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ABSTRACT

Does Extreme Temperature Exposure Take a Toll on Mental Health? Evidence from the China Health and Retirement Longitudinal Study

Long-term exposure to extreme temperatures could threaten individuals' mental health and psychological wellbeing. This study aims to investigate the long-term impact of cumulative exposure to extreme temperature. Differently from existing literature, we define extreme temperature exposure in relative terms based on local temperature patterns. Combining the China Health and Retirement Longitudinal Study and environmental data from the U.S. National Oceanic and Atmospheric Administration from 2011 to 2015, this study demonstrates that heat and cold exposure days in the past year significantly increase the measured depression level of adults over age 45 by 1.75 and 3.00 per cent, respectively, controlling for the city, year, and individual fixed effects. The effect is heterogeneous across three components of depression symptoms as well as age, gender, and areas of residency, and air conditioning and heating equipment are effective in alleviating the adverse impact of heat and cold exposure. The estimation is robust and consistent across a variety of temperature measurements and model modifications. Our findings provide evidence on the long-term and accumulative cost of extreme temperature to middle-aged and elderly human capital, contributing to the understanding of the social cost of climate change and the consequent health inequality.

JEL Classification: I12, I18, Q54

Keywords: mental health, climate change, extreme temperature, aging

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1. Introduction

Accelerated climate change, one of the greatest challenges of the 21st century, has significant potential to threaten human beings. In addition to continuing to track and monitor the processes and health risks of global climate change, for the first time, recent studies highlight the worldwide COVID-19 pandemic as adding to the continuing challenge of health risks and economic costs of climate change (Watts *et al.*, 2021). Worldwide warming trends continue to grow, accompanied by severe air pollution and an increasing number of extreme weather events, which rose by 46 per cent from 2000 to 2013 (Watts *et al.*, 2018). These changes have adverse effects on public health, accelerating the spread of climate-sensitive infectious diseases and rising incidences of noncommunicable diseases, such as respiratory and cardiovascular disease, injuries, and death (WHO, 2018). Existing research also emphasizes the significant impact of temperature on health, asserting that even small changes in temperature can pose a significant threat to human health (Watts *et al.*, 2019).

In recent years, investigating the effects of climate change on mental health has become increasingly compelling, as scholars recognize that frequent and unpredictable weather events and severe pollution are directly and indirectly affecting individuals' psychological wellbeing (Fritze *et al.*, 2008). Mental health challenges have determinant effects on health status, in addition to consequent effects on medical cost and economic productivity (Hsieh and Qin, 2018). As climate change has significantly shifted weather patterns and living environments, acting as an increasingly critical contributor to mental health problems, investigating and understanding the effects of climate change on mental health is essential to public health, human capital development, and social welfare alike.

The interaction between the adverse effects of climate change and the characteristics of the elderly presents a challenge to public health and environmental justice. The vulnerability of older people in China warrants increased attention. As of 2016, China's population included

137.6 million elderly citizens, by far the largest in the world (Zhong *et al.*, 2016). According to the most recently available data, in 2018, China ranked first in the world, with 62,000 deaths related to extreme heat among people over 65 years of age (Watts *et al.*, 2021). Analyzing the health risk factors for older people in the context of climate change can broaden our understanding of climate risks to strategically design interventions and corresponding adaptive behaviors to protect the health and wellbeing of China's older population.

Conceptually, the mechanism through which climate change affects mental health contains both direct and indirect pathways (Berry *et al.*, 2010). The direct pathway refers to the psychological stress and trauma associated with the rising frequency, higher intensity, and decreased predictability of weather events and natural disasters. The indirect pathway refers to the impact on mental health implicitly moderated by deteriorating physical status and socioeconomic circumstances. For example, the growing risk of damaged landscapes results in a rising sense of isolation and a diminishing sense of belonging and affiliation (Higginbotham *et al.*, 2006).

The first stream of literature on the subject examines the relationship between extreme temperature and a variety of mental health outcomes, including mental disorders, emotional resilience, and stress. A recent study demonstrates that when the monthly temperature shifts from 25°C–30°C to >30°C in the U.S., the probability of mental health difficulties increases by 0.5 per cent. In addition, each 1°C-over-five-year rise is associated with a 2 per cent increase in the prevalence of mental health issues (Obradovich *et al.*, 2018). Another study finds that people's hedonistic state sharply declines after temperatures become higher than 21°C, based on an analysis through Twitter (IPCC, 2014). Several investigations emphasize increases in hospital admissions and emergency room visits for individuals with mental illness during high temperature periods in Canada (Wang *et al.*, 2014), Australia (Nitschke *et al.*, 2011; Williams *et al.*, 2012), and the United States (Kaiser *et al.*, 2001).

However, research on the effect of long exposure to slow-moving changes remains limited. Most prior research is concentrated on the effect of discrete extreme weather events, such as natural disasters, on mental health. For example, heat and drought are shown to increase the risk of suicide (Page *et al.*, 2007; Carleton, 2017; Burke *et al.*, 2018), and hotter temperatures to intensify psychiatric hospital visits (Hansen *et al.*, 2008; Wang *et al.*, 2014; Chan *et al.*, 2018). Measures of extreme temperature are mainly based on the absolute value of temperature, ignoring long-term adaptive physical and psychological mechanisms. It remains unclear how temperature variations on the local scale – "local extreme temperature" – affect the physiological wellbeing of the population.

Another line of research investigates the effectiveness of different adaptations. Physiological and behavioral adaptations are demonstrated to reduce the adverse effects of heat waves by bolstering public health preparedness (McMichael *et al.*, 2006). Air conditioning (AC) and various types of heating equipment are tools that reduce the adverse effect of extreme temperatures and help individuals adapt to temperature changes.[1] Research reveals the adoption of residential AC to almost entirely explain the decline in fatal diseases related to days of extreme heat with an average temperature exceeding 26°C from 1960 to 2004 (Barreca *et al.*, 2016). In China, research shows that the adoption of AC, as an adaptive behavior, rises during uncomfortable weather in urban areas (Auffhammer, 2014; Yu *et al.*, 2019); however, the role of AC and heating in psychological adaptation to variations in extreme temperature remains an open research question.

To address these unknowns, this study investigates the cumulatively causal relationship between extreme temperature and depression symptoms. The goals are threefold: 1) to estimate the magnitude of slow-moving, climate-caused adversities on individuals' depression symptoms, particularly those of the vulnerable elderly, by constructing a linear probability

[1] For details, please refer to www.cdc.gov/disasters/extremeheat/index.html.

model and controlling for several fixed effects; 2) to investigate the heterogeneity of these effects among different populations, segmented by gender and areas of residency; and 3) to understand the adaptive effect of AC at the individual level in response to extreme temperature. We use the exogeneity of temperature and local temperature variations, applying a fixed-effects model to China Health and Retirement Longitudinal Study (CHARLS) three-year unbalanced panel data. We reveal significant evidence suggesting that local heat and cold exposure during the past year significantly increases the level of depression symptoms by 1.75 and 3.00 per cent, respectively, and somatic symptoms are the most sensitive among the components of depression symptoms. The findings also indicate the critical roles of AC and heating in helping people adapt to local variations in temperature during summer and winter. Finally, the heterogeneity analysis determines that the adverse effects of local extreme temperatures are particularly strong among the elderly, women, and rural residents, in comparison to the middle-age population, men, and urban residents.

The study offers three main contributions to the literature. First, we innovatively characterize slow-moving climate change by defining extreme temperatures on a local scale. A "local extreme temperature day" is defined as one in which the actual local temperature significantly deviates from the historical precedent. Compared with mainstream methods in climate change research, which use the absolute value of temperature as the measurement of extreme temperature, the approach used in this study has notable advantages. Local variation has stronger exogeneity than the absolute value since it controls for the expectation and adaptation to local temperature and long-term living environment by including historical precedents. Using local temperature variations takes local adaptations into account; thus, local variation can more accurately measure the extent of unexpectedness in the temperature.

Second, this study contributes to the small stream of literature exploring the effectiveness of adaptive tools under climate change. Based on the existing literature, it remains unclear whether this adaptive behavior releases psychological pressure and has a protective effect on residents' mental health. Using individual/household level data, this study empirically demonstrates that these adaptive tools have a vital influence in aiding mental adaptation to local extreme temperature exposure. These results also indicate the importance of policies to promote AC and heating devices in China.

Third, we examined differences in the effect of local extreme temperatures based on important socioeconomic factors of age, gender, and areas of residency. We demonstrate that the elderly, females with less social power, and rural residents are vulnerable populations who likely have less access to resources to adjust for extreme temperatures; thus, they are more mentally vulnerable to climate change. To date, minimal research on developing countries estimates the precise magnitude of these climate-induced adversities on vulnerable populations, particularly the elderly, based on large-scale quantification. Understanding how local extreme temperatures heterogeneously affect different populations is valuable for integrating consideration of health inequity into the design of future locally-based policy interventions and responses to extreme temperatures.

The remainder of this study is organized into four sections. Section 2 introduces the data sources and research methods, including basic introductions to the key variables of interest, the descriptive result, the empirical strategies, the sample clean-up and selecting process, and the construction of the empirical model. Section 3 introduces the results of our basic model and results of adaptations. Section 4 performs several robustness tests for the model, and section 5 concludes and discusses the implications of the findings.

2. Data and variables

2.1. Data

2.1.1. Individual-level data

The individual-level data in this study is from the CHARLS in 2011, 2013, and 2015. The data include a high-quality nationally representative sample of Chinese residents ages 45 and older to serve the needs of scientific research on the elderly and population health issues. Its design is based on national health and aging longitudinal survey data implemented by developed countries, such as the Health Retirement Study in the U.S. and the Survey of Health, Aging and Retirement in Europe, collecting basic demographic information, family status, health status, medical service, work, income, assets, and basic community conditions for people aged 45 and over and their spouses.[2]

This study primarily focuses on depression symptoms as the measurement of mental health status. CHARLS applies the simplified version of CES-D (Center for Epidemiologic Studies Depression Scale) to measure individuals' depression and psychological and emotional state, as it is one of the most commonly used self-report measurements of depressive symptomology in household questionnaires (also used in the National Health Survey in the U.S.). The scale includes 10 questions regarding the frequency of 10 scenarios in the past week, presenting both positive and negative alternate questions. Referencing Lei *et al.* (2014), we add the scores of these ten questions to obtain a single depression score, representing a unified depression indicator ranging from 0 to 30 points, with a higher score indicating a higher degree of depression. We further explore different components of depressive symptomatology by categorizing the depressive symptoms into three dimensions (see table 1) (Yen *et al.*, 2000).

{Insert Table 1 about here}

2.1.2 Weather data

The weather data is obtained from the Climate Data Online of the U.S. National Oceanic and Atmospheric Administration (NOAA). This dataset includes daily, monthly, seasonal, and

[2] For details and introductions on the dataset, please refer to the official website at http://charls.nsd.edu.cn/zh-CN.

annual temperature, precipitation, wind, and radar data.[3] The original data is from the real-time and historical climate data of the national standard weather station collected by the China Meteorological Administration.[4] Subsequently, weather stations are divided into specific cities based on the geographic latitude and longitude information of each weather station (if there are multiple stations in a city, the data are averaged). CHARLS data are then matched with the corresponding climate data to obtain the number of exposure days for each individual in 2010, 2012, and 2014. The database used in this study was processed by correcting for error values and significant outliers and removing samples that did not match the city information during the database merging process.

Extreme temperature exposure is measured by the number of local extreme temperature days during the year prior to the interviews (2010, 2012, 2014). Specifically, we calculated the average monthly temperature and standard deviations (SD) in each city based on the data from 1980 to 2010 as the local historical reference. We then compare each day's temperature to its local historical precedents. When the daily average temperature deviates from the local monthly average temperature by more than 1.96 SD, this indicates the daily temperature is statistically significant from the historical average, and such a day is defined as a local extreme temperature day. When the deviation goes up in a hot direction, the day is defined as a heat exposure day, and when the deviation goes down in a cold direction, the day is defined as a cold exposure day. Finally, the cumulative exposure days in the year prior to the interview are calculated as the measure of each individual's exposure level. We will refer to this as local heat exposure and local cold exposure days in the remainder of this study. Based on this measurement, figures 1 and 2 present the total annual number of local heat and cold exposure

[3] Climate Data Online provides free public access to the global historical weather and climate data, including China. For details and introduction of the dataset, please refer to the website athttps://www.ncdc.noaa.gov/cdo-web/,

[4] This raw data is now available directly from the National Weather Science Data Center; see the official website at http://data.cma.cn/.

days for 322 major cities across China in 2017. Almost all cities in China show some extent of extreme temperature exposure, while the heterogeneity is also substantial, ranging from 0 to 357 days.

{Insert Figures 1 and 2 about here}

We further investigate the seasonal patterns of extreme temperature exposure by calculating the local heat and cold exposure days in summer (June to August) and winter (December to February the following year), the two seasons with higher or lower absolute values of temperature that require the use of AC or heating. Based on this division, we examine the effects of extreme temperature exposure on depression symptoms among populations with and without AC or heating. We also include several weather variables in the model as control variables, including wind speed, sunshine duration, relative humidity, air pressure, and fine particulate matter (PM2.5) (Denissen *et al.*, 2008).

We have to acknowledge that one big limitation of CHARLS data is the lack of interview date for households. The visit months are only published for 2015 and the latest release of 2018 data, and visit months for 2011 and 2013 were released in a later update, but no specific visit dates were published for either round of survey. Therefore, we cannot precisely match meteorological data and CHARLS at the date level. The data limits us from discussing and comparing the immediate impacts and short-, medium-, and long-term effects of extreme temperature exposure on the physical health of middle-aged and older adults. Instead, we focus more on the overall effects of long-term cumulative exposures to extreme temperatures in our paper. This limitation is mitigated by the fact that most visits to CHARLS are concentrated in the summer months. The majority of visits are in June-August, with only a very small number of special samples requiring additional surveys in other months (see figure A1 in the online appendix). The small variation in interview months could partly mitigate the bias in the model estimation as a result of the data limitation.

2.2. Descriptive analysis

Table 2 presents the basic characteristics of the main variables. The statistics calculated in the table are adjusted according to the sampling weights provided by the CHARLS database, to ensure that the sample is representative of the characteristics of the country's population. Panel A details the descriptive statistics of CES-D scores, the main outcome variable. The average depression score of the sample is 10.37 points, representing a state of mild depression. Panel B presents the characteristics of the temperature days under different standards. Overall, there are approximately 100 days of heat exposure and 77 days of cold exposure each year throughout the country.

{Insert Table 2 about here}

We also calculate a Z score of local temperature at the daily level for each city.[5] The Z score in table 2, panel B shows the average daily Z score during the past year across all cities in our sample. The Z score represents the extent of deviation from the historical reference temperature. The mean of the Z score is very close to 0, indicating a balance in temperature variation from two directions. The geographical distribution of hot/cold exposure in the CHARLS surveyed area is shown in online appendix figures A2 to A7. Panel C of table 2 shows the basic descriptive statistics of the control variables included in the model.

2.3. Estimation method

To identify the causal effect of extreme temperature exposure on the mental health of elderly individuals, we adopt a panel fixed-effects model that has been widely used in the research on climate economics (Obradovich *et al.*, 2018; Park *et al.*, 2020). To take advantage of panel data, time-demeaned computation is conducted in the fixed-effects model to eliminate the endogenous problem induced by time-invariant variables, as well as the fixed effects at the

[5] $\text{Z score} = \frac{\text{Daily average temperature} - \text{Mean of Historical monthly average temperature}}{\text{Standard deviation of monthly average temperature}}$.

individual level. By using three years of unbalanced panel data from CHARLS, we apply an individual, city, and year fixed effect model as described in equation (1) to include unobservable time, regional and individual heterogeneity into the consideration:

$$Mental\ Health_{it}=\alpha_0+\beta_1 Exposure_{it}+\beta_2 W_{it}+\beta_3 X_{it}+\gamma_i+\eta_c+\mu_t+\varepsilon_{it}\ , \qquad (1)$$

where *i* represents the individual code, *t* represents the year code, and *c* represents the city code; $Mental\ Health_{it}$ denotes the individual mental health outcome variables; $Exposure_{it}$ represents the number of days the individual has been exposed to extreme temperatures in the past year; W_{it} indicates other environmental variables affecting individual mental health, such as precipitation, pollution, and other relevant concerns; X_{it} includes other control variables; η_c is the fixed effect of city level; γ_i is the individual fixed effect that does not change with time; and μ_t is the year-fixed effect. The coefficient of interest is β_1, which represents the average change in depression symptoms when an individual is exposed to one more local extreme temperature day in a year.

The key assumption of this empirical strategy is that the variation in temperature over successive depression status is uncorrelated with unobserved determinants of the depression status for a given individual. In other words, the variation in temperature is considered an exogenous variable in the research design, as there is an understanding that weather events, such as extreme heat and heavy precipitation, are largely unpredictable far in advance, particularly under the climate change process (Andalón *et al.*, 2016; IPCC, 2018). By constructing an index of local extreme temperatures, local variations in temperature are rendered more exogenous than absolute temperature values, as local temperature deviations are portrayed by subtracting historical contemporaneous temperatures, controlling for individual expectations of the environment in which they live, and considering their adaptation to long-term living conditions. The fixed-effects model of panel data also eliminates the endogeneity problem as it does not vary over time in the demeaned identification process, as well as controlling for fixed effects at the city, individual, and year levels.[6]

3. Results

3.1. Basic model

Panel A of table 3 presents the regression results of the basic model. The results indicate that long-term exposure to local extreme temperatures has significant adverse impacts on the depression symptoms of middle-aged and elderly people in China. Specifically, one more extreme heat exposure day increases the CES-D score by 0.0052 units. The yearly average effect of local heat exposure days on sample depression is an increase of 1.75 per cent per year.[7] For local cold exposure, one more local cold exposure day increases depression by 0.0116 units of the CES-D score, and the yearly average effect of local cold exposure on depression is an increase of 0.90 units, which is a 3 per cent increase on the CES-D scale.

{Insert Table 3 about here}

Notably, the magnitude of the impact of cold exposure is almost two times higher than that of heat exposure, suggesting a higher level of sensitivity in the mental health response to cold temperatures. Acute large-scale cold wave events often lead to large-scale influenza, entailing risks to human health (McMichael *et al.*, 2008). Few studies focus on the comparisons between extreme heat and extreme cold. In this paper, we provide one of the first empirical studies to compare the relative magnitude of heat exposure and cold exposure.

Furthermore, the effect varies across three components of depression symptoms. The results suggest that heat exposure primarily disturbs individuals' regular somatic activities and behaviors (such as feeling upset, sleeping, and motivation difficulties), while cold exposure

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[6] Considering the city-specific time trends, we also include the time trends at city level of the basic model in online appendix table A1, which presents the similar results with our basic model.

[7] We compute 0.0052 units * 100.77 heat exposure days * 1/30 = 1.75 per cent, where 30 is the maximum scale of CES-D score.

adversely affects both somatic activities and depression reactions (such as having the blues and feeling lonely and sad). The somatic activity level significantly increases by 1.55 per cent from local heat exposure days, and by 2.2 per cent from local cold exposure days. The depressed reaction is only affected by local cold exposure, increasing by 1.21 per cent, on average.

3.2. Adaptations

AC and heating are two main resources that are used to mitigate the effects of uncomfortable temperatures. To further estimate the size of this mitigation effect, we conduct a subsample analysis of the populations with and without AC/heating. The results in panel A of table 4 illustrate that if there is no AC in a household, the marginal effect of hot exposure days on depression during summer is 1.80 times stronger than in households with AC. From the perspective of yearly average effect, a 0.410-unit (1.37 per cent) increase in depression symptoms occurs due to local heat exposure days for households with AC in summer; however, for households without AC, the yearly average impact will rise to 0.737 units (2.46 per cent). Notably, the effect on the population with AC is no longer significant. Furthermore, local heat exposure predominantly imperils individuals' somatic activity and depression reactions.

{Insert Table 4 about here}

Panel B of table 4 shows that accessing at least one form of heating equipment is effective in mitigating the effect of cold exposure days on depression status. The local cold exposure days during winter have a much stronger negative effect on individuals' depression reactions in households without a heating device than in households with heating devices; however, neither effect is significant for these populations across different dimensions of depression. The yearly average effect of local cold exposure days on sample depression is an increase of 2.00 per cent per winter for households without heating devices, in comparison to a 0.38 per cent increase for households with heating devices. The coefficient for households with at least one heating device is no longer statistically significant, suggesting that extreme temperature primarily deteriorates the mental health status of households without access to such adaptations.

These results suggest that AC and heating effectively aid adaptation to local extreme temperature exposure. In the US, nearly 9 out of 10 homes have AC as a must-have item. Higher levels of prevention awareness and more AC usage led to a reduction in mortality during heatwaves (McMichael *et al.*, 2006); however, in many low-income and lower-middle-income countries, AC remains a relative rarity. Although numerous reports address the negative environmental threats of AC use, without mentioning the benefits of AC/heating on mental health, our results provide vital evidence of the essential need for AC to support human psychological wellbeing during extreme temperature periods. The use of AC and heating equipment as an adaptive behavior in response to climate change certainly presents a double-edged sword. While the results in this section provide important evidence of the importance of AC/heating for human wellbeing, the negative environmental impacts associated with AC cannot be ignored. A higher prevalence of AC can contribute to climate change by raising electricity consumption, increasing greenhouse gas emissions, and amplifying air pollution. Therefore, the future calls for the application of more efficient non-fossil fuel energy sources to reduce the environmental harm caused by AC and heating devices and to take advantage of their role in improving individual adaptation in the meantime (Watts *et al.*, 2019).

4. Heterogeneity analysis

To test the heterogeneity of the reaction to local extreme temperature across populations with different characteristics, we further examine age differences, gender differences, and urban–rural differences. The reason for performing subsample analyses, rather than adding an interactive term in the regression model, is that the compared groups could prove to be systematically different in many ways. Simply adding an interactive term between gender and heat/cold exposure days requires a stronger assumption that the coefficients for the control variables are exactly the same. Detailed regression results can be found in online appendix table A2.

4.1. Difference by age

We first investigate the differences between the middle-aged group (defined as those younger than 60) and the elderly group (defined as those older than 60). The results in figure 3 show that the elderly population is generally more vulnerable in response to both local heat and cold exposure. The adverse effects of local heat exposure are 1.6 times stronger among the elderly group than the middle-aged group, and the negative effects on the middle-aged group are no longer significant. As for local cold exposure, the elderly population is 1.3 times more sensitive than the middle-aged group. Notably, extreme temperatures appear to deteriorate the mental health of the elderly more strongly. Considering that older people have more potential chronic diseases, many previous studies have discussed the vulnerabilities of the elderly physical health status to the advance of climate change, while failing to address mental health status. Our results indicate that the elderly's mental health should also be prioritized.

{Insert Figure 3 about here}

Older people are considered one of the groups that are most vulnerable to the effects of extreme temperatures as they have fewer physical and mental coping mechanisms to adapt to extreme climate conditions than younger populations (Davies *et al.*, 2009; Green *et al.*, 2013; Bourque and Willox, 2014). As a result, the elderly are more likely to suffer negative outcomes from climate change (Haq, 2017) and have a significantly higher mortality risk in extreme weather events (Diaz *et al.*, 2002). Till 2019, China has the largest elderly population (254 million) in the world. (The Lancet, 2022). The interaction between the adverse effects of climate change and the vulnerability of older people poses considerable challenges to both population health and environmental justice.

4.2. Difference by gender

In terms of gender difference, we find a slight difference in the effect of local extreme temperature suggested in figure 4. The marginal effect of local heat exposure on females is slightly higher than on males; however, the gender difference is minimal. The difference becomes insignificant when considering the standard error for both coefficients. In other words, the results indicate that local heat exposure poses threats to both women's and men's mental health on a similar scale; however, the effect of local cold exposure differs by gender. The yearly average effect of local cold exposure is a 4.86 per cent increase in CES-D score for women, which indicates a 4.8 times greater vulnerability than for men.

{Insert Figure 4 about here}

Women and men are considered to have different capacities in terms of adapting to the challenges of climate change, on both individual and group levels. Previous research demonstrates the higher vulnerability of women in managing short-term weather shocks and short-term extreme temperatures (Heyes and Saberian, 2019; Watts *et al.*, 2019; Zivin *et al.*, 2020). Although the likelihood of experiencing mental health challenges increases for both men and women, women are at a disproportionate risk of developing stress-related disorders and depression (Hammen, 2005; Olff *et al.*, 2007). This is because their adaptation to climate change requires more critical information on weather alerts and coping behavior. Particularly in developing countries, women have a historical disadvantage regarding limited information access and resources and have restricted rights and a muted voice in decision-making (McMichael *et al.*, 2006; UNDP, 2011). For these reasons, women appear to be more vulnerable to extreme temperatures in both the short and long run than men. Our results confirm that local cold exposure poses more threats to women's mental health than men's, highlighting the mental vulnerability of women to the threat of extreme temperatures.

We acknowledge that it is difficult to directly compare the results of this study with those of previous studies, as different definitions for extreme temperatures are used. Previous research hardly examines gender differences in local temperature variation reactions or the differences between cold and heat exposures. It remains unclear whether the lack of difference across genders is due to a lack of statistical power to detect the slight heterogeneity. Future research using a larger database is needed to investigate gender differences in reactions to local temperature variations.

4.3. Difference by area of residency

The results in figure 5 reveal the heterogeneity in reactions to local extreme temperatures between rural and urban residents. The population in rural areas appears to be more susceptive to local extreme temperature exposure. The average effect of heat and cold exposure days among the rural population is an increase of 2.15 and 3.13 per cent respectively in the level of depression symptoms; however, the corresponding effects in urban areas are insignificant, indicating that urban residents have a higher adaptive capacity toward local extreme temperatures.

{Insert Figure 5 about here}

These results emphasize the vulnerability of rural residents in the era of climate change and the crucial need to design corresponding policy interventions to protect rural residents from the adverse effects of extreme temperatures. Maintaining the mental health of the rural population is tremendously important to China. Despite rapid urbanization in recent years, the rural population is 41.48 per cent of the total Chinese population (China Statistical Yearbook, 2018). Furthermore, the wellbeing of the rural population is crucial for the whole country because their human capital and productivity have a vital role in providing and producing the natural resources on which the country with the world’s largest population depends.

The rural population is also more vulnerable to extreme weather events and increasingly frequent temperature changes brought by climate change. This is partly because the economic activity and social development in rural areas are interactively dependent on the ecological system, which is becoming more vulnerable to climate change. Additionally, compared with the urban population, the rural population in China has a lower socioeconomic status, which means that they have fewer social resources and a lower capacity to adapt to abnormal natural events. Our results stress that the adverse impact of local extreme temperature on rural populations is more pronounced and makes a complementary contribution to existing literature that aims to understand the disproportionately adverse effect of natural disasters and weather shocks on rural areas (Fritze *et al.*, 2008; Kessler *et al.*, 2008).

5. Robustness check

To verify the robustness of this study, we conduct several checks. First, one of the potential concerns is that migration behavior could bias the estimated result, as people who are intolerant of local weather variations could relocate. To address this concern, we restrict the sample to those who had not lived in another city for more than three months during the last year. The results in table 5, panel A show that the effects among non-migrants are similar to those shown in the basic model, suggesting that the motivation to migrate, if any, is too small to bias the estimation.

{Insert Table 5 about here}

Second, we test various alternative measurements of extreme temperature. Following a definition used in previous literature (Andalón *et al.*, 2016), we relax the threshold of extreme temperatures to 0.7 SD (table 5, panel B). Under this relaxed standard, the point estimates become smaller than in the basic model and insignificant, indicating that 0.7 is too low as the threshold of local extreme temperature on a daily basis. We also use the "daily maximum/minimum temperature," rather than "daily average temperature," to compare with the corresponding local historical precedents (table 5, panel C) and define the local extreme temperature days. The corresponding estimates are similar to those in the basic model.

Additionally, following previous health research on extreme temperature and climate change, we apply a set of absolute indices for measuring extreme temperature in the model. First, we construct the number of days above 30°C and below 0°C, and then separately rerun the model employing each index (table 5, panel D). From the perspective of absolute temperature indicators, one more exposure day below 0°C leads to a significant 0.0103-unit increase in CES-D scores, which also emphasizes the risks of cold exposure. Panel D demonstrates that when the standard of extreme temperature is defined based on absolute temperature, the significance and direction of the coefficients remain stable, while point estimates increase compared with the basic model as expected. Cold exposure also still shows a larger marginal impact on depression symptoms. As in most previous literature, we then apply bins of exposure days based on absolute temperature (i.e., number of days below 0°C, 0–10°C, 10–20°C, and 20–30°C and above 30°C), considering the nonlinearity of temperature (table 5, panel E) following Barreca *et al.* (2016). As for the temperature bins, compared with the referenced group (0 to -10°C), extreme heat (above 30°C) exposure days and extreme cold (below -10°C) exposure days worsen mental health status. Panel E in table 5 indicates that both higher and lower temperatures deteriorate mental health status compared with moderately comfortable temperatures. As expected, point estimates increase as the temperature level becomes more extreme, and heat exposure and cold exposure have a significant negative effect compared with the referenced temperature range. However, these absolute indices do not consider individuals' long-term adaptability to the local environment, stressing coldness and heat from the perspective of objective temperature; thus, there may be slight discrepancies and incomparability with the estimation of the basic model.

To consider the nonlinearity of exposure level, we define five levels of exposure days (table 5, panel F) and the squared term of both heat and cold exposure days in the basic model (table 5, panel G). The results in panels F and G demonstrate that the negative effects of extreme temperature on mental health in the basic model continue to hold considering the nonlinearity. Notably, the magnitude of coefficients increases as exposure days increase, respectively, exposing a monotonic trend, particularly for heat exposure days. Including the squared terms, the deterioration of local cold exposures on mental health status remains, while the effects of heat exposure become statistically insignificant. These results of robustness checks suggest that the baseline results are grounded on different measures of extreme temperature.

Table 5, panels H and I show the result of adding the interaction term to examine whether the AC or heating equipment could mitigate the adverse effects of extreme heat/cold exposures, instead of doing a subsample analysis in our main specification. The result suggests that the depression symptoms are still significantly mitigated if the household is covered by AC or heating equipment when exposed to extreme heat or cold, respectively.

In table 5, panel J, we define severe mental health problems if the CES-D score is over 16 (Radloff, 1977) and examine how the exposure to local extreme heat and cold temperatures affects the probability of having severe depression symptoms. We find that one more exposure day to local extreme heat temperature and local extreme cold temperature slightly increases the probability of showing severe depression symptoms by 0.05 and 0.08 per cent, respectively. The effect of cold exposure is larger than that of heat exposure, which is consistent with our main model.

6. Discussion and conclusions

Although an increasing amount of research is investigating the impact of extreme temperatures, the impact of temperature variation on mental health has not yet been prioritized. In contrast to previous research demonstrating an association between the absolute value of temperature and mental health status, e.g., higher daily temperature and negative feelings, such as being nervous and afraid (Denissen *et al.*, 2008), the results of this study offer further evidence that temperature variation, regardless of its direction, can affect people's depression symptoms. Using large-scale micro-household survey data and nationwide historical climate data, this research reveals the cumulative causal impact of long-term exposure to local extreme temperatures on the mental health of middle-aged and elderly people in China. Taking advantage of the exogeneity of the temperature variation and the rich information of the panel data, we found local temperature variation, particularly cold exposure, to significantly worsen the depression symptoms of individuals in China. Among different aspects of depression measurement, local extreme temperature primarily threatens mental health through somatic activities. We also found that AC and heating equipment appear to be protective for individuals who need to cope with local extreme temperatures. Furthermore, we found that the adverse effect of local extreme temperature is heterogeneously distributed across different populations. The elderly, women and rural residents demonstrate higher mental vulnerability in reaction to cumulative local extreme temperatures.

Our results are consistent with those of Yen *et al.* (2000) indicating that the Chinese population suffers more somatic disturbance than other types of depressive symptoms under extreme temperatures measured by the absolute value of temperature. One possible explanation is that extreme temperature, whether hot or cold, leads to many inconveniences in performing everyday activities, such as falling asleep, and sometimes directly deteriorates the basic routine of some behaviors; for example, by making it difficult to concentrate. Compared with somatic activity, a depressive or positive reaction could be an indirect and deeper disorder of emotions or anxiety; thus, the depressive or positive reaction is more difficult to be aware of. An alternative explanation is that people tend to suppress and tolerate psychological distress because of the stigmatization of mental illness and inadequate mental health care resources in China. Those who are severely depressed are less likely to admit their deeper depressed reactions due to the risk of being stigmatized by others (Yen *et al.*, 2000). Consequently, these results may considerably underestimate the effects generated by extreme temperatures.

Our results have two important policy implications. First, our results address the importance of promoting AC and heating devices in developing countries. In the US, nearly 9 out of 10 homes have an AC as a must-have item, and higher levels of prevention awareness and more AC usage led to a reduction in mortality during heatwaves (McMichael *et al.*, 2006). However, in many low-income and lower-middle-income countries, AC remains a relative rarity. Numerous reports stress the negative environmental effect brought about by AC without mentioning the benefits of AC/heating on mental health. Our results provide critical evidence on the benefits of AC/heating for human psychological wellbeing during local extreme temperature days and address the social benefits of promoting such adaptive tools for vulnerable populations.

Second, the unequal impacts of climate change on mental health have the potential to exacerbate current health and social inequity by heterogeneously affecting different populations subject to pre-existing physical conditions and social deprivation. We found the mental health of the elderly, women, and rural residents to be disproportionately affected by climate change. From a policy perspective, vulnerable populations with chronic diseases, disabilities, and low incomes require additional policy prioritization and adaptive strategies to mitigate the threats of climate change. Such interventions include faster advance warning, public information campaigns, and direct financial support for acquiring adaptive tools.

There is one main limitation of this study. Since CHARLS does not provide specific interview dates, the local extreme temperature days are recorded during the entire year prior to the interview year. This makes it impossible to consider the fixed effect of the interview date in our dataset; however, the fact that a larger proportion of the data is collected during summer (June to September) could mitigate this concern to some extent.

The findings of this study provide evidence of the long-term and accumulative cost of extreme temperature to middle-aged and elderly human capital, contributing to the understanding of the social cost of climate change and related health inequality issues. The results also indicate the valuable necessity of adaptive tools for mitigating the adverse effects of extreme temperatures. Related policies should consider promoting sustainable adaptive tools, such as clean-powered AC and heating equipment, and other technologies that enable individuals to adapt to environmental changes in developing countries. The complex mechanisms through which local extreme temperatures affect depression, cognitive processes, and other emotional and behavioral aspects were investigated in this study. Further research is needed to understand environmental risks on a full spectrum of mental health.

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Competing Interests:

The authors declare none.

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Table 1. CES-D components

Somatic activity	Depressed reaction	Positive reaction
1. I was bothered by things that don't usually bother me	3. I felt depressed	5. I felt hopeful about the future
2. I had trouble keeping my mind on what I was doing	6. I felt fearful	8. I was happy
4. I felt everything I did was an effort	9. I felt lonely	
7. My sleep was restless		
10. I could not get "going"		

Table 2. Summary of statistics

Variable	Observations	Mean	SD	Min	Max
Panel A: Depression symptoms					
Depression	41283	10.37	5.71	0.00	30.00
Panel B: Variation of daily mean temperature					
Z score	41283	0.26	1.05	-4.60	7.08
Heat exposure days	41283	100.77	41.91	4.00	357.00
Cold exposure days	41283	77.53	39.48	0.00	296.00
Heat exposure days during summer	41283	27.72	14.53	0.00	92.00
Cold exposure days during winter	41283	20.23	11.01	0.00	73.00
Panel C: Control variables					
Precipitation	41283	2.74	1.52	0.22	6.96
Wind speed	41283	2.12	0.74	0.84	4.96
Sunshine duration	41283	5.19	1.44	2.13	8.60
Relative humidity	41283	68.59	8.86	42.94	85.01
Air pressure	41283	970.37	62.72	741.89	1016.78
Pm2.5 [a]	41283	37.43	16.81	2.41	74.81
Age	41283	59.93	10.02	0.00	101.00
Age square	41283	3691.95	1250.67	0.00	10201.00
Education group	41283	2.76	1.37	1.00	5.00
ADL/IADL	41283	0.28	0.45	0.00	1.00
Self-reported adult health	41283	3.14	0.99	1.00	5.00
Have chronic disease	41283	0.72	0.45	0.00	1.00
Receive pension	41283	0.45	0.50	0.00	1.00
Receive medical	41283	0.76	0.43	0.00	1.00
Number of children	41283	2.73	1.45	0.00	11.00
Number of sons	41283	1.54	1.02	0.00	8.00
Ln (PCE) [b]	41283	4.23	4.42	0.00	12.93

[a] We apply yearly pm2.5 for the specific city as the control variable for air pollution. Considering that China officially released AQI and Pm2.5 since 2014, we apply yearly average pm2.5 (i.e., 2010, 2012, 2014, respectively) information from Global Annual PM2.5 Grids from MODIS, MISR and SeaWiFS Aerosol Optical Depth (AOD) with GWR, v1 (1998 – 2016) from Socioeconomic Data and Applications Center (SEDAC) at Columbia University (Hammer et al., 2022).

[b] PCE: Personal consumption expenditure, excluding medical expenditure; in RMB

Data source: CHARLS 2011, 2013, 2015 Survey Data.

Table 3. Main results of the basic model

Variables	(1) CES-D	(2) Somatic activity	(3) Depressed reaction	(4) Positive reaction
Heat exposure days	0.0052**	0.0046***	0.0011	-0.0005
	(0.002)	(0.001)	(0.001)	(0.001)
Cold exposure days	0.0116***	0.0085***	0.0047***	-0.0016*
	(0.003)	(0.002)	(0.001)	(0.001)
Precipitation	-0.0042	-0.0031	0.0023	-0.0034
	(0.011)	(0.007)	(0.004)	(0.003)
Wind speed	0.1628	0.1197	0.0104	0.0327
	(0.142)	(0.092)	(0.054)	(0.042)
Sunshine duration	-0.0243	0.0316	0.0401	-0.0960***
	(0.079)	(0.051)	(0.030)	(0.024)
Relative humidity	-0.0235*	-0.0161*	-0.0053	-0.0021
	(0.014)	(0.009)	(0.005)	(0.004)
Air pressure	0.0423	0.0398**	0.0131	-0.0106
	(0.028)	(0.018)	(0.010)	(0.008)
PM2.5	0.0272***	0.0217***	0.0152***	-0.0096***
	(0.010)	(0.007)	(0.004)	(0.003)
Age	0.2490***	0.1345***	0.0275	0.0870***
	(0.081)	(0.044)	(0.029)	(0.028)
Age square	-0.0023***	-0.0013***	-0.0003	-0.0007***
	(0.001)	(0.000)	(0.000)	(0.000)
Work in agriculture	0.0383	0.0021	-0.0009	0.0370
	(0.104)	(0.065)	(0.039)	(0.031)
Education level (Reference group: never attended school)				
Not finish elementary school	0.9848**	0.5816**	0.3178*	0.0854
	(0.435)	(0.275)	(0.181)	(0.111)
Elementary school	-0.2268	-0.1713	0.0100	-0.0655
	(0.516)	(0.338)	(0.208)	(0.135)
Middle school	0.0523	0.0848	0.1772	-0.2096
	(0.623)	(0.404)	(0.245)	(0.165)
High school and above	-0.1961	0.0168	0.1412	-0.3541
	(0.771)	(0.523)	(0.339)	(0.241)
ADL/IADL	1.3183***	0.8371***	0.4243***	0.0570**
	(0.086)	(0.055)	(0.034)	(0.023)
Self-reported adult health	0.6015***	0.4253***	0.2013***	-0.0251**
	(0.042)	(0.026)	(0.016)	(0.012)
Have chronic disease	0.6059***	0.3213***	0.1509***	0.1337***
	(0.149)	(0.096)	(0.054)	(0.047)
Receive pension	-0.3858***	-0.2233***	-0.1548***	-0.0076
	(0.074)	(0.047)	(0.028)	(0.022)

Receive medical	-0.2504**	-0.0068	-0.0437	-0.1999***
	(0.104)	(0.066)	(0.040)	(0.030)
Number of children	-0.0268	0.0222	-0.0225	-0.0265
	(0.079)	(0.048)	(0.029)	(0.023)
Number of sons	-0.0669	-0.0433	-0.0174	-0.0063
	(0.083)	(0.051)	(0.031)	(0.026)
ln (PCE)	0.0258**	0.0199***	0.0108***	-0.0049
	(0.010)	(0.006)	(0.004)	(0.003)
Observations	41,283	41,283	41,283	41,283

Notes: (1) All standard errors are clustered at the county/community level. (2) All models include all control variables and individual-, year-, and city- fixed effects. (3) All models are fixed-effect models. (4) ***, **, and * indicate significance levels of 1, 5, and 10 per cent, respectively.
Data source: CHARLS 2011, 2013, 2015 Survey Data.

Table 4. Results of adaption mechanism

Variables	(1) **CES-D Scores**	(2) **Somatic activity**	(3) **Depressed reaction**	(4) **Positive reaction**
Panel A: Adaption of AC				
Summer if with air conditioner				
Heat exposure days in summer	0.0148	0.0056	0.0035	0.0058
	(0.012)	(0.008)	(0.005)	(0.004)
Observations	10,942	10,942	10,942	10,942
Summer if without air conditioner				
Heat exposure days in summer	0.0266***	0.0173***	0.0086***	0.0007
	(0.007)	(0.005)	(0.003)	(0.002)
Observations	30,341	30,341	30,341	30,341
Panel B: Adaption of Heating				
Winter if with heating				
Cold exposure days in winter	0.0057	0.0018	-0.0005	0.0043
	(0.009)	(0.006)	(0.004)	(0.003)
Observations	29,592	29,592	29,592	29,592
Winter if without heating				
Cold exposure days in winter	0.0298*	0.0144	0.0206***	-0.0052
	(0.018)	(0.011)	(0.007)	(0.006)
Observations	11,658	11,658	11,658	11,658

Notes: (1) All standard errors are clustered at the county/community level. (2) All models include all control variables and individual-, year-, and city- fixed effects. (3) All models are fixed effect models. (4) ***, **, and * indicate significance levels of 1, 5, and 10 per cent, respectively.
Data source: CHARLS 2011, 2013, 2015 Survey Data.

Table 5. Results of robustness checks

	(1)	(2)	(3)	(4)
Variables	**CES-D scores**	**Somatic activity**	**Depressed reaction**	**Positive reaction**
Panel A: Keep only non-migrates				
Heat exposure days	0.0084***	0.0058***	0.0020*	0.0006
	(0.003)	(0.002)	(0.001)	(0.001)
Cold exposure days	0.0155***	0.0102***	0.0060***	-0.0007
	(0.003)	(0.002)	(0.001)	(0.001)
Panel B: Relative indicators – 0.7SD				
Heat exposure days	0.0093***	0.0074***	0.0020	-0.0001
	(0.003)	(0.002)	(0.001)	(0.001)
Cold exposure days	0.0139***	0.0093***	0.0044***	0.0002
	(0.003)	(0.002)	(0.001)	(0.001)
Panel C: Relative indicators – daily maximum/minimum temperatures – 1.96 SD				
Heat exposure days	0.0096***	0.0067***	0.0023*	0.0005
	(0.003)	(0.002)	(0.001)	(0.001)
Cold exposure days	0.0103***	0.0072***	0.0052***	-0.0022*
	(0.004)	(0.002)	(0.002)	(0.001)
Panel D: Absolute temperature indicators				
Exposure days (daily mean temperature>30)	0.0071	0.0033	-0.0015	0.0052**
	-0.008	-0.004	-0.003	-0.002
Exposure days (daily mean temperature<0)	0.0201***	0.0161***	0.0021	0.0020
	(0.007)	(0.004)	(0.003)	(0.002)
Panel E: Absolute temperature indicators				
Exposure days (daily mean temperature<-10)	0.0200**	0.0163***	0.0089**	-0.0053**
	(0.009)	(0.006)	(0.004)	(0.003)
Exposure days (-10<daily mean temperature<=-5)	0.0061	0.0002	0.0072**	-0.0014
	(0.010)	(0.006)	(0.004)	(0.003)
Exposure days (-5<daily mean temperature<=0)	0.0024	0.0010	0.0028	-0.0013
	(0.008)	(0.005)	(0.003)	(0.002)
Exposure days (0<daily mean temperature<=5	0.0055	0.0038	0.0037	-0.0020
	(0.006)	(0.004)	(0.002)	(0.002)
Exposure days (5<daily mean temperature<=10)	0.0025	0.0015	0.0019	-0.0009
	(0.005)	(0.003)	(0.002)	(0.001)
Exposure days (10<daily mean temperature<=15)	0.0050	0.0047*	0.0043***	-0.0040***
	(0.004)	(0.003)	(0.002)	(0.001)
Exposure days (20<daily mean temperature<=25)	0.0032	0.0014	0.0022	-0.0004
	(0.004)	(0.003)	(0.002)	(0.001)
Exposure days (25<daily mean temperature<=30)	0.0007	0.0007	0.0003	-0.0003
	(0.006)	(0.004)	(0.002)	(0.002)
Exposure days (daily mean temperature>30)	0.0212**	0.0157**	0.0027	0.0028
	(0.010)	(0.006)	(0.004)	(0.003)

Panel F: Nonlinear temperature indicators				
40<Cold exposure days<=60	-0.0212	0.1056	-0.0639	-0.0630
	(0.139)	(0.089)	(0.053)	(0.044)
60<Cold exposure days<=80	0.1883	0.3042***	0.0082	-0.1242**
	(0.158)	(0.101)	(0.060)	(0.050)
80<Cold exposure days<=100	0.2829	0.3297***	0.0709	-0.1177**
	(0.182)	(0.117)	(0.069)	(0.056)
Cold exposure days>100	0.3720*	0.4421***	0.0650	-0.1351**
	(0.209)	(0.133)	(0.079)	(0.064)
60<Heat exposure days<=80	0.3995***	0.2096**	0.2350***	-0.0451
	(0.144)	(0.095)	(0.057)	(0.041)
80<Heat exposure days<=100	0.7072***	0.3520***	0.4107***	-0.0555
	(0.164)	(0.108)	(0.065)	(0.046)
100<Heat exposure days<=120	0.8365***	0.4658***	0.4522***	-0.0816
	(0.190)	(0.125)	(0.074)	(0.054)
Heat exposure days>120	0.9435***	0.5816***	0.4036***	-0.0417
	(0.260)	(0.169)	(0.100)	(0.076)
Panel G: Nonlinear temperature indicators				
Heat exposure days	0.0068	0.0112**	0.0006	-0.0050**
	(0.007)	(0.004)	(0.003)	(0.002)
Heat exposure days_2	0.0000	-0.0000	0.0000	0.0000**
	(0.000)	(0.000)	(0.000)	(0.000)
Cold exposure days	0.0277***	0.0174***	0.0128***	-0.0025
	(0.006)	(0.004)	(0.002)	(0.002)
Cold exposure days_2	-0.0001***	-0.0001***	-0.0000***	0.0000
	(0.000)	(0.000)	(0.000)	(0.000)
Panel H: Interaction term with AC				
AC * heat exposure days	-0.0054**	-0.0039**	-0.0026***	0.0010
	(0.003)	(0.002)	(0.001)	(0.001)
Residence has AC	0.8267***	0.4969***	0.2974***	0.0323
	(0.296)	(0.187)	(0.109)	(0.097)
Heat exposure days	0.0118***	0.0080***	0.0035***	0.0002
	(0.002)	(0.002)	(0.001)	(0.001)
Cold exposure days	0.0039	0.0048***	0.0022**	-0.0031***
	(0.003)	(0.002)	(0.001)	(0.001)
Panel I: Interaction term with heating				
Heating * cold exposure days	-0.0025***	-0.0009*	-0.0008	-0.0009*
	(0.001)	(0.000)	(0.001)	(0.000)
Residence has heating	-0.2803**	-0.0929	-0.1071**	-0.0804**
	(0.132)	(0.084)	(0.050)	(0.039)
Heat exposure days	0.0090***	0.0065***	0.0024***	0.0001
	(0.002)	(0.001)	(0.001)	(0.001)
Cold exposure days	0.0081***	0.0062***	0.0037***	-0.0018*
	(0.003)	(0.002)	(0.001)	(0.001)
Panel J: Serve depression symptom (CES-D scores>16)				

Heat exposure days	0.0005***	-	-	-
	(0.000)	-	-	-
Cold exposure days	0.0008***	-	-	-
	(0.000)	-	-	-
Observations	42,780	42,780	42,780	42,780

Notes: (1) All standard errors are clustered at the county/community level. (2) All models include all control variables and individual-, year-, and city- fixed effects. (3) All models are fixed effect models. (4) In panel E, the reference group is the number of exposure days when 15°C<daily mean temperature<=20°C. (5) In panel J, the cutoff of the severe depression symptom is 16 of the score of depression. (6) ***, **, and * indicate significance levels of 1, 5, and 10 per cent, respectively.
Data source: CHARLS 2011, 2013, 2015 Survey Data.

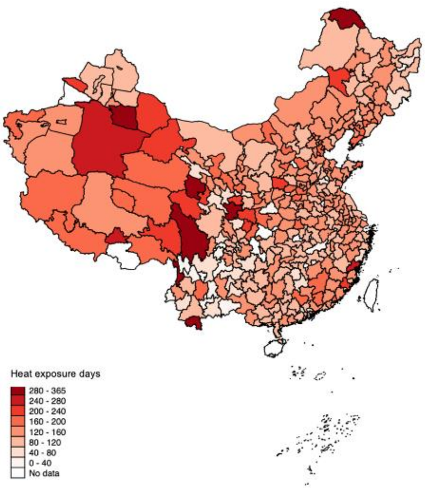


Figure 1. Local heat exposure days in 2017.

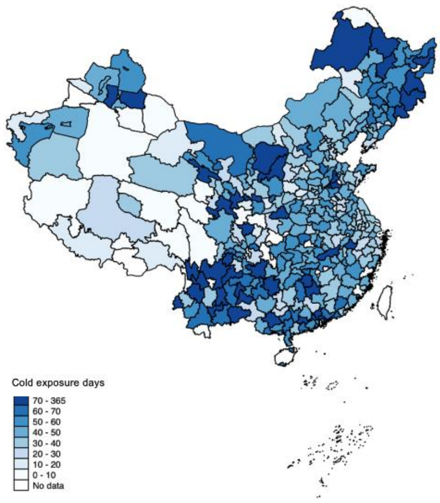


Figure 2. Local cold exposure days in 2017.

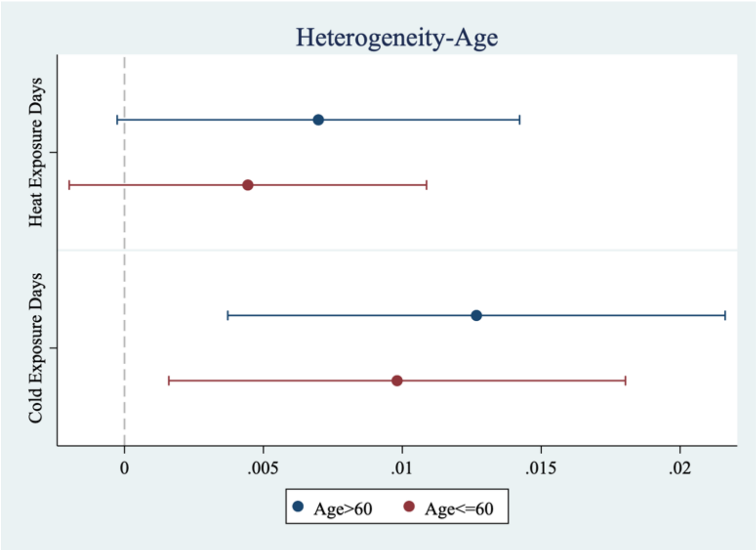


Figure 3. Heterogeneity analysis – age.

Notes: (1) All standard errors are clustered at the county/community level. (2) All models include all control variables and individual-, year-, and city- fixed effects. (3) The coefficient in the graph represents the coefficient of heat/cold exposure days on CES-D score in different age groups.
Data source: CHARLS 2011, 2013, 2015 Survey Data.

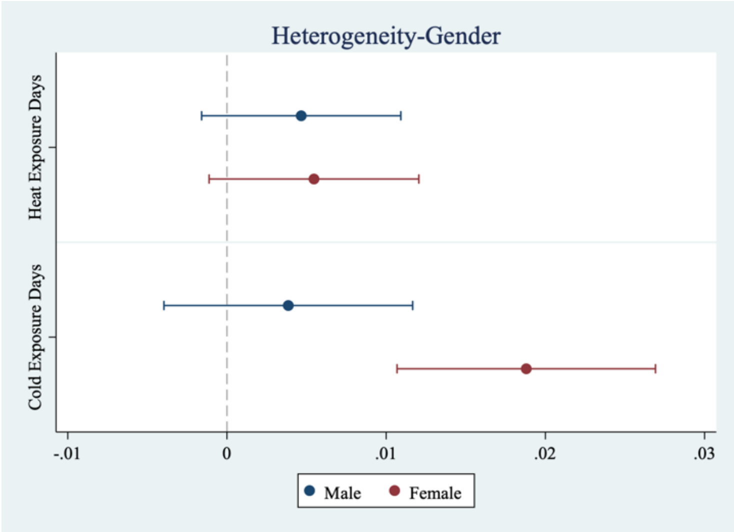


Figure 4. Heterogeneity analysis – gender.

Notes: (1) All standard errors are clustered at the county/community level. (2) All models include all control variables and individual-, year-, and city- fixed effects. (3) The coefficient in the graph represents the coefficient of heat/cold exposure days on CES-D score for males or females.
Data source: CHARLS 2011, 2013, 2015 Survey Data.

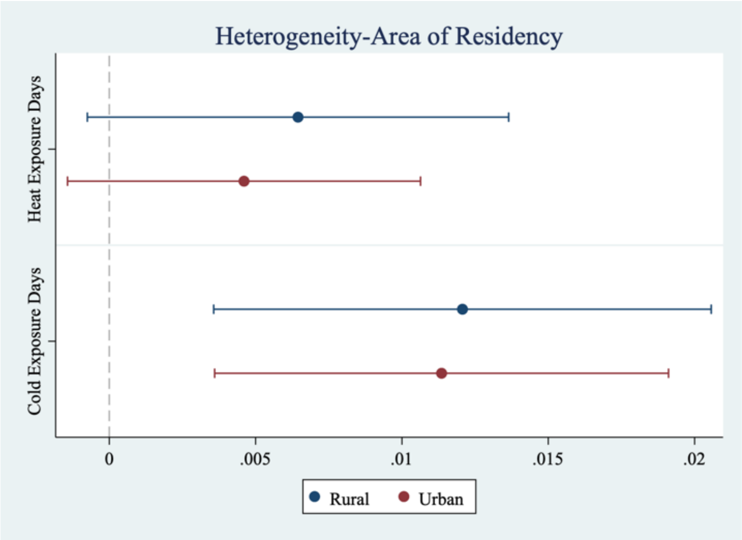


Figure 5. Heterogeneity analysis – area of residency.

Notes: (1) All standard errors are clustered at the county/community level. (2) All models include all control variables and individual-, year-, and city- fixed effects. (3) The coefficient in the graph represents the coefficient of heat/cold exposure days on CES-D score by the area of residency.
Data source: CHARLS 2011, 2013, 2015 Survey Data.

Appendix

Table A1. Main results of the basic model – with city-specific linear trend

	(1)	(2)	(3)	(4)
Variables	**CES-D**	**Somatic activity**	**Depressed Reaction**	**Positive reaction**
Heat exposure days	0.0058**	0.0047***	0.0011	-0.0000
	(0.002)	(0.001)	(0.001)	(0.001)
Cold exposure days	0.0125***	0.0086***	0.0048***	-0.0009
	(0.003)	(0.002)	(0.001)	(0.001)
Precipitation	-0.0030	-0.0030	0.0025	-0.0025
	(0.011)	(0.007)	(0.004)	(0.003)
Wind speed	0.1937	0.1244	0.0134	0.0560
	(0.143)	(0.093)	(0.054)	(0.042)
Sunshine duration	-0.0135	0.0332	0.0412	-0.0879***
	(0.079)	(0.051)	(0.030)	(0.024)
Relative humidity	-0.0237*	-0.0162*	-0.0053	-0.0022
	(0.014)	(0.009)	(0.005)	(0.004)
Air pressure	0.0500*	0.0410**	0.0138	-0.0048
	(0.028)	(0.018)	(0.011)	(0.008)
PM2.5	0.0266***	0.0216***	0.0151***	-0.0101***
	(0.010)	(0.007)	(0.004)	(0.003)
City-specific linear trend	YES	YES	YES	YES
Observations	41,283	41,283	41,283	41,283

Notes: (1) All standard errors are clustered at the county/community level. (2) All models include all control variables and individual-, year-, and city- fixed effects. (3) All models are fixed-effect models. (4) ***, **, and * indicate significance levels of 1%, 5%, and 10%, respectively.
Data source: CHARLS 2011, 2013, 2015 Survey Data.

Table A2. Heterogeneous effects

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	**>60**	**<60**	**Male**	**Female**	**Rural**	**Urban**
Heat exposure days	0.0070*	0.0044	0.0047	0.0055	0.0064*	0.0046
	(0.004)	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)
Cold exposure days	0.0127***	0.0098**	0.0039	0.0188***	0.0121***	0.0114
	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)	(0.041)
Observations	19,992	21,291	19,551	21,728	16,383	24,900
Average depression scores	10.670	10.093	9.375	11.271	10.863	9.627

Notes: (1) All standard errors are clustered at the county/community level. (2) All models include all control variables and individual-, year-, and city- fixed effects. (3) All models are fixed effect models. (4) ***, **, and * indicate significance levels of 1%, 5%, and 10%, respectively.
Data source: CHARLS 2011, 2013, 2015 Survey Data.

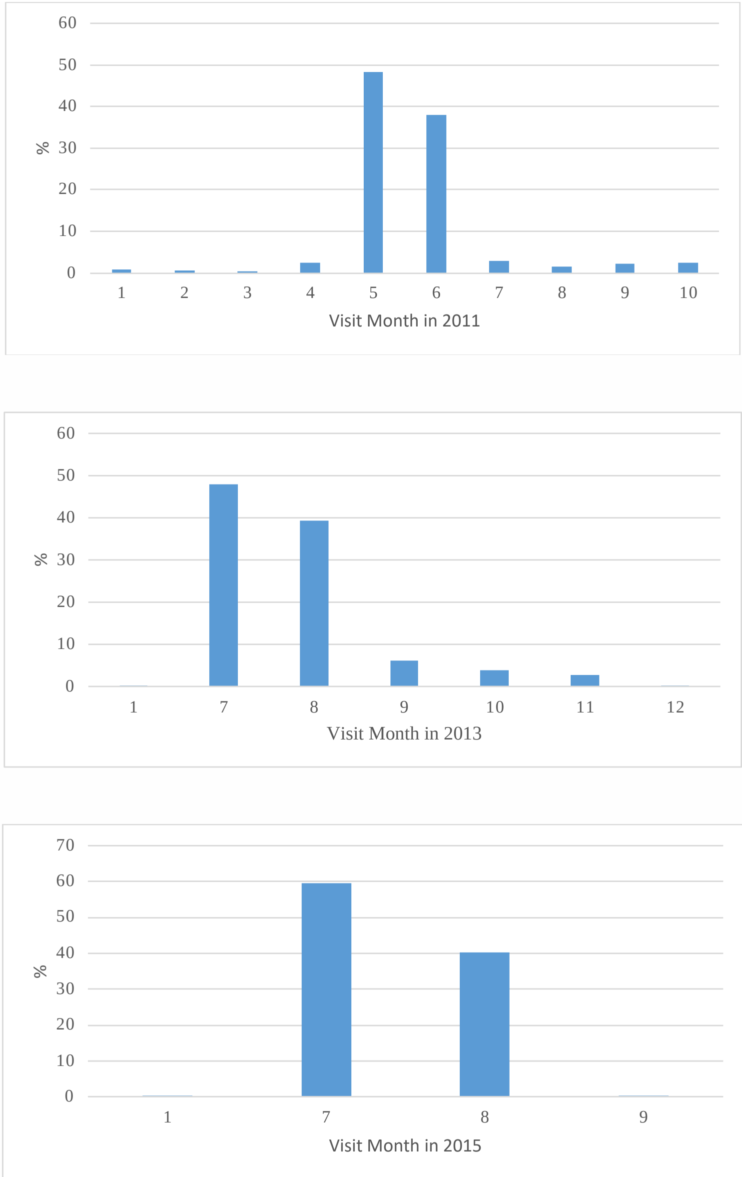
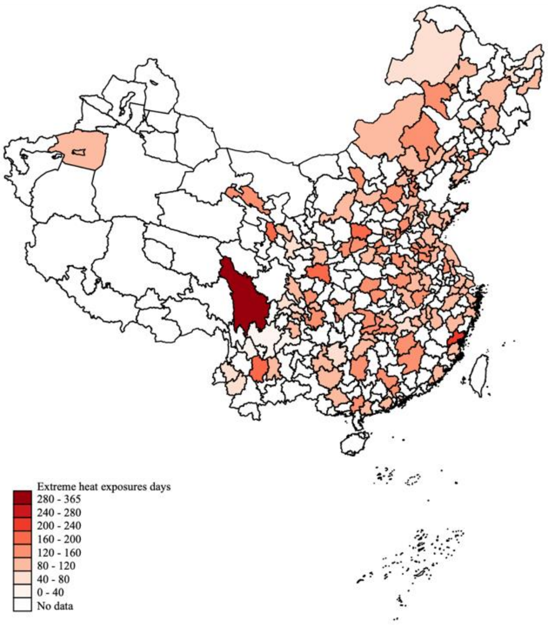


Figure A1. Distribution of interview visit month in CHARLS.



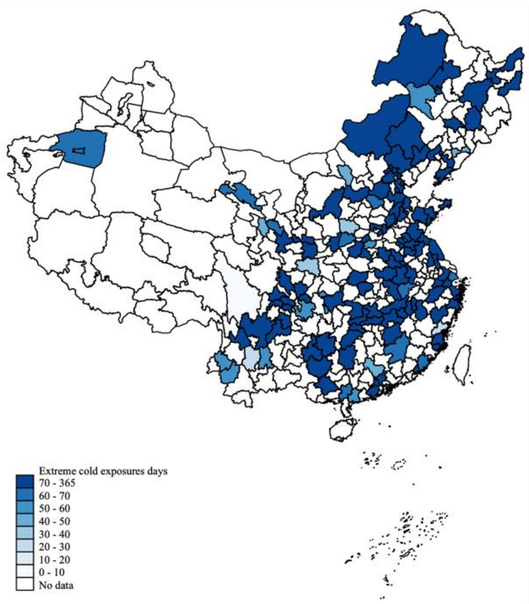
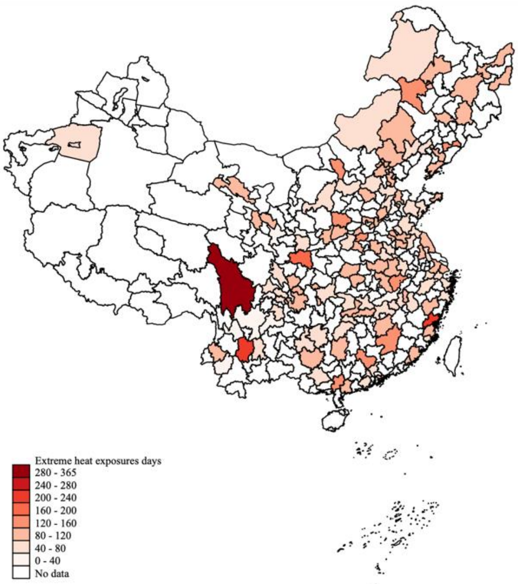


Figure A2. Extreme heat exposures in 2011 of CHARLS**.** **Figure A3.** Extreme cold exposures in 2011 of CHARLS.



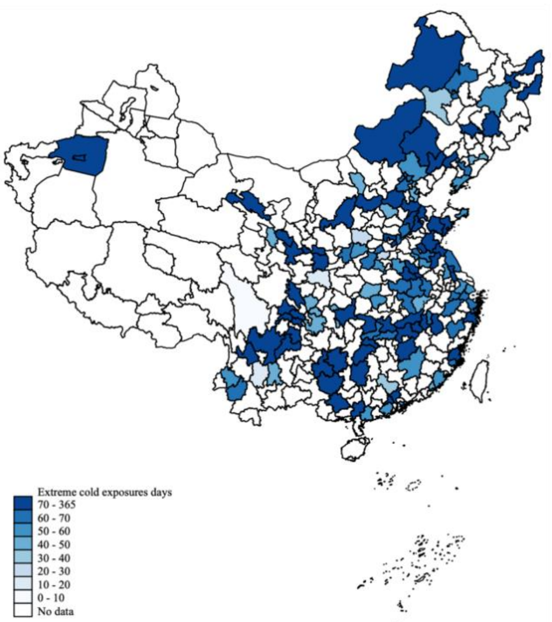


Figure A4. Extreme heat exposures in 2011 of CHARLS**.** **Figure A5.** Extreme cold exposures in 2011 of CHARLS.

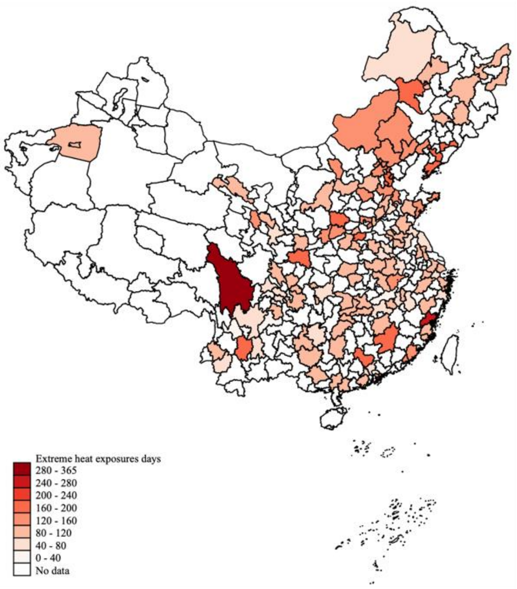


Figure A6. Extreme heat exposures in 2011 of CHARLS.

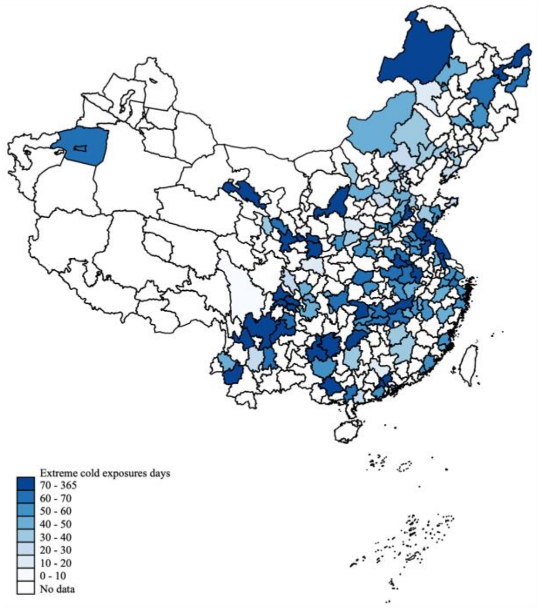


Figure A7. Extreme cold exposures in 2011 of CHARLS.