than 20 °F and greater than 100 °F at the endpoints, and choose the 60°F-70 °F bin as the baseline group, which is 10 °F higher than the baseline group used in the mean temperature framework. Similarly, when using daily minimum temperature, we shift our original 10 temperature bins, as well as the baseline temperature bin, to the left by 10 °F, with less than 0°Fand greater than 80 °F at the endpoints. Both regressions show a similar pattern between temperature and mortality as in the baseline regression, and the heat-related effect is especially large in magnitude and statistically significant.

The temperature variable we have used so far is the value of temperature levels. It may be argued that what really matters is how much the temperature deviates from the local average, because people have adapted to local weather to some extent. Table 6 reports the results using temperature deviation.[27] The table shows a U-shaped pattern between temperature and mortality rates: the more the daily mean temperature deviates from the local average, the higher is the mortality risk. For example, exposure to one additional day with a daily mean temperature over 25 °F higher or lower than the local average

[26] The average number of days, with the daily mean temperature falling into the two coldest bins, are less than one for the southern counties. Therefore, we combine the coldest three bins into one when using observations from southern counties. Similarly, we combine the hottest two bins into one when using observations from northern counties because the average number of days, with the daily mean temperature falling into the highest temperature bin, is less than one for the northern counties.

[27] We first calculate the average of daily mean temperature in our sample period for each county. Then we subtract the local average temperature from the daily mean temperature for each daily observation to form the deviation of daily temperature. At last, we model daily temperature deviation using seven 10°F bins, with −5 °F–5°F as the reference group.

Table 6
Temperature effects on log mortality rate: Using temperature relative to the local average.

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
	All ages	Infants (0–1)	Age 1-14	Age 15-44	Age 45-64	Age 65+
TEMP-AVETEMP						
<=-25F	0.003**	0.005	0.010***	0.000	0.001	0.003*
	(0.001)	(0.004)	(0.002)	(0.002)	(0.001)	(0.001)
−25F–15F	0.002*	0.000	0.008***	0.002	0.002	0.002
	(0.001)	(0.003)	(0.002)	(0.001)	(0.001)	(0.002)
−15F–5F	0.002	0.002	0.004**	0.000	0.000	0.004**
	(0.001)	(0.003)	(0.002)	(0.001)	(0.001)	(0.002)
5F–15F	0.001	0.004**	0.003**	−0.000	0.000	0.003**
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
15F–25F	0.002*	0.002	0.004***	0.003*	0.002	0.004**
	(0.001)	(0.003)	(0.002)	(0.002)	(0.001)	(0.001)
>25F+	0.003*	0.001	0.005**	0.003	0.003*	0.005**
	(0.002)	(0.004)	(0.002)	(0.002)	(0.002)	(0.003)
Observations	1421	1421	1421	1421	1421	1421
R-squared	0.680	0.682	0.793	0.770	0.796	0.660

Note: Regressions are weighted by the corresponding population in a county-year. All regressions include controls for specific humidity and precipitation and county and year fixed effects. Column (1) also controls for age structure. Standard errors are clustered at the county level.
***p < 0.01, **p < 0.05, *p < 0.1.

increases the mortality rate by 0.3%, which is equivalent to 1.65 annual deaths per 100,000 persons. The regressions by age show similar patterns as in Table 2.

3.5. Predicted impact of climate change on mortality rates

As shown in Fig. 3, HadGEM2-ES predicts that China will experience more extremely hot days and fewer extremely cold days by 2061–2080. While the increase in hot days would result in higher mortality rates, the impact is likely to be counteracted by the decrease in cold days. However, the overall impact is very likely to be positive, because most of the decrease lies in the middle of the temperature distribution where mortality rates are relatively low. Specifically, HadGEM2-ES predicts that under RCP8.5 the number of days with daily mean temperature in the highest two bins will increase by 55 days, while that in the lowest two bins will only decrease by 8 days.

To obtain more precise results, we predict the impact of temperature change based on the regression results reported in column 3 in Table 1. We calculate the impact of predicted temperature change as follows:

$$\text{Impact} = \sum_j \widehat{\theta_1^j} \times \frac{\sum_c \Delta TEMP_c^j \times population_c}{\sum_c population_c}. \tag{2}$$

We first calculate the predicted change of the number of days per year in each temperature bin by taking a population weighted average of all the sample counties' data, and then multiply it by the corresponding impact on mortality obtained from the regression results. As the impact is a linear function of the parameters from the regression, we can easily calculate the variance of the predicted impact using the covariance matrix from the baseline regression.

The results are presented in Table 7. The first three columns report the predicted impacts of temperature change in the lowest two, middle six, and highest two temperature bins. Column (4) reports the total impact of the predicted temperature change. We calculate the estimation in the medium term (2041–2060) and the long term (2061–2080) under RCP2.6 and RCP8.5, respectively. Several findings are worth mentioning. First, the results are consistent in all scenarios such that the predicted change in the number of hot days (>80 °F) will significantly raise the mortality rate, and the predicted change in the other temperature bins will significantly reduce the mortality rate. Second, the predicted aggregate temperature impact is positive for all scenarios. Third, under RCP2.6, the difference between the medium-term and long-term impacts is almost unnoticeable, but under RCP8.5, the long-term temperature impact (14.2% increase in mortality rate) is more than twice the medium-term impact (0.63% increase in mortality rate), indicating that if global carbon emissions continue to rise, so will the health cost of temperature change.

We next move to monetize the economic cost of climate change by focusing our analysis on the long-term impact (the health cost in the medium term can be easily calculated by using the same method). In the long run, temperature change is predicted to cause an increase of 2.4% in the mortality rate under RCP2.6, which is equivalent to 13.22 deaths per 100,000 persons. Under RCP8.5, the predicted values are 14.2% and 78.24 deaths, correspondingly. Using the future 2070 population projection, 1.25 billion in mainland China, the future temperature change is predicted to result in 0.17 million and 0.98 million

Table 7
Predicted impact of climate change on log mortality rate.

		Impact of change in days with temperature			Total temperature impact
		<20F	20–80F	>80F	
Medium-term (2041–2060)	RCP 2.6	−0.013**	−0.011	0.049**	0.025
		(0.005)	(0.009)	(0.02)	(0.02)
	RCP 8.5	−0.021**	−0.029**	0.113***	0.063**
		(0.009)	(0.017)	(0.039)	(0.036)
Long-term (2061–2080)	RCP 2.6	−0.012**	−0.011	0.047**	0.024
		(0.005)	(0.009)	(0.019)	(0.02)
	RCP 8.5	−0.032**	−0.064**	0.238***	0.142**
		(0.013)	(0.028)	(0.075)	(0.066)

Note: The estimates are based on the regression reported in column (3) in Table 1. Standard errors are clustered at the county level.
***p < 0.01, **p < 0.05, *p < 0.1.

excess deaths per year under RCP2.6 and RCP8.5, respectively.[28] World Bank (2007) estimates the value of a statistical life (VSL) in China,[29] which reflects people's willingness to pay to avoid mortality risk, to be approximately 1 million CNY. Hence, the health cost of excess deaths caused by temperature change will be roughly as large as 0.17 trillion CNY per year under RCP 2.6, equivalent to 0.21% of China's GDP in 2017 (about 82.5 trillion), and 0.98 trillion CNY per year under RCP 8.5, accounting for 1.19% of China's current GDP.

It needs to be stressed that the health cost estimation of future climate change cannot be entirely accurate and only provides a rough forecast. First, our estimation is based on the assumption that other conditions remain unchanged except for temperature. In fact, with the development of the economy and more knowledge of climate change issues, households may adopt better adaptive measures, alleviating temperature effects on health. In this sense, the health cost of climate change could be overestimated. Second, we only consider the cost of increased mortality but not morbidity, which leads to underestimation of the health cost of climate change. Finally, we only use one climate change model in our estimation, ignoring climate uncertainty, which could also lead to inaccurate projections (Burke et al., 2015).

4. Temperature effects on household adaptation behavior

4.1. Empirical strategy and summary statistics

Adaptation is one of the most important strategies in response to global warming and increasing risks in extreme temperature events. We estimate the following reduced-form model to study households' adaptation behavior toward temperature changes:

$$Y_{lt} = \sum_{j} \delta_1^j TEMP_{lt}^j + \sum_{j'} \delta_2^{j'} HUMD_{lt}^{j'} + \sum_{j''} \delta_3^{j''} PREC_{lt}^{j''} + \rho_l + \omega_t + \mu_{lt} \tag{3}$$

where Y_{lt} indicates per capita energy consumption or the increase in AC ownership in province l and year t. *TEMP*, *PREC*, and *HUMID* are the same weather variables as in equation (1), except that, to represent the temperature exposure of an average person in the province, they are aggregated to the province level by using the counties' population in 2010 as weights. ρ_l and ω_t are province fixed effects and year fixed effects, respectively.

Residential energy consumption is a common measure of adaptation behavior in response to climate or temperature change. To obtain the per capita energy consumption for the whole province, as well as for the urban and rural areas of the province, we calculate the total amount of energy consumption of all households in each area by using information from the China Energy Statistical Yearbook, and then divide the energy consumption by the corresponding population size.

The usage of AC is one of the most important adaptation measures and is found to play an important role in reducing the effects of extreme temperatures. The impacts on total energy consumption may be confounded by other effects, because temperature is likely to influence the energy demand for basic needs.[30] In this sense, it is better to study the usage of AC directly. However, data on daily usage of AC, such as AC electricity consumption, are unavailable in any large-scale survey. We

[28] The population projection is from the 2017 version of the World Population Prospects database provided by the United Nations Population Division (2017).
[29] VSL is defined by the sum of individuals' willingness to pay for a small risk reduction that adds up to one statistical life. For example, if the risk of death is reduced by 1 per 100,000 persons annually, it will save one statistical life in a population of 100,000. The amount that the 100,000 people would pay together for the risk reduction is known as the VSL. World Bank (2007) uses the same VSL for people of all ages, because it fails to find consistent evidence that willingness to pay for mortality risk reduction falls later in life.
[30] Energy consumption for cooking or heating bath water can be influenced by temperatures. For example, some people may use unheated water for the bath on hot days.

Table 8
Summary statistics for energy consumption and AC ownership.

Variable	Obs	Mean	Std.Dev.	Min	Max
Per capita energy consumption (kg coal equivalent)					
Total	270	212.4	123.3	30.62	769.4
Urban	270	270.3	178	49.86	1444.5
Rural	270	172.5	147.9	15.01	858
Increase of AC ownership per 100 households					
Urban	268	5.54	6.37	−16.8	31.2
Rural	248	3.18	5.34	−17.3	35.8

thus focus our analysis on AC ownership instead. The explained variable we use is the increase in the average number of ACs owned per 100 households in a province-year, for urban and rural households separately. Then the coefficients of temperatures measure the effects on the net increase or diffusion of residential AC.

Although AC is a durable good, annual temperature fluctuation is likely to influence people's AC purchasing behavior for several reasons. Firstly, it may be that extremely hot or cold days are so unpleasant for the households that it overcomes the fixed cost of acquiring an air conditioner. The AC saturation rate is still relatively low in China.[31] Encountering extreme temperatures, households may want to install an AC in a room that has not been equipped with an AC yet to help them get through current tough weather. Secondly, households may be present bias. They may care so much about current welfare so they choose to buy more ACs even when faced with temporary shocks. Thirdly, it's likely that temperature shocks can influence households' anticipation. When the temperature becomes abnormally hot or cold, they are not sure whether this abnormal temperature will sustain in the future. For example, if this summer is hot, they may anticipate another hot summer coming in the next year. In despite of these possible explanation, we have to admit that we are unable to disentangle them in the paper, leaving room for further study.

The summary statistics on energy consumption and increased AC ownership are shown in Table 8. Average per capita energy consumption in the residential sector is about 212 kg of coal equivalent. There is a wide gap between urban and rural areas. On average, a person living in an urban area consumes 0.6 times more energy than a person living in a rural area. The increase in AC ownership is also larger for urban households.[32] Considering that AC ownership is much larger in urban areas (82.9 ACs per 100 households) than in rural areas (18.8 ACs per 100 households), the gap will persist given current growth rates of AC ownership in the two areas.

5. Results

The estimation results on adaptation behavior are shown in Table 9. As shown in column (1), cold temperatures significantly result in increased energy consumption. For example, exposure to one additional day with a daily mean temperature below 10 °F (relative to the 70°F-80 °F range[33]) leads to an increase of 4.3 kg coal equivalent in per capita residential energy consumption. However, the heat-related effect is relatively small and statistically insignificant. Deschênes and Greenstone (2011) and Barreca (2012) report that households in the United States increase their energy consumption statistically significantly when faced with hot temperatures. Our results imply that the Chinese population may be under-protected against hot days.

Separate regressions show a huge disparity between urban and rural areas. As shown in columns (2) and (3) in Table 9, residential energy consumption in urban areas is obviously more responsive to temperature change, and the effects of cold temperatures are especially large and statistically significant. In rural areas, however, all the coefficients are small and statistically insignificant. For the relationship between AC ownership and temperature, column (4) shows a U-shaped relationship for urban households. That is, urban households purchase more ACs when the temperature is too high or too low.[34] However, again, the increase in AC ownership is unresponsive to temperature in rural areas (column (5)).

The results on energy consumption and increase in AC ownership show little evidence of self-protection for rural households. Research has shown that AC plays a vital role in mitigating the effects of extreme temperatures. Therefore, it is likely that the health of rural people is more sensitive to extreme temperatures. This is consistent with the findings in Burgess et al. (2014), who use Indian data and show that high-temperature days have a substantially larger effect on the mortality rate

[31] In China, central AC is not common in residential buildings. Most families use mini split ACs, usually installing one AC in each room. Average AC ownership rates are 83.2 and 19.7 ACs per 100 households in urban and rural areas, respectively, which is relatively low considering that each apartment usually has a living room and two or three bedrooms.

[32] The observation for AC ownership is less than 270 because of missing data. The increase in AC ownership is negative for some observations, possibly due to disposal of old ACs or households moving into new houses.

[33] Because energy consumption or AC ownership is lowest when the temperature is between 70 °F and 80 °F in most regressions, the baseline group in Table 9 is the 70°F-80 °F bin, to make the results more readable.

[34] We do robustness checks by using household-level data from the Urban Household Survey of 16 provinces and also find that urban households purchase more ACs when experiencing more days with extreme temperatures.

Table 9
Temperature impacts on household adaptation behaviors.

VARIABLES	(1)	(2)	(3)	(4)	(5)
	Energy consumption			Increase in AC ownership	
	Total	Urban	Rural	Urban	Rural
TEMP ≤ 10 F	4.292*	8.779**	0.320	0.355**	−0.088
	(2.183)	(3.788)	(1.533)	(0.164)	(0.114)
TEMP = 10F–20F	3.373**	6.528**	0.882	0.420**	−0.079
	(1.475)	(3.168)	(1.024)	(0.174)	(0.106)
TEMP = 20F–30F	3.161**	6.106**	1.065	0.283*	0.065
	(1.303)	(2.931)	(1.162)	(0.157)	(0.098)
TEMP = 30F–40F	1.394	3.190	0.641	0.259**	−0.000
	(1.437)	(3.554)	(0.765)	(0.121)	(0.096)
TEMP = 40F–50F	1.192	2.478	0.443	0.194	0.030
	(1.368)	(3.072)	(0.755)	(0.120)	(0.086)
TEMP = 50F–60F	−0.063	0.385	0.081	0.088	0.061
	(0.883)	(1.849)	(0.615)	(0.089)	(0.058)
TEMP = 60F–70F	−0.052	0.636	−0.353	0.142**	0.058
	(1.319)	(2.573)	(0.525)	(0.057)	(0.058)
TEMP = 80F–90F	0.011	0.117	−0.035	−0.077	0.031
	(0.659)	(1.181)	(0.544)	(0.105)	(0.095)
TEMP = 90F+	0.691	0.060	0.473	0.569***	0.064
	(1.078)	(1.863)	(1.255)	(0.144)	(0.155)
Observations					
R-squared	270	270	270	268	248

Note: All regressions include controls for specific humidity and precipitation and province and year fixed effects. Standard errors are clustered at the province level.
***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

in rural areas. The fact that energy consumption or increased AC ownership is unresponsive to temperature variation in rural areas has important implications for public policy. The results at least suggest that more support is called for to protect rural households from extreme temperatures.

6. Conclusion

This paper has investigated the impacts of extreme temperatures on mortality rates in China, to shed light on the health-related costs of climate change. We find a robust, U-shaped relationship between temperature and mortality rates, which implies that extremely cold or hot temperatures will lead to excess deaths. The temperature effects we find are much larger than those found for the United States, indicating that the problem of extreme temperatures is more challenging for the developing world, which has limited resources. Moreover, the impacts of extreme temperatures are largest for the elderly population, mainly through excess deaths caused by cardiovascular disease. This places especially more pressure on rapidly aging countries such as China.

The estimates on household adaptation behavior show that the effect of hot temperatures on residential energy consumption is small, while urban households statistically significantly increase their purchase of ACs on hot and cold days. However, this self-protection behavior is not observed in rural areas, possibly due to limited resources.

Our results have some important policy implications. First, we find that extreme temperatures lead to more premature deaths. And our prediction using the HadGEM2-ES model shows that under RCP2.6 the annual mortality rate will increase by 2.4% in 2061–2080 relative to 2004–2012, due to temperature change, while RCP8.5 predicts a mortality increase as large as 14.2%. Therefore, the control of GHG emissions has profound health benefits.

Second, the findings from regressions by age and cause of death can help to develop better preventive measures. For example, we find an effect as large as 1% of deaths caused by one additional hot day with mean temperature above 90 °F for the old, which is mainly caused by cardiovascular disease. Thus, more attention should be paid to the elderly, especially those with heart disease.

Third, we find that rural households are under-protected from extreme temperatures. As health is one of the major components of human capital, climate change may result in increased inequality. Relevant policies should be inclined toward the rural areas to build up rural residents' ability to adapt to climate change. For instance, ACs could be included in the government's subsidy program for rural appliance purchases.

Acknowledgements

We gratefully acknowledge the support from the National Natural Science Foundation of China (grant number 71503012). We thank the editor and two anonymous referees for their extremely valuable suggestions. We also thank seminar participants at 1st Workshop in Economics of Environment, Energy and Climate at Peking University (2016), EfD Environment for Development Initiative 11th Annual Meeting (2017), China Economics Annual Conference at Ningxia University (2017) and Public Economics Workshop at Delhi School of Economics (2018) for their helpful comments. The usual disclaimer applies.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jeem.2019.05.004.

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