China Economic Review 77 (2023) 101894

Contents lists available at ScienceDirect

China Economic Review

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

Extreme temperatures and out-of-pocket medical expenditure: Evidence from China

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ARTICLE INFO

JEL:
Q50
Q53
Q54
I13
I14
I15

Keywords:
Climate change
Extreme temperatures
Out-of-pocket medical expenditure
Health burden
Future predictions

ABSTRACT

We estimate the causal effect of extreme temperatures on out-of-pocket medical expenditure. To do so we match data from three waves of China Family Panel Studies, a nationally representative longitudinal survey for China, with daily weather records in the county in which the person lives. We find that both extreme cold and extreme heat increase expenditure and that the effect of hot days on out-of-pocket medical expenditure is collectively larger than that of cold days. Extreme temperatures increase time engaged in sedentary activities and contribute to sleep disruption and energy poverty, which adversely affect physical and mental health. Combining our preferred estimates with daily temperature projections from recent climate models, we find that out-of-pocket medical expenditure would increase by 2.290–6.149% in the medium term (2041–2060), depending on whether measures are taken to curb greenhouse gas emissions. Our study highlights a growing, but previously neglected, burden stemming from climate change.

1. Introduction

One of the adverse effects of climate change is that it has increased the medical burden on households. We lack evidence, though, on the causal effect of extreme temperatures, a main manifestation of climate change, on out-of-pocket medical expenditure borne by patients. In this study we examine how extreme temperatures have affected out-of-pocket medical expenditure in China. The Chinese context provides an ideal setting in which to situate our study. While over 95% of the Chinese population is covered by public healthcare, few people have commercial health insurance and out-of-pocket payments, especially for accessing specialized treatment, make up the major component of healthcare expenditure (Fu, Zhao, Zhang, Chai, & Goss, 2018). China also has a large and growing aging population who are prone to chronic diseases, many of whom require specialized treatments that are not covered by public healthcare. Many chronic diseases, especially those associated with the cardiovascular and respiratory systems, are particularly sensitive to extreme temperatures (see e.g. Haines & Ebi, 2019; Wang et al., 2019; Yang et al., 2015).

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https://doi.org/10.1016/j.chieco.2022.101894
Received 16 March 2022; Received in revised form 6 October 2022; Accepted 16 November 2022
Available online 28 November 2022
1043-951X/

Understanding the causal effect of extreme temperatures on out-of-pocket medical expenditure is crucial for at least three reasons. First, existing studies have consistently shown that exposure to extreme temperatures, particularly heat stress, can lead to higher rates of morbidity (Agarwal, Qin, Shi, Wei, & Zhu, 2021; Deschenes, Greenstone, & Guryan, 2009; Mullins & White, 2019; Obradovich, Migliorini, Mednick, & Fowler, 2017; White, 2017) and mortality (Barreca, Clay, Deschenes, Greenstone, & Shapiro, 2016; Deschenes & Greenstone, 2011; Karlsson & Ziebarth, 2018; Rocha & Soares, 2015), both of which can be expected to significantly increase healthcare expenditure.[1] The health impacts of climate change are arguably difficult to avoid. Unlike ambient air pollution, which can be avoided through simply wearing facemasks, the cost of shielding from ambient heat stress is potentially much higher; for instance, the use of air-conditioned transportation, such as private cars, which remain expensive and less prevalent in developing countries.

Second, out-of-pocket medical expenses are closely related to people's wellbeing. Large out-of-pocket medical expenditure impedes consumption (Bai & Wu, 2014) and is widely regarded as a major cause of impoverishment among patients, especially those suffering from chronic disease (Barcellos & Jacobson, 2015; Card, Dobkin, & Maestas, 2008; Meng et al., 2012; Wagstaff, Lindelow, Jun, Ling, & Juncheng, 2009). The medical burden imposed on households from out-of-pocket expenses has been shown to crowd out investment in human capital and other productive assets, thus trapping the household into long-term poverty (Chen & Jin, 2012; Liu, 2016).

Third, when out-of-pocket medical expenditure exceeds what patients reasonably expect it should be, this can be a source of distrust and even conflict with physicians, both of which are growing concerns in China (Nie et al., 2018; Yan, 2018). Healthcare providers in China are allowed to recover their cost by charging for services and the margins are higher for specialized treatments that are typically not covered by public healthcare. This also provides health providers with incentives to generate profits through, for example, over prescription or overtreatment, which impose heavy financial burdens on patients.

We link data on individual-level medical expenditure by respondents across three waves of the China Family Panel Study (CFPS), which is a nationally representative longitudinal survey administered between 2014 and 2018, to daily weather records from 820 weather stations situated across China. To capture potential nonlinear effects, we adopt a semi-parametric approach that divides the distribution of daily mean temperatures into a set of temperature bins and estimates their impact on out-of-pocket medical expenditure. We control for individual fixed effects, which enables us to identify the causal effect of daily temperature on medical expenditure using the plausibly exogeneous variation in the temperature distribution to which each respondent was exposed over time. Note that, our sample covers the record-breaking 2017 heatwave that occurred from the 21st to the 25th of July and saliently affected half of the national population (Kang & Eltahir, 2018). It significantly increases the observations of extreme warm days, and therefore, improves the identification of the temperature effect on medical expenditure at the high end of the temperature distribution (Graff Zivin & Neidell, 2014).

We find that temperature exerts a nonlinear effect on out-of-pocket medical expenditure, but the effect is strongest at hotter temperatures. Extreme cold temperature, defined as daily mean temperature below −7 degrees Celsius (°C), increases out-of-pocket medical expenditure. Moderately warm temperature, in the range 16 °C–21 °C, increases out-of-pocket medical expenditure by 0.85%, relative to a day in the reference range 10 °C–16 °C. This effect grows progressively for higher temperatures and more than triples to 2.80% when the mean temperature is above 32 °C. These baseline results are robust to a variety of ways to measure temperature and other sensitivity checks.

The baseline nonlinear pattern is heterogeneous across different cohorts. We find that both cold and heat stress impose a larger medical burden on males, possibly because they are more likely to work outdoors. Consistent with the results from epidemiological studies, we find that cold stress imposes a larger medical burden on elderly cohorts. We find that those who report being in poor health are less responsive to ambient stress, possibly because they have intentionally avoided being exposed to extreme temperatures. We also find that heat stress imposes a larger medical burden on rural and poor cohorts, implying that global warming may exacerbate income and rural-urban inequality. Estimates across different public healthcare schemes provide consistent results that temperature effects are much larger among those enrolled in the New Rural Cooperative Medical Scheme (NRCMS), which is a scheme exclusively for the rural population. Finally, we uncover suggestive evidence of acclimatization, in which respondents in southern China are more tolerant to heat stress while northern respondents are more tolerant to cold stress.

We examine the mechanisms underpinning these results and find suggestive evidence that extreme temperatures increase the medical burden on households through impairing both physical and mental health. By exploiting detailed records on a set of daily activities of respondents in CFPS, we show that the established temperature–health relationship is mediated through sedentary activities and sleep disruption. We also find that extreme temperatures are positively related with proclivity to be in energy poverty and that energy poverty, in turn, is associated with adverse health impacts.

Combining our baseline estimates with daily temperature projections from eight very recent climate models from the Coupled Model Intercomparison Project (CMIP6), used in the latest IPCC sixth assessment report, we simulate changes in future out-of-pocket medical expenditure due to climate change. We find that medical expenditure would increase by 2.290–6.149% in the medium term between 2041 and 2060, depending on policy interventions to curb greenhouse gas emissions. Given that both extreme heat and cold increases out-of-pocket medical expenditure, the moderate increase in out-of-pocket medical expenditure can be attributed to there being fewer extreme cold days in the future, which somewhat offset the effects of hotter days.

We contribute to the literature on the environment and medical expenses in three ways. First, we distinguish between the effect of temperature on public and private medical expenditure. Most existing studies that have examined the relationship between ambient temperature and medical expenses have focused on *total* medical expenditure and done so within the context of developed countries.

[1] Other related studies exploit the long-term effect of weather shocks during one's early, but critical, life stages and find persistently negative effects on adult outcomes (see e.g. Dinkelman, 2017; Hyland & Russ, 2019; Maccini & Yang, 2009).

For instance, White (2017) and Karlsson and Ziebarth (2018) estimate total medical expenditure by multiplying average cost per each hospital visit by the number of visits predicted from their estimated temperature-morbidity relationship. Estimates using this approach, though, are subject to potentially large errors. More crucially, this approach does not differentiate between public and private medical expenditures, for which the underlying incentives are different for both patients and healthcare providers (Iizuka, 2012; Lu, 2014). To the best of our knowledge, Agarwal et al. (2021) is the only related study that makes a distinction between public and private medical expenditures. We differ from that study in other ways, which we detail below.

As the second contribution, we provide the estimates of projected out-of-pocket medical expenditure by the middle of this century due to global warming, using simulated daily temperatures from the latest climate models. These estimates are important because projections of the healthcare burden due to global warming is imperative to healthcare planning and lays the foundations for future healthcare reforms.

Finally, we also complement the studies that explore the effect of ambient air pollution on medical expenditure (see e.g. Barwick, Li, Rao, & Zahur, 2018; Deryugina, Heutel, Miller, Molitor, & Reif, 2019; Yang & Zhang, 2018). While weather variables, including temperatures, are routinely controlled in these studies, none of them discuss and even report the estimated effects on medical expenditure. In our analysis, we incorporate air quality index (AQI) at the same spatial scale and instrument it with the strength of thermal inversions occurred in the same exposure window. While our horse race regression results demonstrate that air pollution exerts a larger effect than that of extreme temperatures, the aggregate burden stemming from climate change is arguably larger because of its global nature.

The closest study in the literature to ours is Agarwal et al. (2021), who provide estimates of the aggregated effects of extreme temperatures on out-of-pocket medical expenditure, using inpatient visit claims from 47 Chinese cities.

We differ from Agarwal et al. (2021) in important ways. The first is Agarwal et al. (2021) focus exclusively on urban patients who arguably have access to more generous public healthcare. Our paper explores a nationally representative panel; in which, nearly two-thirds of respondents are from more vulnerable, rural households, who used to cover the much of medical burden themselves Second, Agarwal et al. (2021) only consider individuals who have been charged and, therefore, recorded by healthcare providers, which may induce selection bias along health status. This issue is mitigated in our paper as we study a sample of randomly selected individuals and their reported out-of-pocket medical expenditure are not necessarily paid to healthcare provider (e.g. private pharmacy). Third, we use an individual-level panel which enables us to control for individual fixed effects. Agarwal et al. (2021) employ cross-sectional administrative data, which cannot control for time-invariant individual attributes (Obradovich et al., 2017; Obradovich, Migliorini, Paulus, & Rahwan, 2018). These individual attributes, however, are crucial in that they are strongly related to one's innate health and, therefore, susceptibility to temperature shocks. Fourth, unlike Agarwal et al. (2021), we examine the channels through which temperature influences out-of-pocket medical expenditure and find that temperature changes contribute to increases in time engaged in sedentary activities, sleep disruption and energy poverty, which adversely affect physical and mental health. Fifth, Agarwal et al. (2021) do not we provide estimates of the projected out-of-pocket medical expenditure due to global warming.

Our main findings are different than Agarwal et al. (2021) in terms of both the focus and magnitude of the estimates. They find that an additional warm day would generate two billion RMB additional medical expenditure nationwide; of which, 0.2 billion RMB would be borne by patients themselves. By contrast, we provide individual-level estimates, suggesting that patients and their families have to pay at least 181.89 RMB for each extreme warm day.[2]

2. Background

2.1. Climate change in China and related health burdens

The average temperature in China has increased by 1.2 °C since the 1960s, which is faster than the global rate of warming (Wang et al., 2019). Without taking steps to mitigate warming, average temperature is predicted to be 4–6.4 °C warmer by the end of this century (Piao et al., 2010). Climate change can have direct adverse effects on health. Epidemiological studies show that exposure to heat stress may induce physiological changes, exacerbating hypertension and increasing the risk of heart failure (Yang et al., 2015). Higher temperatures can also impair human health via altering disease patterns. Warm temperatures, together with limited precipitation, are conducive for vectors and pathogens, which facilitate the incidence and transmission of infectious diseases (Gething et al., 2010). Bi, Shi, and Liu (2020) show that warmer temperatures in China have induced diseases such as dengue, malaria and hemorrhagic fever with renal syndrome (HFRS).

There are also indirect channels through which climate change can negatively affect human health. As a result of higher ambient temperatures, people may reduce time allocated to outdoor activities, which adversely affect both physical and mental health (Graff Zivin & Neidell, 2014; Haines & Ebi, 2019; Heaney, Carrión, Burkart, Lesk, & Jack, 2019). Higher temperatures depress worker productivity, result in crop failure and greater incidence of violent conflict, each of which impede nutrient intake and access to healthcare (Blakeslee & Fishman, 2018; Burke & Emerick, 2016; Chen, Chen, & Xu, 2016; Hsiang, Burke, & Miguel, 2013; Yu, Lei, & Wang, 2019; Zhang, Chen, & Zhang, 2018; Zhang, Deschenes, Meng, & Zhang, 2018). Vulnerable cohorts including women, the elderly, young children and people with preexisting conditions are more prone to these indirect channels. Moreover, higher

[2] Our findings are not directly comparable with those of Agarwal et al. (2021). We cannot aggregate our estimated, individual-level, out-of-pocket medicial expenditure due to extreme warm days to the population level and compare it to the Agarwal et al. (2021) estimate, as their sample is not nationally representative and covers 47 Chinese cities only.

temperatures can increase the incidence of energy poverty (Feeny, Trinh, & Zhu, 2021; Li, Smyth, & Yao, 2022), which has been shown to negatively affect both physical and mental health (Awaworyi Churchill & Smyth, 2021; Awaworyi Churchill, Smyth, & Farrell, 2020; Zhang, Appau, & Kodom, 2021).

2.2. Healthcare burden in China

Out-of-pocket payments account for a disproportionate share of total medical expenditure in China. In 2001, patients covered two-thirds of medical expenditure out of their pockets. While a set of national healthcare reforms halved this figure to 36% in 2017, it is still much higher than other countries at comparable levels of development (Fu et al., 2018). The share of out-of-pocket expenses is even higher for specialized care needed to treat many chronic diseases that are exacerbated by global warming.

Three basic health insurance schemes have been established by the central government, and implemented at the discretion of local authorities, to alleviate the financial burden of healthcare on patients. The Urban Employee Basic Medical Insurance (UEBMI) is compulsory for all urban employees in the formal sector, while other urban residents can voluntarily participate in the Urban Residents Basic Medical Insurance (URBMI). Rural residents, regardless of their employment status, are covered by the New Rural Cooperative Medical Scheme (NRCMS). These three public schemes together cover over 95% of the population in China. Commercial medical insurance, by contrast, is still in its relative infancy. Using the China Health and Nutrition Survey, Wu and Ercia (2021) estimate that only 2.5% of people were enrolled in commercial medical insurance in China in 2015, accounting for just 3.6% of total medical expenditure.

Out-of-pocket expenses under the public healthcare schemes are high for several reasons. First, public healthcare premiums are modest, limiting the range of treatments on which they can provide reimbursements. Patients who need prescribed drugs and clinical checks outside the public healthcare's designated list, which are usually the premium offerings, have to pay for them themselves. Second, all three healthcare schemes have established complex deductibles, co-payments and ceiling rules to share the financial cost with patients, making the minimum expenditure in order to seek reimbursement high (Wagstaff et al., 2009). Several studies have found that the reimbursement rate for inpatient care is between 8% and 15%, much lower than the statutory rate of 44% (Yi, Zhang, Singer, Rozelle, & Atlas, 2009; Zhang, Ma, Chen, & Gao, 2017). Third, because the schemes are administered at the discretion of local authorities, reimbursement rates depend on local fiscal capacity and, hence, vary substantially across China. This makes medical affordability a particularly pressing challenge in less developed areas, in which fiscal constraints mean that reimbursements from public healthcare schemes are lower. Finally, all healthcare schemes are geographically segmented. Migrants who utilize local medical services need to fully cover their expenditure first and seek later reimbursement in their hometowns.

2.3. Reimbursement policy of China's public healthcare

Reimbursement is dependent upon the quantity and quality of medical services that patients receive, rather than the specific disease(s) with which they are diagnosed. Patients with severe diseases, though, tend to have lower reimbursement rates, because they utilize more medical services and often tap services that are outside the designated list. The designated list, which is further divided into a drug list, clinical check list and inpatient care list, is the main reference point for claiming reimbursement. Take the drug list as an example - cheap and widely used drugs are fully reimbursed, while some highly specialized and more expensive drugs, if on the list, are partially reimbursed. Drugs not on the list have to be fully paid for by patients themselves and, thus, greatly contribute to out-of-pocket medical expense. The same logic applies to the clinical check and inpatient care lists.

It is important to realize that the designated lists are different across each of the three types of public healthcare. Because it has a higher premium, UEBMI has more deductibles, a higher reimbursement ceiling, and covers a wider range of medical services. On the other hand, reimbursements are much lower for those enrolled in NRCMS, therefore, exposing many rural households to potentially larger healthcare burdens (Yi et al., 2009).

3. Dataset and empirical strategy

3.1. CFPS

We use three waves of the CFPS survey administered in 2014, 2016 and 2018 to estimate the relationship between temperature and out-of-pocket medical expenditure.[3] The CFPS, which was launched in 2010 by the Institute of Social Science Surveys (ISSS) with Peking University, employs a multistage probability sampling procedure. It is nationally representative, covering 162 counties or districts (counties thereafter) across 25 mainland provinces that represent 95% of the total population in China. During the first wave,

[3] The 2010 wave recorded total medical expenditure rather than out-of-pocket medical expenditure. While the 2012 wave also recorded out-of-pocket medical expenditure, the definition was different. In the 2012 wave, respondents were asked what their medical expenditure was in "the last calendar year", which is not linked to the month of the interview. Beginning in the 2014, the timeframe changed to a rolling year, defined as the 12 months preceding the interview month.

the CFPS completed interviews with 33,600 individuals living in 14,798 households. These individuals were reinterviewed biennially. Due to strict migration controls associated with the household registration system (*hukou*) in China, approximately 93% of individuals living in rural counties in 2010 had been living in the same counties since their birth.[4] This feature ensures that migrant workers, whose exposure to temperature anomalies are harder to pinpoint, are less likely to bias our estimates.[5]

We employ the restricted version of CFPS that provides information on interview month and county of residence for each respondent, enabling us to match them with county-level weather variables. We exclude individuals for whom the interview date is not recorded and those who did not provide their residential address.

Table 1 summarizes the main variables used in the analysis. The upper part contains a set of individual-level variables. In our sample, 95% of respondents reported having out-of-pocket medical expenditure. The mean out-of-pocket medical expenditure was 2842 RMB, accounting for 14.39% of net per capita annual income. This figure implies that the medical burden is universal and large in the context of China. The large medical burden, however, is unlikely to be due to generally poor health. Most respondents self-reported that they were in good health and only a small portion of respondents suffered sleep disruption and different forms of mental health problems. Regular smokers and drinkers accounted for <25% of respondents. By contrast, over 40% of respondents reported regularly engaging in outdoor physical exercise.

3.2. Daily weather data

We obtain weather data from the China Meteorological Administration (CMA). Specifically, we use daily observations from 820 synoptic weather stations, which consistently record mean temperature, maximum temperature, precipitation, atmospheric pressure, wind speed, the direction of maximum wind speed, relative humidity and the duration of sunshine for the period 1980–2020. Continuous recording can alleviate bias when spatially interpolating weather variables (Auffhammer, Hsiang, Schlenker, & Sobel, 2013). The weather data from the synoptic stations are subject to stringent quality controls. The rate of missing data is <0.1%, and the accuracy of the data is nearly 100%.

Synoptic stations are irregularly placed across China. We employ an inverse distance weighting approach to spatially interpolate weather variables. Following Yu et al. (2019), we first set the cut off distance, which is the radius from the county centroid, at 80 km.[6] Stations within this range are used to construct our measure of county-level weather with less distant stations being given greater weight in the interpolation process. To increase accuracy, we drop stations that are deployed on the top of mountains, where elevations are much higher than usual residential areas.

The lower part of Table 1 reports the interpolated, county-level weather variables. To retain flexibility, we categorize the annual distribution of daily mean temperatures into ten temperature bins: (below −12 °C), [−12 °C -7 °C), [−7 °C -1 °C), [−1 °C 4 °C), [4 °C 10 °C), [10 °C 16 °C), [16 °C 21 °C), [21 °C 27 °C); [27 °C 32 °C) and [32 °C above). Each county, on average, has 1.40 extreme hot days, defined as daily mean temperature above 32 °C and 5.20 extreme cold days, defined as daily mean temperature below −12 °C. However, heat stress is more prevalent because each county, on average, has 37.70 days with daily mean temperatures between 27 °C and 32 °C. Fig. 1 plots the annual distribution of daily temperature bins averaged over the period 2014 to 2018 for four different samples. The distributions are similar between all Chinese counties and counties surveyed by CFPS, implying that CFPS counties are representative of variations in temperature patterns for China as a whole. Counties in northern China have far more days with mean temperature below −1 °C, in contrast to southern counties, in which warm days are more common.

3.3. Climate change prediction data

Future climate data are obtained from the latest Coupled Model Intercomparison Project (CMIP6), which was used in the IPCC sixth assessment report. The CMIP6 released monthly values of minimum and maximum temperatures for the medium term (mean temperatures for 2041–2060) and the long term (mean temperatures for 2061–2080), projected by nine global climate models (GCMs) under four Shared Socioeconomic Pathways (SSP): SSP126, SSP245, SSP370 and SSP585.[7] These pathways are more recent versions of the Representative Concentration Pathways (RCPs): RCP2.6, RCP4.5, RCP6.0 and RCP8.5, that have been applied in previous studies (Yu et al., 2019; Zhang, Guo, Smyth, & Yao, 2022).

We limit our projection to the medium term because of the high uncertainty associated with healthcare reform and the potential for breakthroughs in medical technologies in the long run. Assuming that these factors will be constant in the distant future is unrealistic. Moreover, as we explain below, our projection relies on the historical probability distribution functions of daily mean temperature. Extending this distribution function out to the end of the century would require unrealistic assumptions.

We use future temperature projections from eight of the nine GCMs at 2.5-min spatial resolution (about 4.5 km at the equator); the

[4] The *hukou* or household registration system limits where Chinese citizens may live, work and obtain public health care or schooling. Citizens can physically move to other places with better ambient environment. However, without registering their local *hukou*, migrants are excluded by local government from assessing those social benefits.

[5] In robustness checks, we exclude those who had moved, and those without a local *hukou*, and get qualitatively the same results.

[6] We use alternative cut off distances, at 40 km and 160 km, and the results are qualitatively the same. Full regression results are available upon request.

[7] The nine GCMs are as follows: BCC-CSM2-MR, CNRM-CM6–1, CNRM-ESM2–1, CanESM5, GFDL-ESM4, IPSL-CM6A-LR, MIROC-ES2L, MIROC6, MRI-ESM2–0. Detailed information can be found athttps://www.worldclim.org/data/cmip6/cmip6climate.html

Table 1
Summary statistics.

Variables	Obs.	Mean	Std. Dev.	Min	Max
Individual-level variables					
OOP (Amount)	50,558	2842	9267	0	510,000
OOP > 0 (Yes = 1)	50,558	0.950	0.219	0	1
Gender (Male = 1)	50,558	0.462	0.499	0	1
Age	50,558	38.11	25.76	0	95
Elderly cohort Age > 45 (Yes = 1)	50,558	0.507	0.500	0	1
Educated (High School & above Yes = 1)	50,558	0.213	0.409	0	1
Good health (Yes = 1)	50,558	0.588	0.492	0	1
Sleep disruption (Yes = 1)	50,558	0.148	0.355	0	1
Smoking (Yes = 1)	50,558	0.243	0.429	0	1
Drinking (Yes = 1)	50,558	0.120	0.326	0	1
Outdoor exercise (Yes = 1)	47,045	0.425	0.494	0	1
Net income per capita	49,012	19,753	59,481	0	5,660,000
Feel lonely (Yes = 1)	31,327	0.0388	0.193	0	1
Feel unhappy (Yes = 1)	31,338	0.0857	0.280	0	1
Feel sad (Yes = 1)	31,338	0.0312	0.174	0	1
County-month level variables					
AQI index	1944	76.45	27.37	29.26	188.4
Thermal inversion strength	1944	−0.465	0.374	−2.510	0
Thermal inversion occurrences	1944	40.18	21.33	0	109.4
County-year level variables					
(below −12°)	810	5.195	17.03	0	132
[−12 °C -7 °C)	810	7.215	12.83	0	51
[27 °C 32 °C)	810	37.70	36.34	0	153
[32 °C above)	810	1.402	3.500	0	22

Notes: individual-level variables are obtained and constructed from CFPS wave 2014 to wave 2018. Air quality data is obtained from CNEMC and weather data is compiled from CMA. The station-level weather and air quality data are interpolated to their local county counterparts by using inverse-distance weighting.

scale at which the temperature variables are available for all Chinese counties.[8] We focus on SSP126 and SSP585, which reflect two extreme emission pathways, in the medium-term. SSP126 assumes a more equal and sustainable development path, with few challenges to mitigation and adaptation to climate change. By contrast, SSP585 follows a "business-as-usual" scenario, with greenhouse gases emissions growth unchecked for the rest of the century.

We follow Hsiang et al. (2017) to generate the county-level projections of future daily mean temperature in three steps. First, using daily mean temperature over the period 1980–2014, we construct monthly mean temperature and monthly probability distribution functions of daily mean temperature for all sampled counties. Second, we compute the projected changes in monthly mean temperature for each county, which is the difference between projected monthly mean temperatures and the historical mean temperatures. Third, we assume that the distribution of projected daily mean temperature mirrors its historical distribution and construct each county's distribution of daily mean temperatures in the medium term, consistently for the two emission pathways – SSP126 and SSP585.

3.4. Air quality index

We use an air quality index (AQI), which comprises six air pollutants, ($PM_{2.5}$, PM_{10}, SO_2, NO_2, O_3 and CO) to proxy air pollution. We compile the daily AQI from the China National Environmental Monitoring Centre (CNEMC), an automated, real-time, nationwide monitoring network, consisting of 1497 stations across China.[9] The network was established to provide reliable data on air pollution and overcome biases introduced by data manipulation by local officials, seeking to misrepresent their environmental performance (Ghanem & Zhang, 2014; Greenstone, He, Jia, & Liu, 2020). We use the same method and cut off distances to spatially interpolate station-level AQI to its county-level equivalent as we do when constructing the county weather variables. The lower part of Table 1 shows that the mean monthly AQI value is 76.45, which is well below 100, the threshold value for good air quality. Because most monitoring stations are strategically placed in large cities, the interpolated AQI in rural areas could be biased. This issue is exacerbated in our context, as over half of the counties surveyed in CFPS are in rural areas. Thus, as an alternative measure of pollution, we use satellite derived $PM_{2.5}$ concentration, which are obtained from van Donkelaar, Martin, Li, and Burnett (2019), to address this concern. In robustness checks, we find that the results using this proxy are qualitatively similar.

Air pollution is endogenous to human health and, hence, medical expenditure (Arceo, Hanna, & Oliva, 2016; Fan, He, & Zhou,

[8] GFDL-ESM4 did not provide future temperature variables under the SSP585 pathway. Hence, we exclude it.
[9] The official website of the data portal is: https://air.cnemc.cn

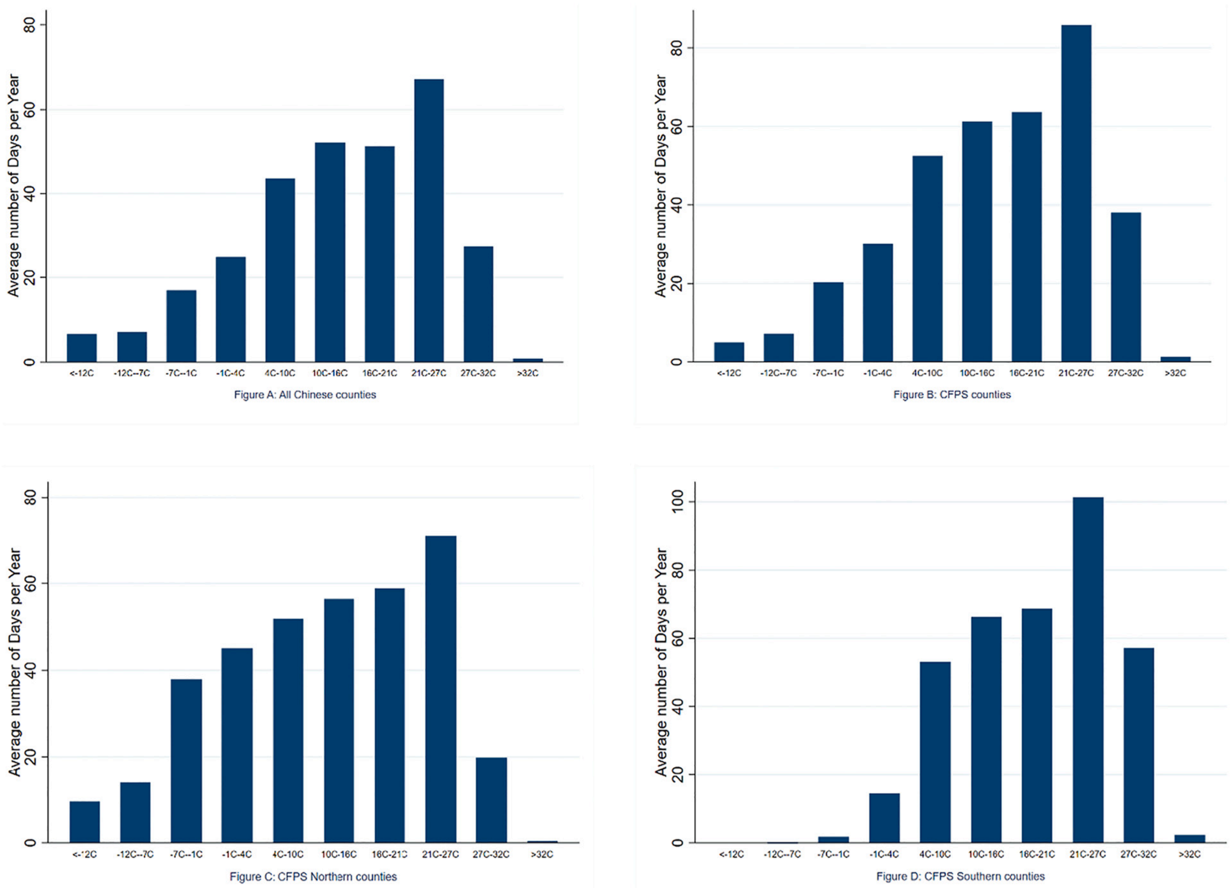

Fig. 1. Daily temperature distribution between 2014 and 2018, by different samples.
Notes: Daily temperature distribution is averaged across counties and years. The dividing line between northern and southern China roughly follows the Huai River and Qinling Mountains, along which the average temperature in January is around zero Celsius (See Fan et al., 2020).

2020; Jans, Johansson, & Nilsson, 2018). We instrument for the AQI with thermal inversions. When thermal inversions occur, the temperature in the upper atmospheric layer is higher than that in the lower layer, thereby trapping air pollution at the surface. The formation of thermal inversions is a complex atmospheric phenomenon and is typically independent of factors that could influence out-of-pocket medical expenditure. Specifically, we use the strength of thermal inversions, which is constructed from NASA's MERRA reanalysis dataset. It is defined using the 110 m layer temperature minus the 340 m layer temperature.[10] A positive difference indicates the nonexistence of thermal inversion and is truncated to zero. A negative difference indicates the existence of a thermal inversion, and its magnitude captures the inversion strength. We aggregate the inversion strength, which is measured at six-hourly frequency, into an exposure window spanning the 12 months preceding the interview. One advantage of using the strength measure is that it has greater predictive power in counties in which thermal inversions are very frequent. As shown in the lower part of Table 1, some counties in the CFPS sample recorded over 100 thermal inversion occurrences, implying that it happened almost constantly.[11]

3.5. Empirical strategy

To examine the effects of daily temperatures on out-of-pocket medical expenditure, we estimate the following specification:

$$ln\_OOP_{ict} = \sum_{m} \beta^m Temp_{ct}^m + \delta' W_{ct} + \delta \widehat{AQI}_{ct} + \gamma_i + \varphi_{py} + \lambda_s + \varepsilon_{ict} \tag{1}$$

Out-of-pocket medical expenditure was constructed based on answers to the following question in the CFPS, which has consistently been asked since 2014:

[10] We also define thermal inversion strength using alternative layers and obtain very similar results. Full results are available upon request.
[11] The number of maximum thermal inversion occurrences is 124 (4 times a day*31 days).

"*In the past 12 months, medical expenditure paid by you, including with funds borrowed from relatives (but excluding reimbursements or what can be claimed) was _ RMB?*"

We first convert the amount into real terms using the prefectural-level CPI before transforming the value into logarithm form. For a small number of individuals with zero out-of-pocket medical expenditure, we convert them to one before taking the logarithm transformation. The results are almost identical if we instead exclude them.

We categorize the distribution of daily mean temperatures in the 12 months preceding the interview into m temperature bins $\sum_m Temp_{jt}^m$. We divided the distribution of county-level daily temperature, measured in degrees Celsius, into 10 bins: (below −12 °C), [−12 °C -7 °C), [−7 °C -1 °C), [−1 °C 4 °C), [4 °C 10 °C), [10 °C 16 °C), [16 °C 21 °C), [21 °C 27 °C); [27 °C 32 °C) and [32 °C above).[12] This semi-parametric approach imposes a minimal number of functional form restrictions and allows flexible estimation of nonlinear effects across various daily temperature values. To illustrate, $Temp_{ct}^{10}$ [32 °C above) is the number of days with daily mean temperature above 32 °C in county c in the 12-month exposure window preceding the CFPS interview. The semi-elasticity β^m captures the marginal effect of an extra day in which the temperature is in bin m, relative to a day in the reference temperature bin [10 °C 16 °C), which is omitted to avoid perfect multicollinearity. W_{ct} refers to a set of other weather variables; namely, air pressure, relative humidity, accumulated precipitation, sunshine duration, wind speed and the direction of maximum wind speed, over the same exposure window. Following Jones (2021), all weather controls are in the form of flexible third-degree polynomials. We isolate the exogenous component of AQI, denoted by$\widehat{AQI}_{ct}$, by using thermal inversion strength. We do not employ two-stages least squares (2SLS) in the main results, given that air pollution is not the focus of this study and 2SLS is generally considered to be less efficient than OLS (Greene, 2018).[13] We control for various fixed effects to improve the causal identification of temperature effects. Individual fixed effects,γ_i, captures unobserved and time-invariant characteristics of each respondent. The prefecture-by-year fixed effects, φ_{py}, capture annual shocks that are specific to each prefecture, such as changes in reimbursement policy. In addition, we also control for seasonal and public healthcare fixed effects in different specifications.

We exploit the longitudinal structure of the CFPS to identify the causal effect of temperature on out-of-pocket medical expenditure. Specifically, we compare the medical expenditure incurred by the same respondents over time and relate it to plausibly exogeneous variation in the temperature distribution. While the length of exposure window is fixed at 12 months, CFPS interviews were carried out in different months and, therefore, the exposure window within each wave varies across respondents. This feature of the dataset introduces an extra source of variation that improves our causal identification.

We cluster the standard errors at the individual and county-by-year levels. This approach controls for the autocorrelation in medical expenditure for the same individual across different survey years as well as the autocorrelation within each county-year cell. Our results are also robust to a set of different clustering methods.

4. Results

4.1. Main results

Table 2 presents the estimates for eq. (1). All estimates are relative to daily mean temperature between 10 and 16 °C, which is the reference category. We start by controlling for individual fixed effects and other weather variables in the form of third-degree polynomials. Column (2) adds fixed effects for the major public healthcare schemes (e.g. UEBMI, URBMI, NRCMI) in which each respondent is enrolled. The estimated temperature effects remain almost the same.[14] In column (3), we further control for seasonal fixed effects of the interview month, which capture the possibility that respondents may exaggerate medical expenditure during specific seasons (eg. if they have allergies in the summer months or influenza in the winter months, making them feel unwell). To allow for spatial heterogeneity in annual shocks, column (4) also controls for prefecture-by-year fixed effects. Fig. A1 plots the relationship between various temperature bins and out-of-pocket medical expenditure.

While both extreme heat and cold significantly increase out-of-pocket medical expenditure, the effect of warm days is collectively larger than that of cold days. The results from our preferred estimates in column (4) suggest that compared to a day in the 10–16 °C bin, an extra day in the 16–21 °C bins leads to a 0.85% increase in out-of-pocket medical expenditure over the 12 months preceding the CFPS interview. An extra day in the 21–27 °C bin and 27–32 °C bin, respectively, leads to a 1.59% and 2.34% increase in out-of-pocket medical expenditure. An extra extreme heat day, defined as daily mean temperature above 32 °C, generates a 2.80% increase in out-of-pocket medical expenditure. The results for extremely hot days benefit from us having data in our sample from the record-breaking 2017 heatwave, which contribute to the estimated effect being precise and significant at 1 % level. By contrast, only extremely cold days, in which the mean daily temperature is below −7 °C, significantly increase medical expenditure. An extra day in the −7 to

[12] Another measure that can capture thermal stress is the heat index, which is a nonlinear combination of temperature and humidity. However, this index is only valid for temperatures above 80 °F (27 °C) and humidity above 40%; therefore, it cannot be calculated for the entire temperature distribution.

[13] We employ 2SLS in our robustness check section in which we control for air pollution and the point estimates for the temperature bins are similar.

[14] The estimated coefficient of UEBMI is negative and marginally significant. By contrast, the estimated coefficients of both URBMI and NRCMI are positive and insignificant, in line with existing findings that the government sponsored healthcare schemes have largely failed to alleviate the financial burden on patients (Lei & Lin, 2009; Wagstaff et al., 2009; Yi et al., 2009). Full regression results are available upon request.

Table 2
Baseline results.

	(1)	(2)	(3)	(4)	(5)
(below −12°)	0.0342***	0.0340***	0.0373***	0.0363***	0.0407***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.005)
[−12 °C -7 °C)	0.0252***	0.0248***	0.0274***	0.0259***	0.0276***
	(0.005)	(0.005)	(0.006)	(0.006)	(0.006)
[−7 °C -1 °C)	0.0074*	0.0073*	0.0095**	0.0081	0.0076*
	(0.004)	(0.004)	(0.004)	(0.005)	(0.004)
[−1 °C 4 °C)	0.0014	0.0014	0.0021	0.0009	0.0018
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
[4 °C 10 °C)	0.0031	0.0030	0.0030	0.0023	0.0020
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
[16 °C 21 °C)	0.0078***	0.0078***	0.0083***	0.0085***	0.0086***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
[21 °C 27 °C)	0.0159***	0.0158***	0.0158***	0.0159***	0.0162***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
[27 °C 32 °C)	0.0235***	0.0235***	0.0231***	0.0234***	0.0227***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
[32 °C above)	0.0250***	0.0250***	0.0276***	0.0280***	0.0258***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Instrumented AQI	0.0663***	0.0661***	0.0594**	0.0642***	No
	(0.023)	(0.023)	(0.023)	(0.023)	No
No. of Obs.	50,558	50,558	50,558	50,558	50,558
Adj-R^2	0.604	0.604	0.604	0.605	0.604
Weather controls	Yes	Yes	Yes	Yes	Yes
Insurance FE	No	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes
Seasonal FE	No	No	Yes	Yes	Yes
Prefecture-by-Year FE	No	No	No	Yes	Yes

Notes: Robust standard errors in parenthesis are clustered at the household and county-year-month levels. The reference temperature bin is [10–16 °C), which is dropped to avoid multicollinearity. AQI refers to the air quality index, which we instrument with the accumulated strength of thermal inversion, defined as the temperature difference between two atmospheric layers over the 12 months exposure window preceding the interview month. Weather controls are air pressure, relative humidity, accumulated precipitation, sunshine duration, wind speed and the direction of maximum wind speed, all in the form of third-degree polynomials. Insurance FE refers to a set of public healthcare schemes including: 1. Public Medical Insurance; 2. Urban Employee Basic Medical Insurance; 3. Urban Resident Basic Medical Insurance; 4. Supplementary medical insurance; 5. New Rural Cooperative Medical Insurance 6. Others (Reference category). * $p < 0.01$, ** < 0.05, *** $p < 0.001$.

−12 °C bin increases out-of-pocket medical expenditure by 2.59% and an extra day below −12 °C generates a 3.63% increase in medical expenditure.

Our results are not due to exposure to air pollution. We control for the AQI, which is instrumented by thermal inversion strength, in columns (1) to (4). In our preferred specification, a one unit exogeneous increase in AQI increases out-of-pocket medical expenditure by 6.42%. Thus, air pollution exerts a much larger effect on out-of-pocket medical expenditure than any of the temperature bins. In column (5), we exclude instrumented AQI and find stronger effects for cold days, but weaker effects for warm days. This is expected because air pollution is more prevalent and severe in winter due to coal-fired public heating and staged air flow in China (Deschenes, Wang, Wang, & Zhang, 2020; Fan et al., 2020; Yang & Zhang, 2018). These changes imply that, without controlling for air pollution, the effect of temperature on out-of-pocket medical expenditure could be biased.

4.2. Heterogeneity

Table 3 examines heterogeneity along several different dimensions. Because some of the estimated coefficients are similar in magnitude, Table A1 performs inter-group difference tests for each temperature bin, indicating whether differences in estimated coefficients are statistically significant and have meaningful implications.

Column (1) and (2) of Table 3a report the estimates, respectively, for male, and females. We find that both cold and heat stress exert a larger effect on males. Table A1 confirms that the differences in estimated coefficients are significant at 5 % or higher levels. A plausible explanation is that males are more likely to work outdoors and, hence, are directly exposed to extreme temperatures. To test this explanation, columns (3) and (4) compare the temperature effects imposed on those working indoors and those working outdoors. We define farmers and workers in temperature uncontrolled environment, such as construction sites and manufacturing plants, as outdoor workers. We find that extreme temperatures impose a much higher medical burden on outdoor workers. In addition, we find that outdoor workers are more vulnerable to warm days than cold days, in line with the fact that there is no effective way to shield ambient heat stress.

Columns (5) and (6) compare ‘young’ and ‘old’ cohorts, employing a cut off age of 45 years old. We find that cold stress imposes a larger medical burden on the older cohort. Older cohorts have a thinner layer of fat under the skin, making them more vulnerable to colder temperatures (Chambers & Vukmanovic-Stejic, 2020). Chronic conditions, such as diabetes, peripheral artery disease and kidney disease, which are more prevalent among the elderly (see eg Liu, Qian, Chen, & He, 2020), can restrict blood flow and lower

Table 3a
Heterogeneity by different cohorts.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Male	Female	Outdoor	Indoor	Young	Old	Good health	Poor health	Urban	Rural
(below −12°)	0.0501***	0.0246***	0.0272***	0.0348*	0.0355***	0.0365***	0.0381***	0.0153*	0.0279***	0.0253***
	(0.008)	(0.007)	(0.008)	(0.020)	(0.008)	(0.007)	(0.008)	(0.008)	(0.010)	(0.006)
[−12 °C -7 °C)	0.0345***	0.0186***	0.0223***	0.0166	0.0165**	0.0326***	0.0272***	0.0215***	0.0210***	0.0202***
	(0.008)	(0.007)	(0.007)	(0.021)	(0.008)	(0.007)	(0.008)	(0.008)	(0.011)	(0.006)
[−7 °C -1 °C)	0.0134**	0.0028	0.0059	0.0121	0.0020	0.0121**	0.0090	0.0018	0.0292***	0.0037
	(0.006)	(0.005)	(0.005)	(0.015)	(0.006)	(0.006)	(0.006)	(0.006)	(0.008)	(0.005)
[−1 °C 4 °C)	0.0048	−0.0033	−0.0023	−0.0032	−0.0046	0.0057	−0.0018	0.0015	0.0159**	−0.0029
	(0.005)	(0.004)	(0.004)	(0.012)	(0.004)	(0.005)	(0.005)	(0.005)	(0.008)	(0.003)
[4 °C 10 °C)	0.0054	−0.0010	0.0009	0.0051	−0.0006	0.0048	0.0037	−0.0045	0.0091	0.0004
	(0.004)	(0.003)	(0.003)	(0.008)	(0.004)	(0.004)	(0.004)	(0.004)	(0.006)	(0.003)
[16 °C 21 °C)	0.0121***	0.0056**	0.0072***	0.0063	0.0083***	0.0085***	0.0082***	0.0086***	0.0034	0.0094***
	(0.003)	(0.003)	(0.003)	(0.007)	(0.003)	(0.003)	(0.003)	(0.003)	(0.005)	(0.002)
[21 °C 27 °C)	0.0190***	0.0136***	0.0172***	0.0111	0.0159***	0.0166***	0.0164***	0.0146***	−0.0009	0.0200***
	(0.004)	(0.003)	(0.003)	(0.008)	(0.004)	(0.003)	(0.004)	(0.004)	(0.006)	(0.003)
[27 °C 32 °C)	0.0290***	0.0192***	0.0220***	0.0228**	0.0260***	0.0222***	0.0253***	0.0206***	0.0083	0.0272***
	(0.004)	(0.004)	(0.004)	(0.010)	(0.004)	(0.004)	(0.005)	(0.004)	(0.006)	(0.003)
[32 °C above)	0.0290***	0.0276***	0.0344***	0.0521**	0.0304***	0.0277***	0.0359***	0.0182*	0.0161	0.0324***
	(0.009)	(0.008)	(0.011)	(0.021)	(0.008)	(0.009)	(0.009)	(0.009)	(0.011)	(0.007)
Instrumented AQI	0.0416	0.0888***	0.1107***	0.0425	0.0625*	0.0724***	0.0608*	0.0776***	0.0804**	0.0807***
	(0.034)	(0.026)	(0.031)	(0.072)	(0.032)	(0.028)	(0.033)	(0.029)	(0.038)	(0.028)
No. of Obs.	23,331	27,194	21,669	3731	24,937	25,621	24,334	15,391	11,240	37,264
Adj-R^2	0.607	0.597	0.595	0.634	0.598	0.587	0.588	0.599	0.621	0.604
Weather controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Insurance FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Seasonal FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City-by-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: *Outdoor* refers to farmers and workers working in an environment in which temperature is uncontrolled. All other respondents are defined as indoor workers. The cutoff age for dividing *Young* and *Old* cohorts is 45 years old. *Good health* refers to respondents who reported being in "Excellent" and "Good" health with remaining respondents being defined as being in poor health. Robust standard errors in parenthesis are clustered at the household and county-year-month levels. The reference temperature bin is [10–16 °C), which is dropped to avoid multicollinearity. AQI refers to the air quality index, which is instrumented by accumulated strength of thermal inversion. Weather controls are air pressure, relative humidity, accumulated precipitation, sunshine duration, wind speed and the direction of maximum wind speed, all in the form of third-degree polynomials. * $p < 0.01$, ** < 0.05, *** $p < 0.001$.

Table 3b
Heterogeneity by different cohorts.

	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
	NRCMS	UEBMI	URBMI	Rich	Poor	South	North	subtropical monsoon	temperate monsoon	temperate continental
(below −12°)	0.0238***	0.0425**	0.0750***	0.0429***	0.0143	No	0.0272***	No	0.0296***	0.0200
	(0.007)	(0.020)	(0.024)	(0.008)	(0.009)	No	(0.007)	No	(0.007)	(0.030)
[−12 °C -7 °C)	0.0210***	0.0232*	0.0744***	0.0249***	0.0234**	−0.0688	0.0194***	0.2337	0.0249***	0.0001
	(0.006)	(0.020)	(0.027)	(0.008)	(0.010)	(0.087)	(0.006)	(0.147)	(0.007)	(0.024)
[−7 °C -1 °C)	0.0069	0.0021	0.0621***	0.0126**	0.0027	0.0436**	0.0005	0.0427***	0.0100*	−0.0041
	(0.005)	(0.015)	(0.022)	(0.006)	(0.007)	(0.017)	(0.005)	(0.016)	(0.006)	(0.018)
[−1 °C 4 °C)	−0.0019	−0.0005	0.0543***	0.0022	0.0017	0.0019	−0.0010	0.0002	0.0009	0.0089
	(0.004)	(0.013)	(0.019)	(0.005)	(0.006)	(0.008)	(0.005)	(0.008)	(0.006)	(0.015)
[4 °C 10 °C)	0.0008	0.0028	0.0142	0.0031	0.0054	−0.0023	−0.0025	−0.0026	−0.0051	0.0029
	(0.003)	(0.010)	(0.011)	(0.004)	(0.004)	(0.004)	(0.005)	(0.004)	(0.005)	(0.013)
[16 °C 21 °C)	0.0094***	0.0007	−0.0091	0.0024	0.0057	0.0112***	0.0125***	0.0106***	0.0124***	0.0004
	(0.002)	(0.008)	(0.010)	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)	(0.004)	(0.008)
[21 °C 27 °C)	0.0182***	0.0134	0.0009	0.0073**	0.0128***	0.0187***	0.0200***	0.0186***	0.0181***	0.0054
	(0.003)	(0.011)	(0.012)	(0.004)	(0.005)	(0.004)	(0.004)	(0.004)	(0.005)	(0.008)
[27 °C 32 °C)	0.0249***	0.0132	0.0090	0.0117	0.0190***	0.0224***	0.0306***	0.0219***	0.0316***	−0.0086
	(0.003)	(0.012)	(0.012)	(0.014)	(0.005)	(0.004)	(0.005)	(0.004)	(0.006)	(0.012)
[32 °C above)	0.0199**	0.0471**	0.0295	0.0214	0.0281**	0.0314***	0.0376**	0.0344***	0.0383	0.0082
	(0.008)	(0.019)	(0.025)	(0.019)	(0.013)	(0.008)	(0.018)	(0.008)	(0.023)	(0.041)
Instrumented AQI	0.0843***	0.0982	0.0595	0.0586*	0.1039***	0.1157**	0.0817***	0.0824	0.0835***	0.2675*
	(0.027)	(0.070)	(0.073)	(0.033)	(0.037)	(0.057)	(0.026)	(0.053)	(0.029)	(0.154)
No. of Obs.	32,862	4750	2307	17,787	11,048	21,909	28,620	22,758	19,565	7417
Adj-R^2	0.608	0.638	0.649	0.626	0.619	0.599	0.611	0.599	0.614	0.613
Weather controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Insurance FE	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Seasonal FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City-by-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: *NRCMS, UEBMI* and *URBMI* refer to respondents enrolled in New Rural Cooperative Medical Insurance, Urban Employee Basic Medical Insurance and Urban Resident Basic Medical Insurance, respectively. *Rich* and *Poor* respondents are defined relative to their local average income levels. *South* and *North* subsamples are determined by the dividing line between northern and southern China, which roughly follows the Huai River and Qinling Mountains, along which the average temperature in January is around zero Celsius (See Fan et al., 2020). Robust standard errors in parenthesis are clustered at the household and county-year-month levels. The reference temperature bin is [10–16 °C), which is dropped to avoid multicollinearity. AQI refers to the air quality index, which is instrumented by accumulated strength of thermal inversion. Weather controls are air pressure, relative humidity, accumulated precipitation, sunshine duration, wind speed and the direction of maximum wind speed, all in the form of third-degree polynomials. * $p < 0.01$, ** < 0.05, *** $p < 0.001$.

body temperature. This makes older cohorts more susceptible to colder temperatures and increases the likelihood that they will demand more medical care in colder weather. Table A1 confirms that the differences in estimated coefficients on cold days between young and old cohorts are highly significant. In Table A2, we use a cutoff age of 65 years old to sperate young and old cohorts. Cold stress now imposes a much larger medical burden on the older cohort. Given their poorer health status, those aged over 65 are also more vulnerable to heat stress.

In columns (7) and (8), we divide respondents according to their health status. We find, somewhat surprisingly, that those who report being in poor health, are less responsive to both cold and heat stress. A potential explanation could be that those who are in poor health have intentionally avoided being exposed to extreme temperatures.

In columns (9) and (10), we divide the sample into urban and rural cohorts. We find that heat stress imposes a larger medical burden on the rural cohort, but not their urban counterparts. Likely reasons for this result are that the rural public healthcare scheme (NRCMS) is much less generous than the urban schemes and rural cohorts have access to more limited medical resources, both of which would impose a larger medical burden.

Empirical studies have consistently provided evidence that all three basic healthcare schemes and, in particular, the NRCMS, have failed to reduce the financial risk of poor health among poor households (Lei & Lin, 2009; Wagstaff et al., 2009; Yi et al., 2009). Wagstaff and Lindelow (2008) and You and Kobayashi (2011) even suggest that the healthcare schemes have exacerbated the financial risk associated with poor health for low-income individuals through encouraging over prescription and overtreatment.

In columns (11)–(13) of Table 3b, we divide our respondents according to the public healthcare scheme in which they are enrolled. Extreme temperatures, particularly heat stress, have significantly more salient effects among those enrolled in NRCMS, which is consistent with our explanation for the results in columns (9) and (10). On the other hand, UEBMI, which offers the most generous healthcare package, largely obviates the effects of extreme temperatures on out-of-pocket medical expenditure.

In columns (14) and (15), we divide our sample into high- and low- income respondents, which are defined relative to their local average income levels.[15] These relative measures are only weakly associated with ambient environment and, therefore, are less likely to suffer from endogeneity concerns. We find that heat stress imposes a much larger medical burden on the poor cohort. The poor cohort has limited resources and is less able to defend against heat stress. For instance, poor households are less likely to install air conditioners, which is one of the most effective ways to alleviate heat stress (Barreca et al., 2016; Yu et al., 2019). Moreover, poor households which have installed air conditioners, tend to use them less frequently because of a limited budget for energy. The poor cohort is also more likely to work in the informal sector, in which they may be more directly exposed to heat stress. By contrast, we find that cold stress exerts similar effects on both rich and poor cohorts. One explanation for this result is that poor households could mitigate the effects of the cold by relying on cheap, traditional fuels, such as firewood and straw, for their heating needs (Démurger & Fournier, 2011; Zhang et al., 2022).

Next, we assess heterogeneity based on whether respondents are in the northern part of China, where the weather is colder, or southern part of China, where temperatures are warmer. We find suggestive evidence of acclimatization, in which southern respondents can tolerant greater heat stress while northern respondents can tolerant greater cold stress. In Table A1, we show that the estimated coefficients for warm days are significantly different between southern and northern cohorts, which further provides statistical evidence of acclimatization. Finally, we divide our sample according to climate zones and report the results in columns (18)–(20). We find consistent evidence that people in temperate climatic zones are less tolerant to heat stress.

5. Robustness checks

We perform a series of robustness checks to confirm our findings. In our main results, consistent with the recommendations of Dell, Jones, and Olken (2014) we do not include demographic and economic controls to avoid the problem of “over controlling”. As a first check we add *hukou* type, educational attainment and marriage status as additional controls.[16] Table A3 shows that our results are not sensitive to controlling for these variables.

Next, we employ a new dependent variable which scales out-of-pocket medical expenditure by household income. This new dependent variable takes into account the budget constraint of households. For instance, richer households may choose more sophisticated medical services that are not covered by public healthcare schemes. In that case, higher out-of-pocket medical expenditure is less relevant to extreme temperatures. Table A4 reports the estimates in which the dependent variable is replaced by out-of-pocket medical expenditure scaled by household income. The five columns resemble the design of Table 2 and consistently show evidence that extreme cold and warm days significantly increase the ratio of out-of-pocket medical expenditure to household income. These results demonstrate that our main findings are not affected by incorporating the household budget constraint into the analysis.

We then change the reference temperature bin from 10 to 16 °C to 16–21 °C, which is used in Ranson (2014). Existing studies have commonly employed the most comfortable temperature bin as the reference group. While 10–16 °C appears to be the most comfortable temperature bin for northern respondents, the warmer bin, 16–21 °C, might be preferred among southern respondents. For instance,

[15] In CFPS, to elicit income status respondents are asked the following question: “What is your income level relative to others in your local area?” There are five options from one to five, where one refers to “very low” and five to “very high”. To sharpen our comparison, we exclude respondents who report “same as the local average”.

[16] In a set of unreported regression results, we also include smoking and drinking behaviors in our preferred specification in column (4) in Table 2. The results are qualitatively the same. We do not control for them in the main results because smoking and drinking could be correlated with ambient temperatures, thus becoming bad controls.

White (2017) suggests 15.6–18.3 °C as the most appropriate reference temperature bin in warm regions. Table A5 shows that our results are not sensitive to using this alternative temperature bin as the reference group.

We also construct temperature bins using daily maximum temperature to isolate the effects of peak temperatures within a day. Table A5 finds that heat stress now imposes a smaller medical burden on respondents. This is because maximum temperature does not fully reflect exposure to heat stress throughout the day. By contrast, we find cold days exert a much larger medical burden on respondents because using daily maximum temperature mechanically implies lower daily mean temperature and, therefore, larger cold stress.

As a further check on temperature bins, we halve the size of the temperature bins from 6 °C to 3 °C, which allows greater flexibility in estimating the temperature effects. The results, which are presented in Table A6, are consistent with our baseline results. The daily mean temperature continues to exhibit a nonlinear effect on out-of-pocket medical expenditure and the effects are still disproportionally stronger at hotter temperatures.

TableA7 reports the results using the 2SLS estimator. The point estimates for the temperature bins are similar in magnitude to those from the OLS estimator, albeit, as expected, the standard errors increase slightly. By contrast, the point estimate for AQI is almost double that of the baseline effect. One advantage of using the 2SLS estimator is that we can assess the strength of the relationship between AQI and its instrument, thermal inversion. We find the strength of thermal inversion exerts a stable effect on AQI, and is highly significant, across specifications. The magnitude of the F statistics is around 530, which is in the range found in existing studies (Fu, Viard, & Zhang, 2021; Sager, 2019). It is comfortably larger than the first stage F threshold of 104.7 proposed by Lee, McCrary, Moreira, and Porter (2021), implying that thermal inversion is not a weak instrument for air quality.

To show that the effect of temperature on medical expenditure is contemporaneous with out-of-pocket medical expenditure, we extend the exposure window from 12 months to 24 months. We simultaneously include a parallel set of temperature bins spanning 13 to 24 months preceding the CFPS interview.[17] Table A8 shows that, while our main results remain qualitatively the same, the lagged temperature bins between 13 and 24 months have a small and insignificant effect on out-of-pocket medical expenditure.

A potential concern with using the AQI is that it is constructed from data collected from ground air quality monitoring stations, most of which are deployed in major cities with dense population. However, over half of the counties surveyed in CFPS are in rural areas, which contributes to measurement errors and may confound the estimated effects of temperature, due to its correlation with air pollution. To address this concern, we employ monthly $PM_{2.5}$ concentrations data over the period 2010–2019 from van Donkelaar et al. (2019). This dataset is derived through fitting satellite aerosol optical depth (AOD) retrievals with a chemical transport model.[18] It is available at the $0.01^{\circ} \times 0.01^{\circ}$ resolution level for mainland China.[19] We merge the satellite derived $PM_{2.5}$ dataset with a map of Chinese counties and extract the spatially averaged monthly $PM_{2.5}$ concentrations for each county surveyed in CFPS. Table A9 replicates Table 2 except that AQI is replaced with $PM_{2.5}$. We continue using thermal inversion strength to isolate exogeneous variation in $PM_{2.5}$. All estimates for temperature are similar to the results in Table 2 using AQI. We find that $PM_{2.5}$ exerts a significant and larger effect on out-of-pocket medical expenditure than the AQI, in which $PM_{2.5}$ is only one component of the index. This is consistent with $PM_{2.5}$ being known to penetrate deep into the lungs and carry toxins to other organs that have serious health implications. Even a mild dose of $PM_{2.5}$ is known to reduce labor productivity, and trigger short-term anxiety and depression (Chang, Graff Zivin, Gross, & Neidell, 2019; Zhang, Chen, & Zhang, 2018; Zhang, Deschenes, et al., 2018; Zhang, Zhang, & Chen, 2017). High levels of $PM_{2.5}$ irritate the respiratory and cardiovascular systems, leading to aggravated asthma, lung disease and cardiac disease (He, Liu, & Zhou, 2020).

It could be the case that respondents in a specific province are driving the results.[20] To examine this possibility, we test the sensitivity of our baseline estimates to excluding provinces on a case-by-case basis. The estimates using our preferred specification, along with the 95% confidence intervals, are summarized in Fig. A2. All plots closely resemble the shape of our full sample result presented in Fig. A1, suggesting that our baseline results are not likely to be driven by respondents in a specific province.

Next, we address the potential threat from endogenous sorting. Extreme temperatures may induce respondents to move, which may bias our estimates. Note, that the individual fixed effects should absorb all initial sorting based on adverse weather events including extreme temperatures and, therefore, only individuals who moved in our sample period can potentially bias the estimates (Deschenes et al., 2020; Fu et al., 2021). While the *hukou* policy severely limits the extent to which people can move from their birthplace, 6.44% of respondents moved permanently between waves in the CFPS. We first focus on respondents who are employed locally. Then, we use the respondents with local *hukou* only. Table A10 shows that the results using these two restricted samples are qualitatively the same to our baseline estimates. As such, we conclude that endogenous sorting is unlikely to be biasing our estimates.

We explore to what extent our baseline results are sensitive to alternative choices of clustering. Table A11 re-estimates our preferred specification under different assumptions as to the clustering of the standard errors. Column (1) is our baseline estimate, with two-way clustering and clustered standard errors at the individual and county-year levels. In column (2), we change the county-year to county-year-month clustering, which allows error terms to be autocorrelated within a county-year-month cell. In column (3), we

[17] We cannot extend the exposure window beyond 24 months because the gap between two consecutive interviews are about 24 months on average.

[18] AOD measures the extinction of the solar beam by dust and haze and can be used to predict pollution.

[19] The AOD retrievals are obtained from multiple satellites including NASA Moderate Resolution Imaging Spectroradiometer (MODIS), the Multi-angle Imaging Spectroradiometer (MISR) and SeaWIFS. The detailed construction process is discussed in van Donkelaar et al. (2019). We thank Professor Aron van Donkelaar for sharing the restricted and monthly-frequency $PM_{2.5}$ concentrations with us.

[20] Municipalities including Beijing, Tianjin, Shanghai, Chongqing have provincial status in China. As such, we also call them “provinces” for simplicity.

aggregate the clustering level from county-year to county, allowing for any autocorrelation within each county. In columns (4) and (5), we instead employ one-way clustering and cluster at county-year and county level, respectively. Our results remain robust.

We also perform a placebo test by regressing future temperatures on out-of-pocket medical expenditure. We use the 12 months exposure window after the interview month and construct the same temperature bins. Table A12 reports the regression results. Reassuringly, none of future temperature bins is significant.

Our main estimates are identified through exploiting variations in the daily temperature distribution. However, households may acclimatize to the local climate and take precautionary measures, such as purchasing private healthcare insurance, to cope with warmer temperatures in the future. If this is the case, temperature effects on out-of-pocket medical expenditure could be biased. To address this concern, we use temperature shocks to improve causal identification, as unusually warm temperatures are largely unexpected. We construct a set of seasonal-specific temperature shocks based on the concept of the z-score, in which positive temperature shocks are defined as follows:

$$Z_{ct}^{S} = \frac{\left(T_{ct}^{s} - \mu_{c}^{s}\right)}{\sigma_{c}^{s}}$$

$$TS_{ct}^{S} = 1 \text{ if } Z_{ct}^{S} > 1.5$$

S is an index for one of the four seasons. T_{ct}^{s} refers to the seasonal-specific mean temperature for county c within the exposure window t; σ_{c}^{s} and $\mu_{c}^{s}$are respectively the standard deviation and the long-term mean temperature of season S, which we derive using daily observations from 1980 to 2013. Hence, Z_{ct}^{S}captures the extent to which a county's seasonal-specific temperature deviates from its long-term mean value. We use 1, 1.5 and 2 as threshold z-scores to define small, medium and large temperature shocks, respectively. We only consider positive shocks as fewer counties have experienced negative temperature shocks over the timeframe of the study, due in large part to global warming.

Table A13 reports the results. We find that unusually hotter summers have a consistent and significant effect on out-of-pocket medical expenditure. This result is consistent with our main finding that warmer days contribute to individuals' healthcare burden, but also isolate the season in which the effect is strongest.

As a final robustness check, we examine the sensitivity of our results to attrition bias and missing observations. Attrition is a common issue with longitudinal surveys. In the CFPS, the percentage of third wave (2014) participants that were reinterviewed in the fifth wave (2018) was 65.1%; thus, putting the attrition rate at 34.9%.[21] Another issue is non-response, which generates missing observations that could lead to non-sampling errors in surveys. Because responses in CFPS were collected via face-to-face interviews, non-response was due to respondents who did not know the answer or refused to provide a response. The non-response rates for our dependent variable, out-of-pocket medical expenditure, were 2.28, 1.67 and 0.05%, respectively for the 2014, 2016 and 2018 waves. The key issue is whether attrition and non-responses, which leads to missing observations, are random. If they are non-random and are correlated with our dependent variable, this suggests potential self-selection bias or non-response bias.

We examine the sensitivity of our results to non-response bias by employing inverse probability weighting (Fitzgerald, Gottschalk, & Moffitt, 1998). Assuming missing observations are selective on the observed covariates, we first estimate a binary model of non-response, conditional on the set of covariates and fixed effects used in our preferred specification. The results, which are reported in Column 1 of Table A14, suggest that there is no correlation between temperature and the probability of having a missing observation for out-of-pocket medical expenditure in the survey. Second, we apply weights that are derived as the inverse of the estimated propensity of reporting an observation in the sample. The results, which are reported in Column 2 of Table A14, exhibit a similar nonlinear relationship between temperatures and the medical burden to that observed in our baseline results. These results viewed together suggest that non-response bias is not a concern.

We then conduct multiple imputations to examine how our results change when we impute values for out-of-pocket medical expenditure for missing observations. Multiple imputation is an iterative form of stochastic imputation, in which instead of imputing values for a single value, the distribution of the observed data is used to impute values for multiple variables (Johnson & Young, 2011; White, Royston, & Wood, 2011). The results, which are reported in Table A15, show that our main findings remain robust.

6. Mechanisms

We now examine the mechanisms underlying the established relationship between temperature and out-of-pocket medical expenditure. The most obvious and direct mechanism operates through health effects. To explore this, we use the following model:

$$Health_{ict} = \sum_{m} \beta^{m} Temp_{ct}^{m} + \delta' W_{ct} + \delta A\widehat{QI}_{ct} + \gamma_{i} + \varphi_{py} + \lambda_{s} + \varepsilon_{ict} \tag{2}$$

$Health_{ict}$refers to a set of physical and mental health variables which are available in CFPS. We first use two self-reported questions to elicit the physical health status of respondents. One asks whether respondents suffered physical discomfort in the two weeks

[21] The percentage of first wave (2010) participants that were reinterviewed in the fifth wave (2018) was 60.03%; thus, putting the attrition rate between first and fifth waves at 39.97%.

preceding the interview. We create a dummy variable for respondents who had fever, diarrhea, cough or palpitations, all of which could be potentially related to extreme temperatures.[22] As we have discussed in the background section, reimbursements under the public healthcare in China are not linked to specific diseases, but depend on a specified list of medicines and medical services. Even health conditions that require relatively moderate medical interventions can still generate out-of-medical expenditure. For instance, if patients prefer more specialized medicines which are not on the list, they have to cover the expenditure themselves. In addition, physicians often subscribe clinical checks that are outside the reimbursement list; thus, generating substantial out-of-pocket medical expenditure. This appears to be near universal in China, as only 2553 out of 50,558 observations, or 5% of our sample, had zero out-of-pocket medical expenditure.

The CFPS asks those who reported suffering physical discomfort whether they had visited a doctor. This behavioral response is crucial as visiting a doctor is the most fundamental channel to generating out-of-pocket expenditure.[23]

A major concern with self-reported health data is that they may not accurately measure changes in physical health. Miller, Johnson, and Wherry (2021) argue that changes in self-reported heath may reflect evolving awareness of health problems or interactions with health professionals, rather than actual changes in physical health. As such, we exploit information on physician-diagnosed diseases to objectively measure respondents' physical health. The CFPS records chronic diseases diagnosed by physicians within six months preceding the interview.[24] We focus on chronic diseases associated with the digestive, respiratory and circulatory systems which are sensitive to ambient temperatures (Donaldson, Seemungal, Jeffries, & Wedzicha, 1999; White, 2017; Zanobetti, Neill, Gronlund, & Schwartz, 2012). We use a dummy variable set equal to one if the respondent was diagnosed with any of the relevant chronic diseases.

We use a linear probability model to examine these mechanisms. While logit /probit models, using the maximum likelihood estimator, are more efficient with a binary dependent variable, with such models we are unable to control for a large number of fixed effects. Our results remain qualitatively the same using both logit and probit models, albeit we are forced to drop either individual fixed effects or county-by-year fixed effects.[25]

Table 4 reports the regression results. In column (1), we find that heat stress significantly increases the probability of reporting physical discomfort, while the effect of cold stress is smaller and less significant. In column (2), we find that for those who suffered physical discomfort, heat stress also significantly increases the probability of going to a doctor. By contrast, cold stress exerts an insignificant effect, possibly because cold temperature disincentivizes people to leave their home. It is well known that many hospital visits are for ailments that do not require emergency and intensive care (Taubman, Allen, Wright, Baicker, & Finkelstein, 2014). Hence, it is plausible that any factor that increases the cost of seeking treatment, such as bad weather, will decrease the rate at which individuals seek treatment. Relative to a warm day, the cost of seeking treatment on cold days is arguably higher, as patients must wear more clothes and use private transportation to keep warm. More importantly, cold temperatures may exacerbate existing symptoms, such as coughing and a runny nose. Using administrative hospital records in California, White (2017) shows that are considerably fewer hospital visits on cold days. In column (3), we find a significant relationship between temperature and chronic diseases diagnosed by physicians. In Table A16, we shorten the exposure window to six months, the same period within which chronic diseases are diagnosed and find less significant results. This finding likely reflects that chronic diseases have complicated causes and that exposure to extreme temperatures over a much shorter period is less likely to induce them.[26]

These results are only suggestive because 1) the detailed date of diagnosis is missing, making it difficult to match with temperature data; 2) the length of exposure window for which extreme temperatures induce detectable health impacts remains unclear and will not necessarily be six or 12 months; and 3) the biological linkages between temperature and chronic diseases are complex. This, we may omit some diseases that are indirectly related to extreme temperatures (Donaldson et al., 1999; Zanobetti et al., 2012).

We next address how temperature affects mental health. A large number of studies have found that high temperatures can significantly worsen mental health (see eg. the survey in Liu et al., 2021). For instance, heat stress has been associated with greater irritability, symptoms of depression and incidence of suicide (Mullins & White, 2019). Extreme heat can also contribute to increased aggression, incidence of domestic violence and increased use of alcohol or other substances, designed to cope with stress (Otrachsenko, Popova, & Tavares, 2021; Ranson, 2014). We follow Zhang, Zhang, and Chen (2017) and make use of three self-reported mental health measures, which are consistently available in CFPS in the 2014, 2016 and 2018 waves. The questions ask respondents to indicate how often they feel: 1. sad, 2. unhappy and 3. lonely in a typical week. The options are: 1. never (less than one day); 2. sometimes (1–2 days); 3. often (3–4 days) and 4. most of the time (5–7 days). These measures are based on the Center for Epidemiological Studies Depression (CES—D) scale, which is designed to capture rates of depression in the general population. In separate specifications, we

[22] The options available for respondents in CFPS are: 1. Fever; 2. Pain; 3. Diarrhea. 4.Cough; 5. Difficulty in breathing; 6. Cannot focus attention; 7. Difficulty in walking; and 8. Palpitations.

[23] Ideally, we would like to know the number of times that respondents visiting doctors, as this is a better indicator of out-of-pocket medical expenditure. However, CFPS does not records doctor visits on the intensive margin. We thank one of our referees for making this valuable suggestion.

[24] The actual questions in CFPS are: "During the past six months, have you had any doctor-diagnosed chronic disease?" If the answer is yes, it continues: "What was your doctor's diagnosis of the disease you suffered from?"

[25] Full regression results employing logit and probit models are available upon request.

[26] We would like to have also examined the effects of extreme temperature on different types of diseases that are most sensitive to extreme temperature. While CFPS records 22 different categories of chronic diseases, most of them have very few cases diagnosed over the six-month period, reducing statistical power to detect heterogeneity. Table A17 provides the number of cases diagnosed for each of 22 chronic diseases. Many of them have fewer than 100 cases and the leading three diseases are attached to digestive, respiratory and circulatory diseases which we have used in our analysis. We thank our referees for making this valuable suggestion.

Table 4
Temperature effects on physical health.

	(1)	(2)	(3)
	Physical discomfort (Yes = 1)	Visited physician (Yes = 1)	Diagnosed chronic diseases (Yes = 1)
(below −12°)	−0.0002	0.0502	0.0005
	(0.0001)	(0.043)	(0.001)
[−12 °C -7 °C)	0.0017	0.0867**	0.0006
	(0.0012)	(0.040)	(0.001)
[−7 °C -1 °C)	−0.0009	0.0277	−0.0006
	(0.001)	(0.033)	(0.001)
[−1 °C 4 °C)	−0.0018**	0.0367	0.0009
	(0.001)	(0.029)	(0.001)
[4 °C 10 °C)	−0.0000	0.0487**	0.0003
	(0.001)	(0.021)	(0.001)
[16 °C 21 °C)	0.0008*	0.0483**	0.0011***
	(0.000)	(0.021)	(0.000)
[21 °C 27 °C)	0.0022***	0.0546**	0.0011**
	(0.001)	(0.022)	(0.000)
[27 °C 32 °C)	0.0038***	0.0578**	0.0016***
	(0.001)	(0.025)	(0.001)
[32 °C above)	0.0046***	0.1070***	0.0020**
	(0.001)	(0.034)	(0.001)
Instrumented AQI	0.0055	0.2178	0.0051
	(0.007)	(0.185)	(0.004)
No. of Obs.	44,093	13,622	42,111
Adj-R^2	0.561	0.605	0.571
Weather controls	Yes	Yes	Yes
Insurance FE	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes
Seasonal FE	Yes	Yes	Yes
City-by-Year FE	Yes	Yes	Yes

Notes: *Physical discomfort* is a dummy which is set to one if respondents reported having fever, diarrhea, cough or palpitations, in the two weeks preceding the interview. *Visited physician* is a dummy variable which equals one for those had visited a doctor. *Diagnosed chronic diseases* is a dummy indicating whether respondents were diagnosed with chronic diseases by physicians within six months preceding the interview. All estimations employ a linear probability model. Robust standard errors in parenthesis are clustered at the household and county-year-month levels. The reference temperature bin is [10–16 °C), which is dropped to avoid multicollinearity. AQI refers to the air quality index, which is instrumented by accumulated strength of thermal inversion. Weather controls are air pressure, relative humidity, accumulated precipitation, sunshine duration, wind speed and the direction of maximum wind speed, all in the form of third-degree polynomials. * $p < 0.01$, ** < 0.05, *** p < 0.001.

use a dummy variable set equal to one if the respondent indicated feeling sad, unhappy or lonely at least three days per week. We then follow Zhang, Zhang, and Chen (2017) to create an index that captures overall mental health status. The index is calculated as the sum of options chosen across the three mental health indicators.

Table 5 reports the results. We find that extreme temperatures, particularly heat stress, significantly increases the probability of feeling sad and lonely. The estimated effects are consistent, but less significant, for the unhappy dummy. Our finding remains qualitatively the same for using the overall mental health index. Note that these results are only suggestive because mental health questions refer to the week preceding the CFPS interview. To mitigate confounding factors over a long period, In Table A18 we make use of the temperature distribution in the one-month period preceding the interview, where we find less significant effects on mental health. A possible explanation is that most interviews are carried out in July and August, thus limiting variation in the temperature variables.

We examine various daily activities, which are consistently recorded in the CFPS, to consider how extreme temperatures may affect physical and mental health. Regular and gentle outdoor exercises, such as postprandial walking, are important parts to the life of Chinese people and are widely practiced. In turn, postprandial walking has measurable health benefits, such as reducing postprandial hyperglycemia among individuals with type-II diabetes (Colberg et al., 2009; DiPietro, Gribok, Stevens, Hamm, & Rumpler, 2013). Heat stress, however, makes such gentle exercise uncomfortable and encourages people to reallocate their time to indoor mostly sedentary activities. CFPS does not record information on the extent of outdoor exercises so we cannot directly measure this. Instead, we use measures of indoor sedentary activities to proxy the extent to which extreme heat encourages people to engage in less outdoor activities. Exposure to ambient stress motivates people to reallocate time from outdoors to indoors, which increases sedentary behaviors (Graff Zivin & Neidell, 2014). Sedentary behaviors may reduce net calories expended and increase body weight and obesity risk (Deschenes et al., 2020). We use average hours spent watching television and browsing the internet to capture the intensity of daily sedentary activities.

We also consider sleeping patterns. Heat stress can make it difficult to sleep. Lack of sleep impairs cognitive functioning and increases susceptibility to many chronic illness (Mullins & White, 2019; Obradovich et al., 2017). We create a sleep disruption dummy equal to one if the respondent reported suffering sleep disruption in the past month.

Table 6 reports the results. We find that heat stress significantly increases the number of hours spent watching television and browsing the internet. In column (2), we find that heat stress, even when it is relatively mild, can cause sleep disruption. These results provide suggestive evidence that sedentary activities and sleep disruption are potential explanations underlying the established

Table 5
Temperature effects on mental health.

	(1)	(2)	(3)	(4)
	Feel Sad (Yes = 1)	Feel unhappy (Yes = 1)	Feel lonely (Yes = 1)	Overall mental health index
(below −12°)	0.0088*	0.038*	0.0017	0.0090***
	(0.004)	(0.002)	(0.001)	(0.003)
[−12 °C -7 °C)	0.0002	0.0002	0.0021**	0.0149**
	(0.004)	(0.001)	(0.001)	(0.007)
[−7 °C -1 °C)	−0.0009	0.0018	0.0014*	0.0024
	(0.003)	(0.001)	(0.001)	(0.006)
[−1 °C 4 °C)	0.0014	0.0009	0.0005	0.0036
	(0.002)	(0.001)	(0.001)	(0.004)
[4 °C 10 °C)	−0.0003	−0.0000	−0.0002	−0.0029
	(0.002)	(0.001)	(0.000)	(0.003)
[16 °C 21 °C)	0.0013	0.0002	0.0003	−0.0008
	(0.001)	(0.001)	(0.000)	(0.003)
[21 °C 27 °C)	0.0030**	0.0001	0.002*	0.0049
	(0.001)	(0.001)	(0.001)	(0.003)
[27 °C 32 °C)	0.0057***	0.002*	0.007***	0.0083**
	(0.002)	(0.001)	(0.002)	(0.004)
[32 °C above)	0.0075**	0.004***	0.008***	0.0110**
	(0.003)	(0.001)	(0.001)	(0.005)
Instrumented AQI	0.0142	0.0074	0.0033	0.0023
	(0.016)	(0.006)	(0.005)	(0.004)
No. of Obs.	23,350	23,340	23,328	23,304
Adj-R^2	0.667	0.587	0.566	0.711
Weather controls	Yes	Yes	Yes	Yes
Insurance FE	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes
Seasonal FE	Yes	Yes	Yes	Yes
City-by-Year FE	Yes	Yes	Yes	Yes

Notes: All dependent variables are self-reported mental health measures. The first three dummies respectively denote whether the respondent indicated feeling sad, unhappy or lonely at least three days per week. *The Overall mental health index* is based on Zhang et al. (2017b) and is calculated as the sum of options chosen across the three mental health indicators. Robust standard errors in parenthesis are clustered at the household and county-year-month levels. The reference temperature bin is [10–16 °C), which is dropped to avoid multicollinearity. AQI refers to the air quality index, which is instrumented by accumulated strength of thermal inversion. Weather controls are air pressure, relative humidity, accumulated precipitation, sunshine duration, wind speed and the direction of maximum wind speed, all in the form of third-degree polynomials. * $p < 0.01$, ** < 0.05, *** $p < 0.001$. A linear probability model is used.

temperature–health relationship. Table A18 also reports the results using the one-month exposure window and finds weaker effects for sleep disruption.

We also examine whether, and to what extent, air conditioners can mitigate the negative effect of extreme temperatures on sleep disruption. The 2014 wave asked a question about air conditioners and, in that year, around 35% of sampled households had the device. Columns (3) and (4) divides the sample into households with and without air conditioners. We find that temperature effects are largely muted among households which have installed air conditioners. Note that this result is only suggestive because air conditioning is an endogenous choice, and we only have one year of such information.

Finally, we examine whether energy poverty mediates the relationship between extreme temperatures and out-of-pocket expenditure. Energy poverty refers to a situation that households are unable to spend a sufficient share of their income on desirable energy services, in order to maintain a comfortable indoor temperature. Heat stress has been shown to increase residential energy consumption (Davis & Gertler, 2015; Deschenes & Greenstone, 2011; Zhang et al., 2022) and induce energy poverty (Feeny et al., 2021; Li et al., 2022). The reason for this is that extreme heat increases the cost of cooling, such as running air conditioners. Existing studies have found that households in energy poverty have a higher incidence of physical and mental health problems in developed and developing countries (Awaworyi Churchill et al., 2020; Zhang et al., 2021; Zhang & Smith, 2007).

We employ four measures of energy poverty, which are widely used in the existing literature. The first measure is a dummy variable indicating whether the share of income spent on energy is higher than 10%, the threshold that was first proposed by Boardman (1991). The second measure limits the 10% measure to low-income households, whose income is below the third decile of the household income distribution (Kahouli, 2020). The income distribution is province specific given highly uneven development across China. The third measure defines households as energy poor if their energy expenditure to income ratio exceeds twice the provincial-specific median ratio (Moore, 2012). The final measure is the low-income high cost (LIHC) measure proposed by Hills (2011), which classifies households as energy poor if their energy expenditure is above the median level of energy expenditure in their province, while their residual household income is below 50% of the median household income in their province.

Because energy poverty is defined at the household level, we analyze a household panel and replace individual fixed effects with household fixed effects. Table 7 reports the results. We find that only warmer days and, particularly extreme warm days, significantly increase the probability of being in energy poverty. By contrast, cold stress has an insignificant effect on energy poverty, due, in large part, to subsidized public heating in cities (Fan et al., 2020) and wide availability of solid fuels for heating in rural areas (Démurger &

Table 6
Temperature effects on daily activities.

	(1)	(2)	(3)	(4)
	Watching TV & Internet browsing	Sleep disruption (Yes = 1)	Sleep disruption (AC = 1)	Sleep disruption (AC = 0)
(below −12°)	−0.0483	0.0047*	−0.0311*	0.0060*
	(0.074)	(0.003)	(0.016)	(0.003)
[−12 °C -7 °C)	−0.0577	−0.0061*	0.0050	−0.0057
	(0.086)	(0.003)	(0.014)	(0.004)
[−7 °C -1 °C)	0.0162	−0.0018	0.0083	−0.0026
	(0.046)	(0.002)	(0.005)	(0.002)
[−1 °C 4 °C)	−0.0487	−0.0019	−0.0093***	−0.0020
	(0.037)	(0.001)	(0.003)	(0.002)
[4 °C 10 °C)	−0.0252	0.0027**	0.0017	0.0037**
	(0.035)	(0.001)	(0.003)	(0.002)
[16 °C 21 °C)	−0.0023	0.0063***	−0.0021	0.0088***
	(0.025)	(0.001)	(0.003)	(0.001)
[21 °C 27 °C)	0.0682***	0.0049***	−0.0048**	0.0082***
	(0.023)	(0.001)	(0.002)	(0.001)
[27 °C 32 °C)	0.0827***	0.0107***	0.0012	0.0140***
	(0.025)	(0.001)	(0.002)	(0.001)
[32 °C above)	0.3318***	0.0197***	0.0083**	0.0232***
	(0.066)	(0.003)	(0.003)	(0.006)
Instrumented AQI	0.1035**	0.0192***	0.0179***	0.0227***
	(0.043)	(0.002)	(0.003)	(0.002)
No. of Obs.	47,825	50,558	15,408	30,931
Adj-R^2	0.652	0.495	0.549	0.479
Weather controls	Yes	Yes	Yes	Yes
Insurance FE	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes
Seasonal FE	Yes	Yes	Yes	Yes
City-by-Year FE	Yes	Yes	Yes	Yes

Notes: *Watching TV & Internet browsing* refers to number of hours spent watching television and browsing the internet. *Sleep disruption* is a dummy which equals one if respondents suffered sleep disruption in the month preceding the interview. The last two columns estimate the temperature effects on sleep disruption for households with and without an AC separately. Robust standard errors in parenthesis are clustered at the household and county-year-month levels. The reference temperature bin is [10–16 °C), which is dropped to avoid multicollinearity. AQI refers to the air quality index, which is instrumented by accumulated strength of thermal inversion. Weather controls are air pressure, relative humidity, accumulated precipitation, sunshine duration, wind speed and the direction of maximum wind speed, all in the form of third-degree polynomials. * $p < 0.01$, ** < 0.05, *** $p < 0.001$.

Fournier, 2011). We do not control for air quality here as it could be a bad control. Extreme temperatures increase the demand for electricity consumption which generates air pollution. Li et al. (2022) find that air pollution is a cause of energy poverty.

7. Climate change and out-of-pocket medical expenditure

We simulate the changes in future out-of-pocket medical expenditure due to climate change. Table 8 summarizes the projected changes for selected temperature bins by each of the eight GCMs, under different combinations of emission pathways within the medium term. Overall, China is expected to experience inevitable warming, reflected in there being fewer cold days and more extreme heat days. Under SSP126, the sustainable and the most desirable pathway, the number of days above 32 °C would increase by 0.210–0.423 days in each year in the medium term. By contrast, under the SSP585 pathway in which no countervailing measures are taken to curb greenhouse gas emissions, the number of days above 32 °C would increase by 0.321–1.006 days in each year in the medium term. These changes are sizable, when measured relative to 1.402, the mean number of extreme heat days for counties surveyed in CFPS during the period 2012–2018.

Combining our baseline estimates in column (4) of Table 2 with those projected changes in daily temperatures, we simulate the changes in future out-of-pocket medical expenditure in China. Under the most sustainable path, out-of-pocket medical expenditure is expected to increase by 2.290–3.595% in the medium run. Under the business-as-usual path, however, out-of-pocket medical expenditure is expected to increase by 2.659–6.149% in the medium run. The moderate increase in out-of-pocket medical expenditure reflects that there will be fewer extreme cold days in the future, which, to some extent, will offset the medical burden due to more extreme heat days.

8. Concluding remarks and policy implications

This study has estimated the causal effects of temperature on out-of-pocket medical expenditure. Combining nationally representative household data CFPS with daily weather data at the county level over the 2014–2018 period, we find that both cold and heat stress significantly increase the medical expenditure at the individual level. However, the effect of warm days on out-of-pocket medical expenditure is collectively larger than that of cold days. We find that sedentary activities, measured by time spent on the internet and

Table 7
Temperature effects on energy poverty.

	(1)	(2)	(3)	(4)
	10%	*Adj.10%*	*2 M*	*LIHC*
(below −12°)	0.0007	0.0051	0.0012	0.0032
	(0.0095)	(0.0079)	(0.0093)	(0.0105)
[−12 °C -7 °C)	−0.0027	0.0010	−0.0057	−0.0242***
	(0.0098)	(0.0100)	(0.0100)	(0.0114)
[−7 °C -1 °C)	−0.0065	0.0012	−0.0054	−0.0145
	(0.0072)	(0.0070)	(0.0078)	(0.0093)
[−1 °C 4 °C)	−0.0071	−0.0053	−0.0087	−0.0098
	(0.0052)	(0.0048)	(0.0061)	(0.0068)
[4 °C 10 °C)	−0.0024	−0.0007	−0.0043	−0.0049
	(0.0032)	(0.0029)	(0.0036)	(0.0042)
[16 °C 21 °C)	−0.0001	−0.0008	0.0009	−0.0004
	(0.0017)	(0.0017)	(0.0019)	(0.0022)
[21 °C 27 °C)	0.0030	0.0017	0.0045**	0.0047**
	(0.0019)	(0.0019)	(0.0021)	(0.0022)
[27 °C 32 °C)	0.0024	0.0010	0.0044**	0.0027
	(0.0020)	(0.0019)	(0.0022)	(0.0026)
[32 °C above)	0.0037*	0.0020	0.0069***	0.0074***
	(0.0020)	(0.0020)	(0.0023)	(0.0028)
No. of Obs.	34,273	34,273	34,273	34,273
Weather controls	✓	✓	✓	✓
Household FE	✓	✓	✓	✓
County-by-Year FE	✓	✓	✓	✓
Seasonal FE	✓	✓	✓	✓
City-specific time trend	✓	✓	✓	✓

Note: Dependent variables are four measures of energy poverty. *10%* a dummy variable indicating whether the share of income spent on energy is higher than 10%, *Adj.10%* limits the 10% measure to low-income households, whose income is below the third decile of the household income distribution. *2 M* defines households as energy poor if their energy expenditure to income ratio exceeds twice the provincial-specific median ratio. Low-income high cost (LIHC) classifies households as energy poor if their energy expenditure is above the median level of energy expenditure in their province, while their residual household income is below 50% of the median household income in their province. A linear probability model is used. Robust standard errors in parenthesis are clustered at the household and county-year-month levels. The reference temperature bin is [10 °C 16 °C), which is dropped to avoid multicollinearity. Weather controls are air pressure, relative humidity, accumulated precipitation, sunshine duration, wind speed and the direction of maximum wind speed, all in the form of third-degree polynomials. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 8
Predicting the changes in future out-of-medical expenditure.

2041–2060 SSP126

GCMs	(below −12 °C)	[−12 °C 7 °C)	[16 °C 21 °C)	[21 °C 27 °C)	[27 °C 32 °C)	[32 °C above)	ΔOOP(%)
BCCCSM2 MR	−0.1098	0.0081	−0.3135	−0.4892	1.1453	0.3685	2.2899
CANESM5	−0.2511	−0.1648	−0.3775	0.0288	1.7202	0.4225	3.5949
CANESM5	−0.1176	−0.0627	−0.4557	−0.1980	1.3753	0.3301	2.8510
CNRMESM21	−0.1595	−0.0644	−0.4498	−0.1293	1.3076	0.2863	2.5278
IPSLCM6ALR	−0.1489	−0.0176	−0.5120	0.0832	1.3528	0.2408	2.9503
MIROC6	−0.0565	−0.0201	−0.3779	−0.0917	1.0253	0.2098	2.2626
MIROCES2L	−0.1842	−0.0775	−0.2855	0.0760	1.1190	0.2295	2.2699
MRIESM20	−0.0387	0.0018	−0.4953	−0.1488	1.3517	0.2815	3.1579

2041–2060 SSP585

GCMs	(below −12 °C)	[−12 °C 7 °C)	[16 °C 21 °C)	[21 °C 27 °C)	[27 °C 32 °C)	[32 °C above)	ΔOOP(%)
BCCCSM2 MR	−0.2262	−0.0972	−0.5437	−0.3711	1.7378	0.6013	3.6252
CANESM5	−0.4093	−0.3034	−0.5238	−0.0556	2.6225	1.0060	6.1486
CANESM5	−0.2300	−0.1386	−0.6027	−0.2344	1.8286	0.5580	3.7620
CNRMESM21	−0.1864	−0.1080	−0.5890	−0.2005	1.6926	0.4390	3.4143
IPSLCM6ALR	−0.2747	−0.1147	−0.6830	0.0663	2.2326	0.5653	5.0381
MIROC6	−0.1715	−0.1112	−0.3950	−0.1023	1.4217	0.3333	2.8513
MIROCES2L	−0.2594	−0.1387	−0.3652	0.0213	1.4263	0.3211	2.6592
MRIESM20	−0.1695	−0.1048	−0.5742	−0.1257	1.7999	0.4802	`3.9817

Notes: The unit is days for various temperature bins. ΔOOP refers to percentage change in out-of-pocket medical expenditure.

watching television, and sleep disruptions, which adversely affect physical and mental health are channels linking extreme temperatures to medical expenditure. Moreover, we find that extreme temperatures increase medical expenditure through inducing energy poverty.

Our results suggest that out-of-pocket medical expenditure will increase by 2.290–6.149% in the medium term depending on whether measures are taken to curb greenhouse gas emissions. While our results imply that climate change will inevitably increase the medical burden on households in the future, some of the effects of hotter weather will be offset by having fewer extremely cold days.

Our results have several implications for policies that could be designed to alleviate the medical burden stemming from climate change. First, more could be done to reduce the stress placed on workers who are directly exposed to the ambient environment. While measures typically exist to reduce the adverse effects of extreme weather events on health, this ignores that less extreme warmer temperatures may also induce extra health burdens. These identified effects are likely to become more important because of climate change.

Second, we find that temperature effects on out-of-pocket medical expenditure fall disproportionately on those less able to afford it; namely, low income and rural cohorts. Much concern has been expressed about growing income inequality and rural-urban inequality in China (eg. Knight, 2014). Our results suggest that climate change will potentially exacerbate these inequalities. Under the existing system, the generosity of public healthcare is largely linked to local fiscal capacity, implying that people in poor areas are expected to shoulder the larger medical burden themselves. To address this issue, the central government could allocate direct fiscal subsidies to finance medical expenditure in poor areas. In addition, the central government could also accelerate regional integration of public healthcare. This would lower the cost for hundreds of millions of migrant workers who may need to tap healthcare services outside their hometowns.

Third, in terms of the channels, the government could initiate public health campaigns to warn of the potential health risks associated with sleep disruption and too much sedentary activities. Relatedly, the government could establish community-based and temperature-controlled recreational centers to effectively reduce sedentary activities and encourage community engagement. To alleviate sleep disruptions caused by heat stress, the government could provide subsidies to poor households to install and use air conditioners. While these measures would increase the financial burden on government in the near-term, they are likely to result in less health-related costs long-term.

Data availability

The authors do not have permission to share data.

Acknowledgement

Yao Yao acknowledges the financial support from Shanghai Sailing Project by Shanghai Science and Technology Committee (Grant No. 20YF1434100), Shanghai Eastern Young Scholar program (Grant No. QD20200046), National Natural Science Foundation of China (19BGL227), General Scientific Research Project Education Department of Shaanxi Province (Grant No. 21JK0329). Xue Li acknowledges the financial support from Shanghai Sailing Project by Shanghai Science and Technology Committee (20YF1434000).

Appendix A

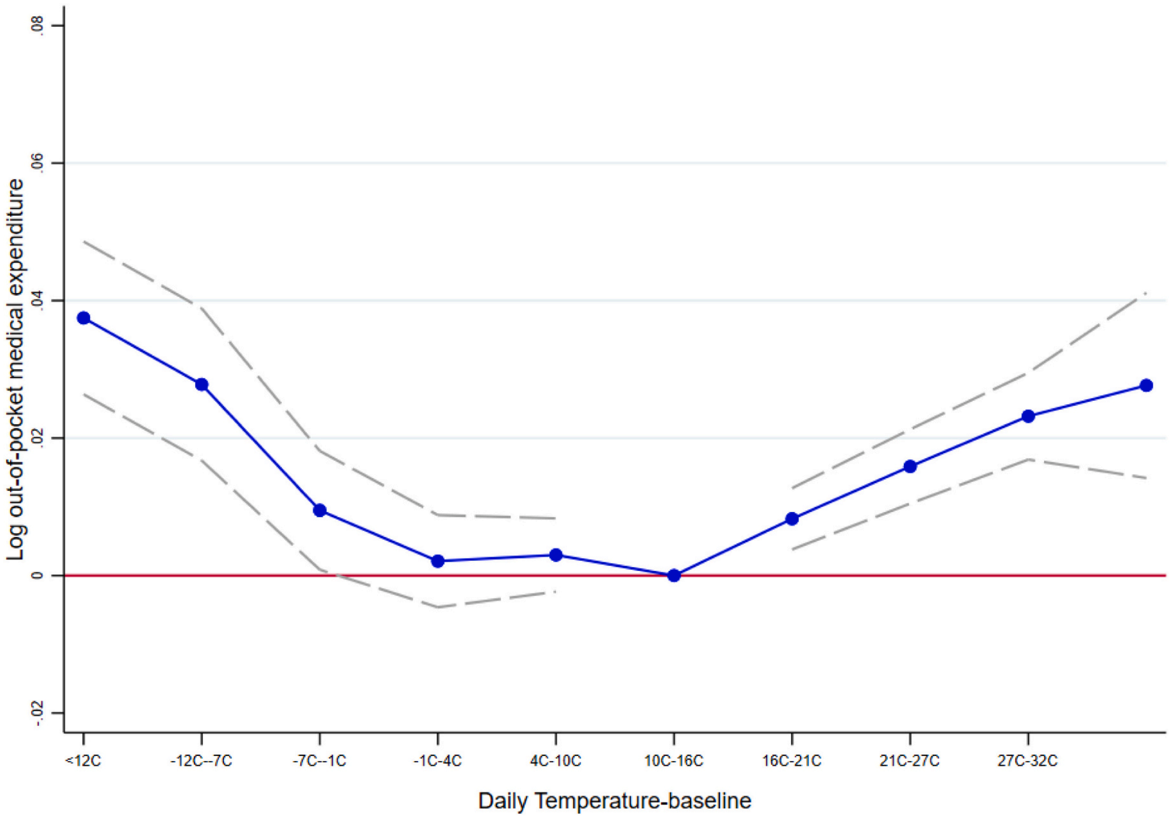

Fig. A1. The relationship between various temperature bins and out-of-pocket medical expenditure.

Note Thos figure represents the estimated relationship between various temperature bins and out-of-pocket medical expenditure using our preferred specification Column (4) in Table 2. The reference temperature bin is [10–16 °C), which is dropped to avoid multicollinearity. AQI refers to the air quality index, which is instrumented by the accumulated strength of thermal inversion, Weather controls are air pressure, relative humidity, accumulated precipitation, sunshine duration, wind speed and the direction of maximum wind speed, all in the form of third-degree polynomials. Insurance FE refers to a set of public healthcare schemes consisting of: 1. Public Medical Insurance; 2. Urban Employee Basic Medical Insurance; 3. Urban Resident Basic Medical Insurance; 4. Supplementary medical insurance; 5. New Rural Cooperative Medical Insurance 6. We also control for individual FE, seasonal FE and prefecture-by-year FE.

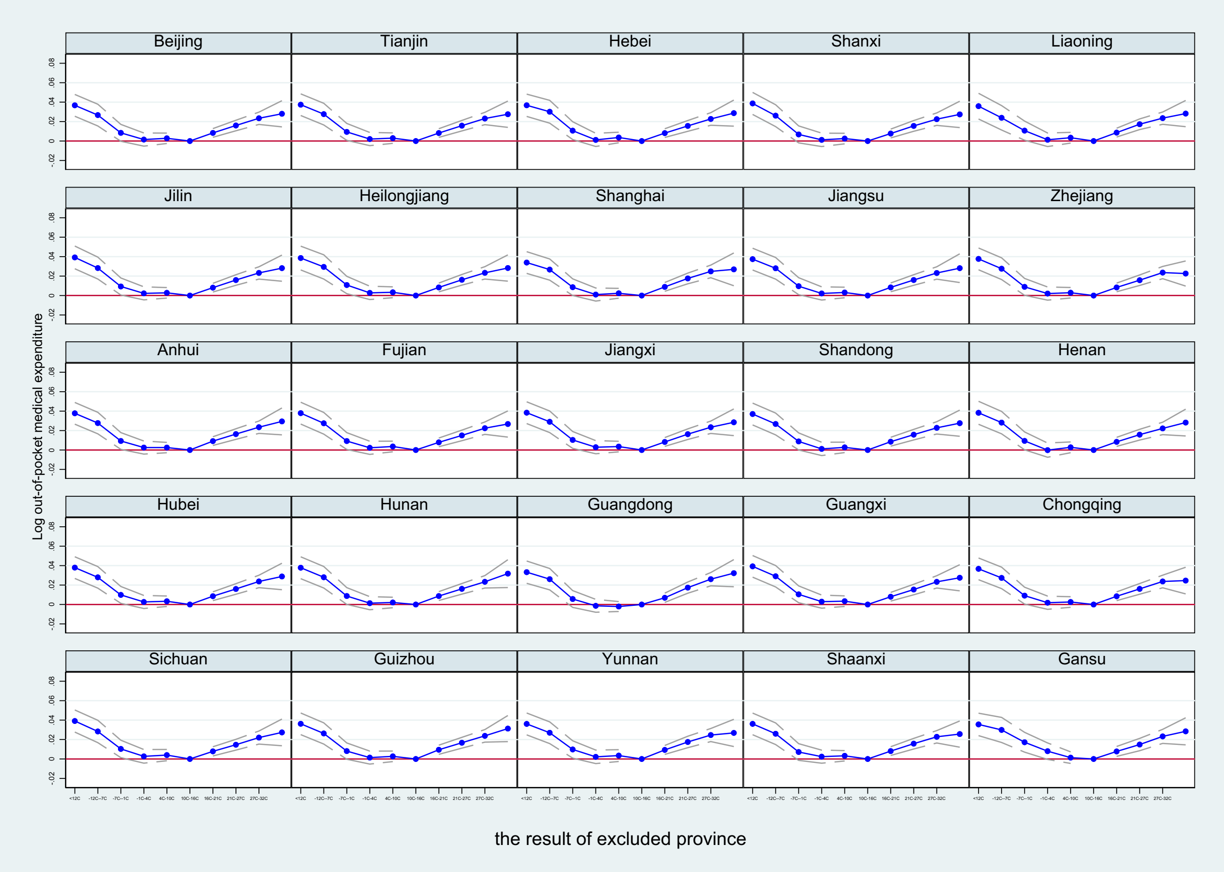

Fig. A2. Excluding one province/municipality in each regression.

Notes: The title of each plot corresponds to the province dropped. The plots denote the estimated relationship between various temperature bins and out-of-pocket medical expenditure using our preferred specification Column (4) in Table 2. The reference temperature bin is [10–16 °C), which is dropped to avoid multicollinearity. AQI refers to the air quality index, which is instrumented by the accumulated strength of thermal inversion, Weather controls are air pressure, relative humidity, accumulated precipitation, sunshine duration, wind speed and the direction of maximum wind speed, all in the form of third-degree polynomials. Insurance FE refers to a set of public healthcare schemes consisting of 1. Public Medical Insurance; 2. Urban Employee Basic Medical Insurance; 3. Urban Resident Basic Medical Insurance; 4. Supplementary medical insurance; 5. New Rural Cooperative Medical Insurance 6. We also control individual FE, seasonal FE and prefecture-by-year FE.

Table A1
Inter-group difference tests.

Groups	Group 1	Group 2	Group3	Group4	Group5	Group6	Group7	Group8	Group9
Group labels	Gender	Working spaces	Age groups	Health status	Residential areas	Healthcare schemes	Income levels	Macro regions	Temperature zones
Columns in Table 3a & 3b	(1) & (2)	(3) & (4)	(5) & (6)	(7) & (8)	(9) & (10)	(11), (12) & (13)	(14) & (15)	(16) & (17)	(18), (19) & (20)
(below −12°)	−0.026	0.008	0.001	−0.023	0.035	−0.017	0.029	0.029	−0.027
	(0.000)	(0.380)	(0.330)	(0.060)	(0.000)	(0.000)	(0.000)	(0.000)	(0.010)
[−12 °C -7 °C)	−0.016	−0.006	0.016	−0.006	0.025	−0.011	−0.002	−0.210	−0.088
	(0.030)	(0.450)	(0.040)	(0.350)	(0.020)	(0.000)	(0.460)	(0.000)	(0.000)
[−7 °C -1 °C)	−0.011	0.006	0.010	−0.007	0.025	0.002	0.003	−0.040	0.043
	(0.040)	(0.410)	(0.050)	(0.300)	(0.000)	(0.190)	(0.250)	(0.000)	(0.000)
[−1 °C 4 °C)	−0.008	−0.001	0.010	0.003	0.012	−0.001	−0.004	−0.001	0.003
	(0.060)	(0.440)	(0.020)	(0.300)	(0.010)	(0.190)	(0.270)	(0.470)	(0.230)
[4 °C 10 °C)	−0.006	0.004	0.005	−0.008	0.004	−0.002	−0.004	0.001	0.000
	(0.090)	(0.330)	(0.040)	(0.210)	(0.150)	(0.160)	(0.220)	(0.390)	(0.430)
[16 °C 21 °C)	−0.006	−0.001	0.000	0.000	−0.003	0.008	0.002	0.002	−0.001
	(0.020)	(0.04)	(0.500)	(0.470)	(0.170)	(0.000)	(0.280)	(0.250)	(0.370)
[21 °C 27 °C)	−0.005	−0.006	0.001	−0.002	−0.004	0.004	0.003	0.001	−0.001
	(0.020)	(0.060)	(0.500)	(0.410)	(0.220)	(0.000)	(0.070)	(0.490)	(0.360)

(continued on next page)

Table A1 (*continued*)

Groups	Group 1	Group 2	Group3	Group4	Group5	Group6	Group7	Group8	Group9
Group labels	Gender	Working spaces	Age groups	Health status	Residential areas	Healthcare schemes	Income levels	Macro regions	Temperature zones
Columns in Table 3a & 3b	(1) & (2)	(3) & (4)	(5) & (6)	(7) & (8)	(9) & (10)	(11), (12) & (13)	(14) & (15)	(16) & (17)	(18), (19) & (20)
[27 °C 32 °C)	−0.010	0.001	−0.004	−0.005	−0.011	0.013	0.007	0.008	−0.008
	(0.020)	(0.460)	(0.220)	(0.300)	(0.040)	(0.000)	(0.050)	(0.020)	(0.080)
[32 °C above)	−0.001	0.018	−0.003	−0.018	0.016	−0.021	−0.002	0.022	−0.006
	(0.440)	(0.330)	(0.400)	(0.040)	(0.090)	(0.000)	(0.470)	(0.010)	(0.340)
Instrumented AQI	0.047	−0.068	0.010	0.017	0.013	−0.025	−0.048	0.000	0.034
	(0.070)	(0.490)	(0.380)	(0.320)	(0.400)	(0.060)	(0.110)	(0.500)	(0.190)

Note: This table reports inter-group difference tests for each temperature bin, indicating whether differences in estimated coefficients are statistically significant and have meaningful implications. The *p*-value of each test are reported in parentheses. For each pair of regressions, the reference temperature bin is [10–16 °C), which is dropped to avoid multicollinearity. AQI refers to the air quality index, which is instrumented by the accumulated strength of thermal inversion, Weather controls are air pressure, relative humidity, accumulated precipitation, sunshine duration, wind speed and the direction of maximum wind speed, all in the form of third-degree polynomials. Insurance FE refers to a set of public healthcare schemes consisting of 1. Public Medical Insurance; 2. Urban Employee Basic Medical Insurance; 3. Urban Resident Basic Medical Insurance; 4. Supplementary medical insurance; 5. New Rural Cooperative Medical Insurance 6. We also control individual FE, seasonal FE and prefecture-by-year FE.

Table A2
Using age 65 as an alternative cutoff for young and old cohorts.

	(1)	(2)
	Young (below 65)	Old (above 65)
(below −12°)	0.0340***	0.0441***
	(0.006)	(0.013)
[−12 °C -7 °C)	0.0212***	0.0540***
	(0.006)	(0.014)
[−7 °C -1 °C)	0.0076*	0.0065
	(0.004)	(0.010)
[−1 °C 4 °C)	0.0002	−0.0002
	(0.003)	(0.009)
[4 °C 10 °C)	0.0018	0.0003
	(0.003)	(0.006)
[16 °C 21 °C)	0.0075***	0.0176***
	(0.002)	(0.005)
[21 °C 27 °C)	0.0152***	0.0269***
	(0.003)	(0.007)
[27 °C 32 °C)	0.0226***	0.0364***
	(0.003)	(0.008)
[32 °C above)	0.0252***	0.0507***
	(0.007)	(0.013)
Instrumented AQI	0.0715***	0.0400
	(0.025)	(0.055)
No. of Obs.	43,152	7406
Adj-R^2	0.604	0.582
Weather controls	Yes	Yes
Insurance FE	Yes	Yes
Individual FE	Yes	Yes
Seasonal FE	Yes	Yes
Prefecture-by-Year FE	Yes	Yes

Notes: In these results the cutoff age for dividing *Young* and *Old* cohorts is changed to 65 years old. Robust standard errors in parenthesis are clustered at the household and county-year-month levels. The reference temperature bin is [10–16 °C), which is dropped to avoid multicollinearity. AQI refers to the air quality index, which is instrumented by the accumulated strength of thermal inversion, Weather controls are air pressure, relative humidity, accumulated precipitation, sunshine duration, wind speed and the direction of maximum wind speed, all in the form of third-degree polynomials. * $p < 0.01$, ** < 0.05, *** $p < 0.001$.

Table A3
Controlling for additional variables.

	(1)	(2)	(3)	(4)	(5)
(below −12°)	0.0363***	0.0329***	0.0354***	0.0367***	0.0317***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
[−12 °C -7 °C)	0.0259***	0.0268***	0.0254***	0.0267***	0.0257***

(*continued on next page*)

Table A3 (*continued*)

	(1)	(2)	(3)	(4)	(5)
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
[−7 °C -1 °C)	0.0081	0.0103**	0.0080*	0.0082*	0.0100
	(0.005)	(0.004)	(0.004)	(0.004)	(0.006)
[−1 °C 4 °C)	0.0009	0.0012	0.0011	0.0011	0.0013
	(0.003)	(0.004)	(0.003)	(0.003)	(0.004)
[4 °C 10 °C)	0.0023	0.0023	0.0023	0.0026	0.0023
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
[16 °C 21 °C)	0.0085***	0.0081***	0.0084***	0.0088***	0.0079***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
[21 °C 27 °C)	0.0159***	0.0152***	0.0156***	0.0163***	0.0146***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
[27 °C 32 °C)	0.0234***	0.0196***	0.0227***	0.0239***	0.0184***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
[32 °C above)	0.0280***	0.0258***	0.0273***	0.0285***	0.0250***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Instrumented AQI	0.0642***	0.0854***	0.0643***	0.0686***	0.0843***
	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)
hukou type	No	Yes	No	No	Yes
Educational attainment	No	No	Yes	No	Yes
Marriage status	No	No	No	Yes	Yes
No. of Obs.	50,558	46,290	50,558	50,558	46,290
Adj-R^2	0.605	0.598	0.605	0.605	0.599
Weather controls	Yes	Yes	Yes	Yes	Yes
Insurance FE	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes
Seasonal FE	Yes	Yes	Yes	Yes	Yes
Prefecture-by-Year FE	Yes	Yes	Yes	Yes	Yes

Notes: All regressions include the number of schooling years, marriage status and *hukou* type. Robust standard errors in parenthesis are clustered at the household and county-year-month levels. The reference temperature bin is [10–16 °C), which is dropped to avoid multicollinearity. AQI refers to the air quality index, which is instrumented by the accumulated strength of thermal inversion, Weather controls are air pressure, relative humidity, accumulated precipitation, sunshine duration, wind speed and the direction of maximum wind speed, all in the form of third-degree polynomials. * p < 0.01, ** < 0.05, *** p < 0.001.

Table A4
Scaling out-of-pocket medical expenditure by household income.

	(1)	(2)	(3)	(4)	(5)
(below −12°)	0.1240	0.1231	0.1763**	0.1879**	0.1879**
	(0.081)	(0.082)	(0.081)	(0.080)	(0.080)
[−12 °C -7 °C)	0.0608	0.0655	0.1167	0.1328	0.1328
	(0.111)	(0.111)	(0.101)	(0.102)	(0.102)
[−7 °C -1 °C)	0.1092	0.1100	0.1425*	0.1571**	0.1571**
	(0.080)	(0.080)	(0.073)	(0.074)	(0.074)
[−1 °C 4 °C)	0.1080**	0.1073**	0.1185**	0.1321**	0.1321**
	(0.050)	(0.050)	(0.052)	(0.053)	(0.053)
[4 °C 10 °C)	0.0381	0.0378	0.0397	0.0473	0.0473
	(0.052)	(0.052)	(0.052)	(0.053)	(0.053)
[16 °C 21 °C)	0.0264	0.0266	0.0268	0.0241	0.0241
	(0.041)	(0.041)	(0.040)	(0.040)	(0.040)
[21 °C 27 °C)	0.0545*	0.0552*	0.0509	0.0495	0.0495
	(0.033)	(0.034)	(0.032)	(0.032)	(0.032)
[27 °C 32 °C)	0.1103***	0.1106***	0.1008***	0.0978***	0.0978***
	(0.033)	(0.034)	(0.033)	(0.032)	(0.032)
[32 °C above)	0.0659***	0.0702***	0.0727***	0.0689***	0.0689***
	(0.013)	(0.014)	(0.010)	(0.018)	(0.018)
Instrumented AQI	0.6678	0.6776	0.5358	0.4779	No
	(0.571)	(0.574)	(0.595)	(0.584)	No
No. of Obs.	45,801	45,801	45,801	45,801	45,801
Adj-R^2	0.475	0.475	0.475	0.475	0.475
Weather controls	Yes	Yes	Yes	Yes	Yes
Insurance FE	No	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes
Seasonal FE	No	No	Yes	Yes	Yes
Prefecture-by-Year FE	No	No	No	Yes	Yes

Notes: The dependent variable is out-of-pocket medical expenditure scaled by household income. Robust standard errors in parenthesis are clustered at the household and county-year-month levels. The reference temperature bin is [10–16 °C), which is dropped to avoid multicollinearity. AQI refers to the air quality index, which we instrument with the accumulated strength of thermal inversion, defined as the temperature difference between two atmospheric layers over the 12 months exposure window preceding the interview month. Weather controls are air pressure, relative humidity, accumulated precipitation, sunshine duration, wind speed and the direction of maximum wind speed, all in the form of third-degree polynomials.

Insurance FE refers to a set of public healthcare schemes consisting of 1. Public Medical Insurance; 2. Urban Employee Basic Medical Insurance; 3. Urban Resident Basic Medical Insurance; 4. Supplementary medical insurance; 5. New Rural Cooperative Medical Insurance 6. Others (Reference category). * $p < 0.01$, ** < 0.05, *** $p < 0.001$.

Table A5
Alternative reference bin and using maximum daily temperature.

	(1)	(2)	(3)
	Baseline	Alternative reference bin [16 °C 21 °C)	Maximum daily temperature
(below −12°)	0.0363***	0.0277***	0.0260***
	(0.006)	(0.006)	(0.007)
[−12 °C -7 °C)	0.0259***	0.0173***	0.0359***
	(0.006)	(0.006)	(0.006)
[−7 °C -1 °C)	0.0081	−0.0005	0.0226***
	(0.005)	(0.005)	(0.005)
[−1 °C 4 °C)	0.0009	−0.0077**	−0.0037
	(0.003)	(0.004)	(0.004)
[4 °C 10 °C)	0.0023	−0.0062*	0.0004
	(0.003)	(0.003)	(0.003)
[10 °C 16 °C)		−0.0087***	
		(0.002)	
[16 °C 21 °C)	0.0085***		0.0036
	(0.002)		(0.003)
[21 °C 27 °C)	0.0159***	0.0073***	0.0138***
	(0.003)	(0.002)	(0.003)
[27 °C 32 °C)	0.0234***	0.0147***	0.0178***
	(0.003)	(0.002)	(0.004)
[32 °C above)	0.0280***	0.0193***	0.0219***
	(0.007)	(0.007)	(0.004)
Instrumented AQI	0.0642***	0.0657***	0.0632***
	(0.023)	(0.023)	(0.024)
No. of Obs.	50,558	50,558	50,558
Adj-R^2	0.605	0.605	0.605
Weather controls	Yes	Yes	Yes
Insurance FE	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes
Seasonal FE	Yes	Yes	Yes
City-by-Year FE	Yes	Yes	Yes

Notes: Baseline results replicate our preferred estimates from Table 2. Column (2) uses the alternative reference temperature bin [16 °C 21 °C). Temperature bins in Column (3) are constructed using daily maximum temperature. Robust standard errors in parenthesis are clustered at the household and county-year-month levels. AQI refers to the air quality index, which is instrumented by the accumulated strength of thermal inversion, Weather controls are air pressure, relative humidity, accumulated precipitation, sunshine duration, wind speed and the direction of maximum wind speed, all in the form of third-degree polynomials. * $p < 0.01$, ** < 0.05, *** $p < 0.001$.

Table A6
Smaller temperature bins.

	(1)
(below −12°)	0.0307***
	(0.006)
[-12C° -9C°)	0.0232***
	(0.008)
[−9 °C -6C°)	0.0117**
	(0.006)
[-6C° -3C°)	0.0031
	(0.006)
[—3C 0C°)	0.0004
	(0.005)
[0C° 3C°)	−0.0040
	(0.005)
[3C° 6C°)	−0.0007
	(0.004)
[6C° 9C°)	−0.0023
	(0.004)
[9C° 12C°)	−0.0015
	(0.004)
[12C° 15C°)	−0.0053*
	(0.003)
[18C° 21C°)	0.0073***
	(0.003)
[21C° 24C°)	0.0148***

(*continued on next page*)

Table A6 (*continued*)

	(1)
	(0.003)
[24C° 27C°)	0.0102***
	(0.003)
[27C° 30C°)	0.0192***
	(0.003)
[30C° above)	0.0213***
	(0.004)
Instrumented AQI	0.0561**
	(0.023)
No. of Obs.	50,558
Adj-R^2	0.605
Weather controls	Yes
Insurance FE	Yes
Individual FE	Yes
Seasonal FE	Yes
City-by-Year FE	Yes

Notes: The size of the temperature bins is halved from 6 °C to 3 °C. The reference temperature bin is [15–18 °C), which is dropped to avoid multicollinearity. Robust standard errors in parenthesis are clustered at the household and county-year-month levels. AQI refers to the air quality index, which is instrumented by the accumulated strength of thermal inversion. Weather controls are air pressure, relative humidity, accumulated precipitation, sunshine duration, wind speed and the direction of maximum wind speed, all in the form of third-degree polynomials. * p < 0.01, ** < 0.05, *** p < 0.001.

Table A7
Results from 2SLS estimator.

	(1)	(2)	(3)	(4)
First-stage results				
(below −12°)	0.0313***	0.0311***	0.0346***	0.0336***
	(0.007)	(0.007)	(0.007)	(0.007)
[−12 °C -7 °C)	0.0246***	0.0241***	0.0265***	0.0250***
	(0.006)	(0.006)	(0.006)	(0.006)
[−7 °C -1 °C)	0.0081	0.0080	0.0099	0.0085
	(0.005)	(0.005)	(0.005)	(0.005)
[−1 °C 4 °C)	0.001	0.0007	0.0016	0.0003
	(0.003)	(0.003)	(0.004)	(0.003)
[4 °C 10 °C)	0.0034	0.0034	0.0032	0.0026
	(0.004)	(0.003)	(0.003)	(0.003)
[16 °C 21 °C)	0.0077***	0.0077***	0.0082***	0.00844***
	(0.002)	(0.002)	(0.002)	(0.002)
[21 °C 27 °C)	0.0157***	0.0156***	0.0157***	0.0158***
	(0.003)	(0.003)	(0.003)	(0.003)
[27 °C 32 °C)	0.0240***	0.0239***	0.0236***	0.0239***
	(0.004)	(0.004)	(0.004)	(0.004)
[32 °C above)	0.0265***	0.0265***	0.0290***	0.0293***
	(0.007)	(0.007)	(0.007)	(0.007)
AQI	0.113***	0.114***	0.101***	0.104***
	(0.033)	(0.033)	(0.034)	(0.034)
Second-stage results				
Thermal inversion strength	0.209***	0.209***	0.207***	0.206***
	(0.009)	(0.009)	(0.009)	(0.009)
F-statistic	527.2	528.4	530.1	543.9
No. of Obs.	50,558	50,558	50,558	50,558
Weather controls	Yes	Yes	Yes	Yes
Insurance FE	No	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes
Seasonal FE	No	No	Yes	Yes
Prefecture-by-Year FE	No	No	No	Yes

Notes: We instrument AQI with the accumulated strength of thermal inversion and estimate all specifications using the 2SLS estimator. Robust standard errors in parenthesis are clustered at the household and county-year-month levels. The reference temperature bin is [10–16 °C), which is dropped to avoid multicollinearity. Weather controls are air pressure, relative humidity, accumulated precipitation, sunshine duration, wind speed and the direction of maximum wind speed, all in the form of third-degree polynomials. * $p < 0.01$, ** < 0.05, *** $p < 0.001$.

Table A8
Longer exposure window.

	(1)	(2)	
	Baseline (Previous 12 months)	Previous 12 months	Previous 13–24 months
(below −12°)	0.0363***	0.0311***	0.0033
	(0.006)	(0.005)	(0.004)
[−12 °C -7 °C)	0.0259***	0.0254***	−0.0002
	(0.006)	(0.005)	(0.004)
[−7 °C -1 °C)	0.0081	0.0070***	−0.0001
	(0.005)	(0.004)	(0.002)
[−1 °C 4 °C)	0.0009	0.0071	0.0035
	(0.003)	(0.053)	(0.002)
[4 °C 10 °C)	0.0023	0.0043	0.0030
	(0.003)	(0.003)	(0.002)
[16 °C 21 °C)	0.0085***	0.0060**	−0.0021
	(0.002)	(0.002)	(0.002)
[21 °C 27 °C)	0.0159***	0.0143***	0.0033*
	(0.003)	(0.003)	(0.002)
[27 °C 32 °C)	0.0234***	0.0231***	−0.0003
	(0.003)	(0.003)	(0.002)
[32 °C above)	0.0280***	0.0257**	−0.0061
	(0.007)	(0.007)	(0.007)
Instrumented AQI	0.0642***	0.0665***	No
	(0.023)	(0.023)	No
No. of Obs.	50,558	50,558	
Adj-R^2	0.605	0.603	
Weather controls	Yes	Yes	
Insurance FE	Yes	Yes	
Individual FE	Yes	Yes	
Seasonal FE	Yes	Yes	
City-by-Year FE	Yes	Yes	

Notes: Column (1) replicates our baseline analysis in which temperature bins are defined only for the 12 months preceding the interview month. Column (2) simultaneously adds a parallel set of temperature bins spanning 13 to 24 months preceding the CFPS interview, in addition to the temperature bins defined for the previous 12 months. Robust standard errors in parenthesis are clustered at the household and county-year-month levels. The reference temperature bin is [10–16 °C), which is dropped to avoid multicollinearity. AQI refers to the air quality index, which is instrumented by the accumulated strength of thermal inversion, Weather controls are air pressure, relative humidity, accumulated precipitation, sunshine duration, wind speed and the direction of maximum wind speed, all in the form of third-degree polynomials. * $p < 0.01$, ** < 0.05, *** $p < 0.001$.

Table A9
Using satellite based $PM_{2.5}$.

	(1)	(2)	(3)	(4)	(5)
(below −12°)	0.0355***	0.0352***	0.0391***	0.0382***	0.0409***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.005)
[−12 °C -7 °C)	0.0243***	0.0238***	0.0271***	0.0256***	0.0277***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
[−7 °C -1 °C)	0.0063	0.0063	0.0086*	0.0073	0.0076*
	(0.004)	(0.004)	(0.004)	(0.005)	(0.004)
[−1 °C 4 °C)	0.0015	0.0014	0.0023	0.0011	0.0018
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
[4 °C 10 °C)	0.0028	0.0027	0.0027	0.0021	0.0020
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
[16 °C 21 °C)	0.0078***	0.0078***	0.0082***	0.0084***	0.0085***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
[21 °C 27 °C)	0.0162***	0.0161***	0.0160***	0.0162***	0.0161***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
[27 °C 32 °C)	0.0235***	0.0234***	0.0229***	0.0232***	0.0227***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
[32 °C above)	0.0257***	0.0257***	0.0277***	0.0281***	0.0259***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Instrumented $PM_{2.5}$	0.0865**	0.0875**	0.0660***	0.0725***	No
	(0.031)	(0.038)	(0.020)	(0.021)	No
No. of Obs.	50,558	50,558	50,558	50,558	50,558

(*continued on next page*)

Table A9 (*continued*)

	(1)	(2)	(3)	(4)	(5)
Adj-R^2	0.604	0.604	0.605	0.605	0.605
Weather controls	Yes	Yes	Yes	Yes	Yes
Insurance FE	No	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes
Seasonal FE	No	No	Yes	Yes	Yes
Prefecture-by-Year FE	No	No	No	Yes	Yes

Notes: In these specifications $PM_{2.5}$ is used instead of AQI. $PM_{2.5}$ is instrumented with accumulated strength of thermal inversion, defined as the temperature difference between two atmospheric layers over the 12 months exposure window preceding the interview month. Robust standard errors in parenthesis are clustered at the household and county-year-month levels. The reference temperature bin is [10–16 °C), which is dropped to avoid multicollinearity. Weather controls are air pressure, relative humidity, accumulated precipitation, sunshine duration, wind speed and the direction of maximum wind speed, all in the form of third-degree polynomials. * $p < 0.01$, ** < 0.05, *** $p < 0.001$.

Table A10
Addressing endogenous sorting.

	(1)	(2)
	Local employed only	Local *hukou* only
(below −12°)	0.0306***	0.0355***
	(0.006)	(0.006)
[−12 °C -7 °C)	0.0236***	0.0254***
	(0.006)	(0.005)
[−7 °C -1 °C)	0.0070	0.0070
	(0.005)	(0.004)
[−1 °C 4 °C)	0.0001	0.0006
	(0.004)	(0.003)
[4 °C 10 °C)	0.0005	0.0025
	(0.003)	(0.003)
[16 °C 21 °C)	0.0078***	0.0090***
	(0.002)	(0.002)
[21 °C 27 °C)	0.0151***	0.0170***
	(0.003)	(0.003)
[27 °C 32 °C)	0.0212***	0.0251***
	(0.003)	(0.003)
[32 °C above)	0.0255***	0.0300***
	(0.007)	(0.007)
Instrumented AQI	0.0722***	0.0706***
	(0.023)	(0.023)
No. of Obs.	44,889	43,102
Adj-R^2	0.605	0.608
Weather controls	Yes	Yes
Insurance FE	Yes	Yes
Individual FE	Yes	Yes
Seasonal FE	Yes	Yes
City-by-Year FE	Yes	Yes

Note: Column (1) restricts our sample to respondents who work locally while Column (2) excludes respondents holding a non-local *hukou*. Robust standard errors in parenthesis are clustered at the household and county-year-month levels. The reference temperature bin is [10–16 °C), which is dropped to avoid multicollinearity. AQI refers to the air quality index, which is instrumented by the accumulated strength of thermal inversion, Weather controls are air pressure, relative humidity, accumulated precipitation, sunshine duration, wind speed and the direction of maximum wind speed, all in the form of third-degree polynomials. * $p < 0.01$, ** < 0.05, *** $p < 0.001$.

Table A11
Alternative choices of clustering.

	Estimated coefficient	Standard error clustering at				
		(1)	(2)	(3)	(4)	(5)
		Individual & County-year	individual & county-year-month levels	Individual & County	County-Year (One way)	County (One way)
(below −12°)	0.0363	(0.006)***	(0.005)***	(0.006)***	(0.007)***	(0.007)***
[−12 °C -7 °C)	0.0259	(0.006)***	(0.005)***	(0.006)***	(0.007)***	(0.008)***
[−7 °C -1 °C)	0.0081	(0.005)	(0.004)**	(0.005)	(0.006)	(0.007)
[−1 °C 4 °C)	0.0009	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)
[4 °C 10 °C)	0.0023	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
[16 °C 21 °C)	0.0085	(0.002)***	(0.002)***	(0.003)***	(0.003)***	(0.003)***

(*continued on next page*)

Table A11 (*continued*)

	Estimated coefficient	Standard error clustering at				
		(1)	(2)	(3)	(4)	(5)
		Individual & County-year	individual & county-year-month levels	Individual & County	County-Year (One way)	County (One way)
[21 °C 27 °C)	0.0159	(0.003)***	(0.003)***	(0.003)***	(0.004)***	(0.004)***
[27 °C 32 °C)	0.0234	(0.003)***	(0.003)***	(0.004)***	(0.005)***	(0.005)***
[32 °C above)	0.0280	(0.007)***	(0.007)***	(0.008)***	(0.010)***	(0.011)***
Instrumented AQI	0.0642	(0.023)***	(0.022)***	(0.025)***	(0.030)***	(0.032)***
No. of Obs.	50,558	50,558	50,558	50,558	50,558	50,558
Adj-R^2	0.605	0.605	0.605	0.605	0.605	0.605
Weather controls	Yes	Yes	Yes	Yes	Yes	Yes
Insurance FE	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
Seasonal FE	Yes	Yes	Yes	Yes	Yes	Yes
Prefecture-by-Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Note: Columns (1), (2) and (3) employ two-way cluster, while Columns (4) and (5) employ one-way cluster. The reference temperature bin is [10–16 °C), which is dropped to avoid multicollinearity. AQI refers to the air quality index, which is instrumented by the accumulated strength of thermal inversion, Weather controls are air pressure, relative humidity, accumulated precipitation, sunshine duration, wind speed and the direction of maximum wind speed, all in the form of third-degree polynomials. * p < 0.01, ** < 0.05, *** p < 0.001.

Table A12
Using future temperature distributions.

	(1)	(2)
	Baseline	Future temperature distribution
(below −12°)	0.0363***	0.0130
	(0.006)	(0.010)
[−12 °C -7 °C)	0.0259***	0.0097
	(0.006)	(0.007)
[−7 °C -1 °C)	0.0081	0.0077
	(0.005)	(0.007)
[−1 °C 4 °C)	0.0009	0.0044
	(0.003)	(0.005)
[4 °C 10 °C)	0.0023	−0.0027
	(0.003)	(0.004)
[16 °C 21 °C)	0.0085***	0.0005
	(0.002)	(0.003)
[21 °C 27 °C)	0.0159***	0.0010
	(0.003)	(0.004)
[27 °C 32 °C)	0.0234***	0.0031
	(0.003)	(0.004)
[32 °C above)	0.0280***	−0.0042
	(0.007)	(0.009)
Instrumented AQI	0.0642***	0.1009***
	(0.023)	(0.037)
No. of Obs.	50,558	50,558
Adj-R^2	0.605	0.605
Weather controls	Yes	Yes
Insurance FE	Yes	Yes
Individual FE	Yes	Yes
Seasonal FE	Yes	Yes
City-by-Year FE	Yes	Yes

Notes: Column (1) replicates our baseline estimates from Table 2. Temperature bins in Column (2) are constructed using daily temperatures over the 12 months *after* the interview. Robust standard errors in parenthesis are clustered at the household and county-year-month levels. The reference temperature bin is [10–16 °C), which is dropped to avoid multicollinearity. AQI refers to the air quality index, which is instrumented by the accumulated strength of thermal inversion, Weather controls are air pressure, relative humidity, accumulated precipitation, sunshine duration, wind speed and the direction of maximum wind speed, all in the form of third-degree polynomials. * p < 0.01, ** < 0.05, *** p < 0.001.

Table A13
Using temperature shocks.

	(1)	(2)	(3)
Spring T.S. > 1.0	0.2542***		

(*continued on next page*)

Table A13 (*continued*)

	(1)	(2)	(3)
	(0.056)		
Summer T.S. > 1.0	0.2774***		
	(0.037)		
Autumn T.S. > 1.0	−0.1195***		
	(0.046)		
Winter T.S. > 1.0	−0.0556		
	(0.058)		
Spring T.S. > 1.5		0.4179***	
		(0.116)	
Summer T.S. > 1.5		0.3465***	
		(0.052)	
Autumn T.S. > 1.5		−0.0523	
		(0.123)	
Winter T.S. > 1.5		0.2316	
		(0.216)	
Spring T.S. > 2.0			0.5355
			(0.525)
Summer T.S. > 2.0			0.2844**
			(0.117)
Autumn T.S. > 2.0			−1.1323
			(1.317)
Winter T.S. > 2.0			0.0000
			(0.000)
Instrumented AQI	0.1058***	0.0763***	0.0831***
	(0.023)	(0.022)	(0.022)
No. of Obs.	50,558	50,558	50,558
Adj-R^2	0.604	0.603	0.602
Weather controls	Yes	Yes	Yes
Insurance FE	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes
Seasonal FE	Yes	Yes	Yes
City-by-Year FE	Yes	Yes	Yes

Note: T.S. refers to seasonal-specific temperature shocks based on the concept of the z-score, AQI refers to the air quality index, which is instrumented by the accumulated strength of thermal inversion. Robust standard errors in parenthesis are clustered at the household and county-year-month levels. Weather controls are air pressure, relative humidity, accumulated precipitation, sunshine duration, wind speed and the direction of maximum wind speed, all in the form of third-degree polynomials. * $p < 0.01$, ** < 0.05, *** $p < 0.001$.

Table A14
Test for non-response bias.

	(1)	(2)
	Non-missing (Yes = 1)	inverse probability weighting
(below −12°)	−0.0002	0.0367***
	(0.000)	(0.005)
[−12 °C -7 °C)	−0.0003	0.0263***
	(0.000)	(0.005)
[−7 °C -1 °C)	−0.0002	0.0084**
	(0.000)	(0.003)
[−1 °C 4 °C)	−0.0003	0.0011
	(0.000)	(0.003)
[4 °C 10 °C)	−0.0005***	0.0025
	(0.000)	(0.002)
[16 °C 21 °C)	0.0001	0.0084***
	(0.000)	(0.002)
[21 °C 27 °C)	0.0000	0.0160***
	(0.000)	(0.002)
[27 °C 32 °C)	0.0001	0.0235***
	(0.000)	(0.002)
[32 °C above)	0.0004	0.0281***
	(0.000)	(0.005)
Instrumented AQI	0.0004	0.0658***
	(0.001)	(0.019)
No. of Obs.	51,631	50,558
Adj-R^2	0.501	0.605
Weather controls	Yes	Yes
Insurance FE	Yes	Yes

(*continued on next page*)

Table A14 (*continued*)

	(1) Non-missing (Yes = 1)	(2) inverse probability weighting
Individual FE	Yes	Yes
Seasonal FE	Yes	Yes
City-by-Year FE	Yes	Yes

Notes: Column (1) assumes missing observations are selective on the observed covariates and we estimate a binary model of non-response conditional on the set of covariates and fixed effects used in our preferred specification. Column (2) applies weights that are derived as the inverse of the estimated propensity of reporting an observation in the sample. Robust standard errors in parenthesis are clustered at the household and county-year-month levels. The reference temperature bin is [10–16 °C), which is dropped to avoid multicollinearity. AQI refers to the air quality index, which is instrumented by the accumulated strength of thermal inversion, Weather controls are air pressure, relative humidity, accumulated precipitation, sunshine duration, wind speed and the direction of maximum wind speed, all in the form of third-degree polynomials. * p < 0.01, ** < 0.05, *** p < 0.001.

Table A15
Regression with imputed out-of-pocket medical expenditure.

	(1) Baseline results (without imputation)	(2) Regression with Imputed values
(below −12°)	0.0363***	0.0367***
	(0.006)	(0.005)
[−12 °C -7 °C)	0.0259***	0.0264***
	(0.006)	(0.005)
[−7 °C -1 °C)	0.0081	0.0084
	(0.005)	(0.005)
[−1 °C 4 °C)	0.0009	0.0011
	(0.003)	(0.003)
[4 °C 10 °C)	0.0023	0.0025
	(0.003)	(0.002)
[16 °C 21 °C)	0.0085***	0.0083***
	(0.002)	(0.002)
[21 °C 27 °C)	0.0159***	0.0159***
	(0.003)	(0.002)
[27 °C 32 °C)	0.0234***	0.0234***
	(0.003)	(0.002)
[32 °C above)	0.0280***	0.0281***
	(0.007)	(0.005)
Instrumented AQI	0.0642***	0.0661***
	(0.023)	(0.019)
No. of Obs.	50,558	51,631
Adj-R^2	0.605	0.605
Weather controls	Yes	Yes
Insurance FE	Yes	Yes
Individual FE	Yes	Yes
Seasonal FE	Yes	Yes
City-by-Year FE	Yes	Yes

Notes: Column (1) reports out baseline estimates from Table 2 while Column (2) imputes values for out-of-pocket medical expenditure for missing observations. Robust standard errors in parenthesis are clustered at the household and county-year-month levels. The reference temperature bin is [10–16 °C), which is dropped to avoid multicollinearity. AQI refers to the air quality index, which is instrumented by the accumulated strength of thermal inversion, Weather controls are air pressure, relative humidity, accumulated precipitation, sunshine duration, wind speed and the direction of maximum wind speed, all in the form of third-degree polynomials. * p < 0.01, ** < 0.05, *** p < 0.001.

Table A16
Temperature effects on physical health - six-month exposure window.

	(1) Diagnosed chronic diseases (Yes = 1) 12-month exposure window	(2) Diagnosed chronic diseases (Yes = 1) 6-month exposure window
(below −12°)	0.0005	0.0016**
	(0.001)	(0.001)
[−12 °C -7 °C)	0.0006	0.0014
	(0.001)	(0.001)
[−7 °C -1 °C)	−0.0006	0.0002
	(0.001)	(0.001)

(*continued on next page*)

Table A16 (*continued*)

	(1)	(2)
	Diagnosed chronic diseases (Yes = 1)	Diagnosed chronic diseases (Yes = 1)
	12-month exposure window	6-month exposure window
[−1 °C 4 °C)	0.0009	0.0006
	(0.001)	(0.001)
[4 °C 10 °C)	0.0003	0.0002
	(0.001)	(0.000)
[16 °C 21 °C)	0.0011***	0.0009**
	(0.000)	(0.000)
[21 °C 27 °C)	0.0011**	0.0004
	(0.000)	(0.000)
[27 °C 32 °C)	0.0016***	0.0001
	(0.001)	(0.000)
[32 °C above)	0.0020**	−0.0022
	(0.001)	(0.002)
Instrumented AQI	0.0051	0.0018
	(0.004)	(0.003)
No. of Obs.	43,111	43,111
Adj-R^2	0.571	0.571
Weather controls	Yes	Yes
Insurance FE	Yes	Yes
Individual FE	Yes	Yes
Seasonal FE	Yes	Yes
City-by-Year FE	Yes	Yes

Notes: Column (2) shortens the exposure window from 12 months to 6 months preceding the interview. AQI refers to the air quality index, which is instrumented by the accumulated strength of thermal inversion, Robust standard errors in parenthesis are clustered at the household and county-year-month levels. The reference temperature bin is [10–16 °C), which is dropped to avoid multicollinearity. Weather controls are air pressure, relative humidity, accumulated precipitation, sunshine duration, wind speed and the direction of maximum wind speed, all in the form of third-degree polynomials. A linear probability model is used. * $p < 0.01$, ** < 0.05, *** $p < 0.001$.

Table A17
Cases diagnosed for each category of chronic diseases.

Chronic diseases categories	# case diagnosed within six months
Certain infectious diseases	76
Parasitic diseases	2
Malignant neoplasms	65
Benign neoplasms & In situ neoplasms	54
Endocrine, nutritional and metabolic diseases	919
Diseases of the blood and blood-forming organs and certain Disorders involving the immune mechanism	95
Mental and behavioral disorders	72
Diseases of the nervous system	149
Diseases of the eye and adnexa	105
Diseases of the ear and mastoid process	31
Diseases of the circulatory system	3288
Diseases of the respiratory system	2086
Diseases of the digestive system	1615
Diseases of the genitourinary system	582
Pregnancy, childbirth and the puerperium	0
Diseases of the skin and subcutaneous tissue	92
Diseases of the musculoskeletal system and connective tissue	1794
Congenital malformations, deformations and chromosomal abnormalities	21
Certain conditions originating in the perinatal period	0
Injury, poisoning and certain other consequences of external causes	66
Others	2
Symptoms, signs and abnormal clinical and laboratory findings, not elsewhere classified	260

Note: The data is from CFPS. We have 50,558 observations at the individual-year level.

Table A18
Temperature effects on mental health and daily activities with a one month exposure window.

	(1)	(2)	(3)	(4)	(5)
	Feel Sad (Yes = 1)	Feel unhappy (Yes = 1)	Feel lonely (Yes = 1)	Overall mental health index	Sleep disruption (Yes = 1)
(below −12°)	0.0023	−0.0079	0.0040	0.0063	−0.0049
	(0.004)	(0.008)	(0.006)	(0.009)	(0.007)
[−12 °C -7 °C)	−0.0138**	0.0050	−0.0072	0.0143**	−0.0119

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Table A18 (*continued*)

	(1)	(2)	(3)	(4)	(5)
	Feel Sad (Yes = 1)	Feel unhappy (Yes = 1)	Feel lonely (Yes = 1)	Overall mental health index	Sleep disruption (Yes = 1)
	(0.006)	(0.009)	(0.006)	(0.007)	(0.008)
[−7 °C -1 °C)	−0.0007	−0.0121***	−0.0030	0.0021	0.0043
	(0.003)	(0.004)	(0.003)	(0.006)	(0.004)
[−1 °C 4 °C)	0.0025	0.0030	0.0006	0.0036	−0.0006
	(0.002)	(0.003)	(0.002)	(0.004)	(0.003)
[4 °C 10 °C)	−0.0010	0.0001	−0.0016	−0.0031	0.0019
	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)
[16 °C 21 °C)	0.0016	0.0053***	0.0018	−0.0007	0.0001
	(0.001)	(0.002)	(0.001)	(0.003)	(0.002)
[21 °C 27 °C)	0.0021*	0.0039**	0.0006	0.0049	0.005***
	(0.001)	(0.002)	(0.001)	(0.003)	(0.001)
[27 °C 32 °C)	0.0032**	0.0066**	0.0022	0.0077**	0.0160***
	(0.002)	(0.003)	(0.002)	(0.004)	(0.002)
[32 °C above)	0.0022	−0.0008	0.0018	0.0102	0.0240***
	(0.003)	(0.005)	(0.003)	(0.007)	(0.005)
Instrumented AQI	0.0012	0.0043	0.001	0.0047	0.0060**
	(0.002)	(0.004)	(0.002)	(0.009)	(0.003)
No. of Obs.	23,350	23,340	23,328	23,304	50,558
Adj-R^2	0.637	0.638	0.626	0.711	0.681
Weather controls	Yes	Yes	Yes	Yes	Yes
Insurance FE	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes
Seasonal FE	Yes	Yes	Yes	Yes	Yes
City-by-Year FE	Yes	Yes	Yes	Yes	Yes

Notes: All columns shorten the exposure window from 12 months to one month preceding the interview. Robust standard errors in parenthesis are clustered at the household and county-year-month levels. The reference temperature bin is [10–16 °C), which is dropped to avoid multicollinearity. AQI refers to the air quality index, which is instrumented by the accumulated strength of thermal inversion, Weather controls are air pressure, relative humidity, accumulated precipitation, sunshine duration, wind speed and the direction of maximum wind speed, all in the form of third-degree polynomials. A linear probability model is used. * $p < 0.01$, ** < 0.05, *** $p < 0.001$. * $p < 0.01$, ** < 0.05, *** $p < 0.001$.

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