

Wu, Wanrui; Liu, Gordon; Pan, Yuhang

Working Paper

Hospital workload and adaptation under climate change: Evidence from the People's Republic of China

ADB Economics Working Paper Series, No. 780

Provided in Cooperation with:

Asian Development Bank (ADB), Manila

Suggested Citation: Wu, Wanrui; Liu, Gordon; Pan, Yuhang (2025) : Hospital workload and adaptation under climate change: Evidence from the People's Republic of China, ADB Economics Working Paper Series, No. 780, Asian Development Bank (ADB), Manila,
<https://doi.org/10.22617/WPS250176-2>

This Version is available at:

<https://hdl.handle.net/10419/322370>

Standard-Nutzungsbedingungen:

Die Dokumente auf EconStor dürfen zu eigenen wissenschaftlichen Zwecken und zum Privatgebrauch gespeichert und kopiert werden.

Sie dürfen die Dokumente nicht für öffentliche oder kommerzielle Zwecke vervielfältigen, öffentlich ausstellen, öffentlich zugänglich machen, vertreiben oder anderweitig nutzen.

Sofern die Verfasser die Dokumente unter Open-Content-Lizenzen (insbesondere CC-Lizenzen) zur Verfügung gestellt haben sollten, gelten abweichend von diesen Nutzungsbedingungen die in der dort genannten Lizenz gewährten Nutzungsrechte.

Terms of use:

Documents in EconStor may be saved and copied for your personal and scholarly purposes.

You are not to copy documents for public or commercial purposes, to exhibit the documents publicly, to make them publicly available on the internet, or to distribute or otherwise use the documents in public.

If the documents have been made available under an Open Content Licence (especially Creative Commons Licences), you may exercise further usage rights as specified in the indicated licence.



<https://creativecommons.org/licenses/by/3.0/igo/>

HOSPITAL WORKLOAD AND ADAPTATION UNDER CLIMATE CHANGE

EVIDENCE FROM THE PEOPLE'S REPUBLIC OF CHINA

Wanrui Wu, Gordon Liu, and Yuhang Pan

NO. 780

May 2025

**ADB ECONOMICS
WORKING PAPER SERIES**

ADB Economics Working Paper Series

Hospital Workload and Adaptation Under Climate Change: Evidence from the People's Republic of China

Wanrui Wu, Gordon Liu, and Yuhang Pan

No. 780 | May 2025

Wanrui Wu (wrwu2016@nsd.pku.edu.cn) is a PhD candidate; Gordon Liu (gordonliu@nsd.pku.edu.cn) is the dean of Institute for Global Health and Development; and Yuhang Pan (yhpan@pku.edu.cn) is an assistant professor at Peking University.

The *ADB Economics Working Paper Series* presents research in progress to elicit comments and encourage debate on development issues in Asia and the Pacific. The views expressed are those of the authors and do not necessarily reflect the views and policies of ADB or its Board of Governors or the governments they represent.



Creative Commons Attribution 3.0 IGO license (CC BY 3.0 IGO)

© 2025 Asian Development Bank
6 ADB Avenue, Mandaluyong City, 1550 Metro Manila, Philippines
Tel +63 2 8632 4444; Fax +63 2 8636 2444
www.adb.org

Some rights reserved. Published in 2025.

ISSN 2313-6537 (print), 2313-6545 (PDF)
Publication Stock No. WPS250176-2
DOI: <http://dx.doi.org/10.22617/WPS250176-2>

The views expressed in this publication are those of the authors and do not necessarily reflect the views and policies of the Asian Development Bank (ADB) or its Board of Governors or the governments they represent.

ADB does not guarantee the accuracy of the data included in this publication and accepts no responsibility for any consequence of their use. The mention of specific companies or products of manufacturers does not imply that they are endorsed or recommended by ADB in preference to others of a similar nature that are not mentioned.

By making any designation of or reference to a particular territory or geographic area in this document, ADB does not intend to make any judgments as to the legal or other status of any territory or area.

This publication is available under the Creative Commons Attribution 3.0 IGO license (CC BY 3.0 IGO) <https://creativecommons.org/licenses/by/3.0/igo/>. By using the content of this publication, you agree to be bound by the terms of this license. For attribution, translations, adaptations, and permissions, please read the provisions and terms of use at <https://www.adb.org/terms-use#openaccess>.

This CC license does not apply to non-ADB copyright materials in this publication. If the material is attributed to another source, please contact the copyright owner or publisher of that source for permission to reproduce it. ADB cannot be held liable for any claims that arise as a result of your use of the material.

Please contact pubsmarketing@adb.org if you have questions or comments with respect to content, or if you wish to obtain copyright permission for your intended use that does not fall within these terms, or for permission to use the ADB logo.

Corrigenda to ADB publications may be found at <http://www.adb.org/publications/corrigenda>.

Notes:

In this publication, “\$” refers to United States dollars.
ADB recognizes “China” as the People’s Republic of China.

ABSTRACT

Climate change poses significant challenges to healthcare systems. This research estimates temperature impacts on hospital workload, using inpatient records from more than 1,000 emergency departments (EDs) in the People's Republic of China between 2013 and 2022. We find inpatient admissions in EDs decrease by 12.3% on days with a mean temperature below -6°C , while increasing by 7.7% on days with a mean temperature exceeding 30°C , compared with a temperature reference of 12°C to 15°C . Heterogeneity analysis indicates that specific departments such as internal medicine, surgery, and pediatrics experience more substantial increases in workload during extreme heat. Temperature also reshapes the patient structure: male patients, child patients, and patients with injuries or respiratory diseases take up a larger proportion of total admissions on extremely hot days. Considering adaptation methods, we show that hospitals temporarily allocate more junior physicians to EDs when the temperature is hot. Hospitals in cities where people have higher incomes and better-heated homes are less sensitive to temperature changes. In terms of monetary burden, we estimate corresponding healthcare expenditures, which suggest that the impact of extreme temperatures is larger on the insured portion of expenditures than it is on out-of-pocket payments. This research highlights the relationship between temperature and workload burden faced by the major healthcare facilities, providing suggestions for the healthcare system to increase personnel and adjust resource allocation in response to climate change.

Keywords: hospital workload, climate change, extreme temperature, healthcare expenditure, People's Republic of China

JEL codes: I10, I12, I18, Q50, Q51, Q54

The authors would like to thank seminar participants at the China Health Economics Forum, the China Health and Development Economics Forum, Harvard University, Fudan University, Peking University, and the Asian Development Bank, and Xi Chen, Olivier Deschenes, Guojun He, Joshua Graff-Zivin, Harlan Krumholz, Xiaoyan Lei, Minhaj Mahmud, Matthew Neidell, Sarah Miller, Albert Park, Xuezheng Qin, Takanao Tanaka, Junjian Yi, Joseph Zveglic, and Eric Zou for helpful comments and suggestions. Financial support from the National Science and Technology Major Project of the Ministry of Science and Technology of the People's Republic of China (PRC) (No. 2023ZD0503501) and the Young Scientists Fund of the National Natural Science Foundation of the PRC (No. 72403005) is greatly appreciated. This study is supported by the High-Performance Computing Platform of Peking University. The authors declare that they have no relevant or material financial interests that relate to the research described in this paper. Any remaining errors are the authors.

I. INTRODUCTION

Climate change-induced increases in the intensity and frequency of extreme temperatures impose considerable challenges on healthcare systems. In addition to physical damage to public infrastructure and electricity systems in various sectors (Rode et al. 2021), healthcare systems face particularly severe capacity constraints, driven by surging demand. Extreme temperatures adversely affect population health, leading to increased healthcare utilization. This surge in demand exacerbates shortages and the uneven distribution of healthcare resources, complicating efforts to achieve universal healthcare (Salas and Jha 2019, IPCC 2023). Strains on healthcare provision can thus result in poorer health outcomes, magnifying the global health impacts of climate change (WHO 2024).

The impacts of climate change on healthcare systems have yet to be fully investigated. Most previous studies have documented that population mortality rises during extremely cold and hot weather events.¹ However, this U-shape relationship between temperature and all-cause mortality may not uniformly reflect the impact of extreme temperature on healthcare utilization and the corresponding workload for healthcare providers. There are at least three reasons for such inconsistency.

First, a larger proportion of healthcare demand is driven by non-fatal health deterioration rather than acute fatal conditions. Existing work has suggested a temperature–morbidity relationship different from the U-shape temperature–mortality relationship. Some studies have found morbidity linearly impacted by temperature (White 2017, Karlsson and Ziebarth 2018, Mullins and White 2019, Agarwal et al. 2021, Aguilar-Gomez et al. 2024, Gould et al. 2024), while others have observed morbidity increases on extreme cold and hot days (Weinberger et al. 2018; Iniguez, Roye, and Tobias 2021).

Second, healthcare demand is influenced not only by health status but also by behavior preferences, which are highly shaped by weather conditions. For instance, extreme temperatures may encourage people to stay indoors to avoid exposure, making individuals with mild symptoms or lower health risks less likely to seek hospital care (Deschenes and Moretti 2009, Graff-Zivin and Neidell 2014).

Third, climate change can impact healthcare demand via income channels, particularly for individuals whose work depends on mild outdoor conditions. Restricted work opportunities under extreme cold and hot climates may lead to lower income and tighter budgets, limiting access to healthcare services (Colmer 2021, Ebi et al. 2021). As these factors can counteract one another in their influence on healthcare demand, they contribute to a complex and nuanced relationship between climate change and the need for healthcare services.

¹ See, for example, Barreca (2012); Barreca et al. (2015, 2016); Carleton et al. (2022); Dell, Jones, and Olken (2014); Deschenes (2014); Deschenes and Greenstone (2011); Deschenes and Moretti (2009); Liao et al. (2023); Mullins and White (2020); Wellenius (2017); Yardley, Sigal, and Kenny (2011).

The relationship between climate change and healthcare utilization is particularly critical in developing countries and emergency departments (EDs), where workloads are already high even under mild temperature conditions (Asaro, Lewis, and Boxerman 2007; Hoot and Aronsky 2008; Lucas et al. 2009; Pearce et al. 2023). In developing countries, the impact is compounded by insufficient infrastructure, limited access to healthcare services, and a higher prevalence of vulnerable populations. According to the World Health Organization (WHO), low-income and lower middle-income countries have only 1.1 and 4.5 medical doctors per 10,000 population, respectively, compared with a number of 35.6 for high-income countries (WHO 2024). The healthcare system of the People's Republic of China (PRC) is one of the most resource-strained and busiest in the world. From 2007 to 2022, the number of ED visits in the PRC increased 4.5-fold, from 51.9 million to 224.2 million (NHC 2024). Public hospitals, in particular, are often overcrowded, with physicians overloaded with too many patients to serve. For example, in 2023, each ED physician served an average of over 2,000 patients (NBS 2024). EDs in these settings often cannot handle sudden increases in patient volume, resulting in longer waiting times, reduced quality of care, and, in some cases, higher mortality rates (Hoot and Aronsky 2008; Carter, Pouch, and Larson 2014; Chan 2018; Woodworth 2020; Ellis and Esson 2021). Moreover, the impacts of extreme temperature may vary across hospitals and departments with different expertise, sizes, and locations, which cannot be fully and directly documented in research focusing on overall population health.

This paper estimates the contemporaneous and cumulative impacts of temperature on workload in EDs in the PRC. We construct a nationally representative dataset linking daily hospital administrative records of inpatient visits to weather information covering 1,113 EDs in the PRC over the period 2013–2022, which covers a population of 1.34 billion (or 94.97% of the total population of the PRC as of 2022). We exploit random daily variations in weather across the locations of hospitals to document how EDs respond to temperature on the day under different ambient temperatures as well as in the period that follows. The workload in EDs is measured via the number of patients hospitalized through EDs and their associated medical expenses on a hospital-department-day unit basis. Our primary focus is on inpatient visits through the ED rather than overall inpatient admissions, as this approach helps minimize confounding factors from pre-scheduled hospitalizations via non-EDs in the hospital. We adopt the non-parametric approach of temperature bins to estimate the nonlinear effects of temperature, emphasizing the impacts of extremely high temperatures over 30°C and extremely low temperatures below -6°C.

We find that daily inpatient visits through EDs in hospitals drop by 12.3% on average on days with a mean temperature below -6°C, and increase by 7.7% on days with a mean temperature exceeding 30°C, compared with days with a moderate temperature range of 12°C to 15°C. The contemporaneous impacts of temperature exhibit a nearly linear pattern, with inpatient visits through EDs steadily increasing as temperatures rise. Our findings reveal a highly sensitive relationship between inpatient admissions and temperature fluctuations. Even if the temperature change is very minor—such as in comparing a day at 12–15°C with one at 15–18°C or 9–12°C—can present remarkable changes in the number of ED-driven inpatient admissions. Our results

remain robust across various specifications, including alternative fixed effects such as hospital fixed effects, week-of-year fixed effects, and hospital-year-month fixed effects. Additionally, we test the robustness using alternative clustering methods, different sets of control variables, and a falsification test. We also examine the robustness of our findings by employing different approaches to construct hospital-centered climate factors.

We find that the effects of extreme high and low temperatures can persist over short- and medium-term periods. Over 8 days, the cumulative impacts of extreme high and low temperatures are 10.9% and -18.7%, respectively, which are 1.5 times greater than their contemporaneous effects. Our extended analysis indicates that the impact of extremely cold temperatures can persist for up to 20 days, whereas the effect of extremely high temperatures tends to diminish and becomes statistically insignificant after 2 weeks.

In terms of medical expenditures, our findings reveal that total health expenditure in a hospital rises by 7.1% on hot days (daily mean temperature $> 30^{\circ}\text{C}$) and drops by 10.4% on cold days (daily mean temperature $< -6^{\circ}\text{C}$). These shifts in medical expenditures are largely driven by changes in inpatient visits, as extreme temperatures significantly affect the volume of cases seeking hospital care. We further examine the medical expenditure according to their copayment schemes. In the PRC, each medical expense can be categorized into three components: publicly insured, commercially insured, and out-of-pocket payments. Our analysis reveals that the insured portion experiences a larger absolute impact. However, on hot days, the growth rate of out-of-pocket payments surpasses that of insured payments, implying that individuals bear a disproportionate share of the major medical expense burden from climate change-driven healthcare demand.

We find that the relationship between temperature and healthcare utilization varies across hospitals, departments, and city characteristics. In the PRC, the hospital system is organized into a tiered structure, with three tiers to reflect the quality, scale, and capabilities of medical institutions. Our analysis reveals that inpatient admissions through EDs in lower-tiered hospitals are more sensitive to temperature fluctuations. This increased susceptibility can be attributed primarily to the fact that the health issues induced by climate change are often relatively mild. These health issues typically do not require highly specialized care—but may necessitate prompt treatment (Sartini et al. 2022). As a result, individuals tend to seek care at lower-tier hospitals, which are more accessible and generally handle less severe cases. By investigating the relationship across sub-departments within EDs, we find the impacts are larger in departments of internal medicine, surgery, and pediatrics. Additionally, EDs located in cities with centralized winter heating and higher income levels are less affected by temperature extremes.

We further examine how temperature reshapes the patient structure in four different dimensions—main diagnosed disease, demographic features (i.e., sex and age), insurance scheme, and disease severity. Corresponding to findings for heterogeneity among departments, we find that cases of injuries, respiratory diseases, endocrine diseases, and digestive diseases increase most during extremely high temperature. For demographic features, we find that male and child patients

take up a larger proportion of patient admissions during extremely hot days. EDs experience a more sensitive change in the number of inpatients participating in Urban Employee Basic Medical Insurance (UEBMI), the major insurance with the average highest reimbursement rate in the PRC, compared with other major insurance types, under extreme temperature. The proportion of patients with relatively milder illnesses increases on hot days, showing a downward shift in the average severity of the inpatient admissions.

We examine whether hospitals can adapt to fluctuations in patient volume caused by weather changes by adjusting the number of healthcare staff. By regressing temperature variations against the number of working doctors, we find that hospitals increase the number of working doctors in EDs to accommodate higher inpatient admissions during hot days. The number of resident doctors—typically the most junior members of the medical team—rises more than that of chiefs or attending physicians. This adjustment of the medical workforce in EDs is more pronounced in tier 2 hospitals and hospitals located in cities with a higher average level of income or without centralized heating.

Overall, the above findings suggest that (i) the temperature–healthcare utilization relationship has a linear pattern, which is different from the U-shape temperature–health relationship; (ii) the impacts can be remarkably stronger in departments such as internal medicine, surgery, and pediatrics, with a larger proportion of the inflow consisting of male patients, children, those with better insurance coverage, and those with milder illnesses; and (iii) hospitals can promptly adapt to the fluctuations in ambient temperature and the corresponding changes in inpatient inflow through personnel management.

Our study contributes to the existing literature on climate and healthcare systems by estimating the relationship between temperature and hospital workload in a developing country. While some studies have been conducted in developed countries, such as the US (White 2017, Mullins and White 2019) and Germany (Karlsson and Ziebarth 2018), few have focused on developing countries (Agarwal et al. 2021, Gould et al. 2024). Previous literature, however, usually uses inpatient data to study the impacts on population morbidity (White 2017, Karlsson and Ziebarth 2018, Mullins and White 2019, Agarwal et al. 2021, Gould et al. 2024). We analyze inpatient admissions at the hospital level to estimate the fluctuation in patient volume, patient structure, and total expenditure caused by extreme temperature for EDs. As discussed in Salas and Jha (2019), there is potential disruption of healthcare infrastructure as a result of extreme weather events; however, this economic research has largely overlooked this issue. Our study fills this gap and finds that healthcare providers face greater demands during periods of extreme high temperatures compared with extreme low temperatures. Furthermore, our study reveals potential changes in patient structure and variations among different medical departments within EDs, highlighting the uneven impacts of temperature on healthcare workload.

Two studies closely related to this research in the literature on climate change and healthcare systems are Aguilar-Gomez, Graff-Zivin, and Neidel (2024) and Agarwal et al. (2021). Aguilar-Gomez, Graff-Zivin, and Neidel study the impact of heat on healthcare utilization and patient

outcomes in Mexico. A key distinction between their study and ours is that the PRC's diverse climate enables us to explore the effects of temperature over a much broader range. Given the narrow temperature range in Mexico, Aguilar-Gomez, Graff-Zivin, and Neidel focus only on the effects of temperatures between 18°C and 34°C. They document a similar pattern—an increase in ED and hospital visits and an increase in mortality during heat events. Our data from the PRC, which includes hospital-day observations at local temperatures below −6°C, allow us to estimate the impact of extremely low temperatures on ED visits and healthcare expenditures.

Agarwal et al. (2021) provide evidence in the PRC using city-level inpatient admission rates as a measurement of population morbidity. We are different from Agarwal et al. in at least two aspects. First, we analyze from a supply-side perspective by aggregating the inpatient volume and expenditure to each individual ED, featuring more about the effects of temperature on the workload of the healthcare system. Second, Agarwal et al. study the population covered by two primary public insurance schemes in the PRC, excluding the population that is commercially insured, insured by other public schemes, or uninsured, which weakens the representativeness of the estimation. In comparison, our data include all inpatient admissions, disregarding their enrollment in health insurance, which allows us to precisely estimate the change in workload and patient structures.² Furthermore, by examining healthcare expenditure and disease severity at the hospital level, our study offers a comprehensive evaluation of the impacts of temperature on healthcare providers, considering changes not only in quantity but also in complexity and cost.

Our findings also contribute to the growing literature on climate change adaptation, specifically providing the first empirical evidence of adaptation through personnel management. Previous literature has documented adaptation strategies in agriculture, transportation, regional development planning, and residential defensive expenditures for undesired weather.³ Beyond these traditional adaptation methods for individuals to mitigate the adverse impact on health in our context, we move one step further to discuss the potential reaction approaches of healthcare providers, given the fluctuations in workloads induced by extreme temperature. As documented in Hwang et al. (2011), additional medical personnel and more flexible allocation of equipment can be solutions to hospital crowding. Our study provides evidence that, in response to increasing patient volume on extremely hot days, hospitals can adapt by increasing the number of practicing doctors serving hospitalized patients in the ED. Our findings suggest junior physicians in hospitals

² Another difference is that Agarwal et al. analyze inpatients through all departments, while we focus more on EDs, which is more related to non-deferrable diseases induced by the extreme temperature. In Agarwal et al.'s setting, the authors find non-results of the contemporaneous effects of temperature. We replicate their approach by examining hospitalizations through all departments, yielding similar statistically insignificant estimates.

³ Creating a mild indoor climate via air conditioning or winter heating (Deschenes and Greenstone 2011; Barreca et al. 2012; Barreca et al. 2016; Yu, Lei, and Wang 2019; Li, Smyth, and Yao 2023) and elevating average income to enhance accessibility and affordability of energy consumption, and therefore improving the resilience of the population during extreme weather events Dell, M., B. F. Jones and B. A. Olken (2014). "What Do We Learn from the Weather? The New Climate-Economy Literature." *Journal of Economic Literature* 52(3): 740-798, Carleton, T., A. Jina, M. Delgado, M. Greenstone, T. Houser, S. L. Hsiang, A. Hultgren, R. E. Kopp, K. E. McCusker, I. Nath, J. Rising, A. Rode, H. K. Seo, A. Viaene, J. C. Yuan and A. T. Zhang (2022). "Valuing the Global Mortality Consequences of Climate Change Accounting for Adaptation Costs and Benefits*." *Quarterly Journal of Economics* 137(4): 2037-2105, Cohen, F. and A. Dechezlepretre (2022). "Mortality, Temperature, and Public Health Provision: Evidence from Mexico." *American Economic Journal-Economic Policy* 14(2): 161-192..

enhance their flexibility to increase healthcare provision when facing a contemporaneous rise in patient volume. We also explore this adaptation method for hospitals of different levels and locations, providing further insights into effective strategies for adapting to climate change.

The rest of paper is organized as follows. Section II introduces the data and the main measurements used. Section III describes the empirical strategies. Section IV provides baseline results of contemporaneous effects of temperature on hospital workload, a set of robustness checks, and the results on cumulative effects. Section V presents heterogeneity analysis. Section VI discusses the change in patient structure corresponding to the change in temperature. Section VII examines adaptation methods for hospitals to use to react to extreme temperatures by adjusting the medical workforce. Section VIII concludes.

II. DATA

We use data from three main sources: the home page of hospitalization records from 1,113 public hospitals in the PRC, hourly weather records from a comprehensive set of ground-based weather stations, and city- and county-level socioeconomic characteristics from various statistical yearbooks in the PRC. We aggregate the case-level hospitalization records to the hospital-by-department-by-day level to measure hospital workload. We then merge the hospital workload data with weather records according to the location of the hospital and link them to local socioeconomic characteristics. Each of the three primary data sources is described in more detail below.

A. Hospital Workload

Data on hospitalization records are collected from 1,113 hospitals across 279 cities in 30 provinces nationwide, covering the period from 2013 to 2022.⁴ The hospitals in our sample are mainly tier 3 and tier 2 hospitals (see panel B of Table 1). To ensure data completeness in the analysis, we restrict our sample to include only full hospitalization records during the research period, excluding patients admitted before 1 January 2013 and those discharged after 31 December 2022. Additionally, we exclude hospitals with only a few hospitalization records—that is, fewer than 360 admissions per month. To avoid the biases related to local epidemic prevention and control policies, we dropped data from the first outbreak of coronavirus disease, from between January 2020 and April 2020.

In our analysis, we focus primarily on patients hospitalized through the ED, as they are mostly likely to represent the acute and immediate health shock (White 2017). In contrast, admissions through other channels often involve non-acute conditions or pre-scheduled surgeries, making them less suitable for capturing sudden health crises. To measure hospital workload, we

⁴ The raw data are not balanced panel data since the electronic medical record system starts from different years in different hospitals. In practice, the sample is restricted to include only hospital with home page records for at least 1 year.

aggregate the daily number of ED admissions at both the hospital level and department levels.⁵ In addition, we examine patient composition by calculating the number and proportion of ED hospitalizations across different age groups, sexes, diagnoses, and insurance types. Specifically, we categorize diagnoses into 19 disease groups based on the first hierarchy of the 10th revision of the International Classification of Diseases (ICD-10-CM). Appendix Table 1 provides detailed definitions and corresponding ICD-10-CM codes for each disease group.⁶ Furthermore, we classify insurance status into five groups: three major public insurance categories, an uninsured group, and a category for individuals covered by other forms of insurance. For healthcare expenditures, we obtain both per patient and aggregated expenditures, payments shared by insurance, and out-of-pocket payments, all measured at the hospital level by the day of admission.

B. Weather

We obtain data on temperature and precipitation from the China Meteorological Data Service Center, an affiliate of the National Meteorological Information Center. This dataset includes hourly records from over 400 land-based weather stations across the PRC, reporting key meteorological variables such as temperature, dew-point temperature, precipitation, and wind speed. To link weather conditions to hospital locations, we calculate hospital-centered daily averages for multiple temperature measures, including ambient temperature, apparent temperature, highest and lowest temperatures, temperature variation (the max–min temperature difference), and precipitation. The detailed computation methods are outlined in Appendix A.

We employ temperature bin models to capture the nonlinear effects of temperature, following established methodologies in the literature (Deschenes and Greenstone 2011; White 2017; Karlsson and Ziebarth 2018; Yu, Lei, and Wang 2019; Agarwal et al. 2021; Cohen and Dechezlepretre 2022). Specifically, we define 14 temperature bins for daily ambient and apparent temperatures, including 12 bins covering 3°C intervals and two extreme temperature bins (below –6°C and exceeding 30°C). Each bin represents the daily-hospital level weather realizations that fall into the range of the bin. In analyzing the impact of daily highest temperature, the bin for temperature exceeding 30°C is further refined into three categories: 30–33°C, 33–36°C, and above 36°C, allowing for a more granular examination of extreme heat effects. Similarly, for daily lowest temperature, the bin for temperatures below –6°C is adjusted to –9°C to –6°C, with an additional bin created for temperatures below –9°C. In addition, we categorize temperature variation (temperature gap within a day) into four bins to assess the impact of fluctuations within a day: 0–5°C, 5–8°C, 8–11°C, and above 11°C.

C. City-Level Socioeconomic Characteristics

We merge the socioeconomic characteristics to each hospital based on their geographically based city-level administrative affiliation. Most of the city-level socioeconomic characteristics are obtained from statistical yearbooks, including gross domestic product (GDP) per capita; share of

⁵ Departments are classified at 2-digit level based on the department codes corresponding to the Directory of Departments in Medical Institutions issued by National Health Commission 2009.

⁶ The Appendix is available at <http://dx.doi.org/10.22617/WPS250176-2>.

GDP in the agriculture sector and the industrial sector; population; number of hospitals, beds, and physicians; and electricity usage.⁷ The county-level nighttime light index, serving as a proxy for economic activity, is obtained from the National Oceanic and Atmospheric Administration nighttime lights dataset, which provides satellite-based measurements of artificial light intensity. Data on centralized winter heating are collected from each city's official announcements regarding the start and end dates of the heating season for each sampled year. Notably, 37% of the cities in our sample implement centralized winter heating from November to March each year.

D. Summary Statistics

The summary statistics for hospital workload data are presented in panel A of Table 1. Our sample includes over 25.5 million ED admissions across 817,344 hospital-days. On average, there are 31.22 ED admissions per day at each hospital, with male patients comprising 52.3% of the total. Patients aged 65 and above account for approximately 36.3% of total visits, while children aged 0–5 take up 9.4%. Average health expenditure per patient during hospitalization is CNY12,666.13 (approximately \$1,800), 35% of this amount being out-of-pocket payments. In panel B of Table 1, we summarize the daily number of physicians in charge of the ED hospitalization patients. On average, each hospital has 29 chief doctors, 38 attending doctors, and 47 resident doctors managing ED patients on a daily basis. Panel C of Table 1 presents the statistics for the climate variables. The lowest hospital-centered daily mean temperature in our sample is -38.38°C , while the highest daily mean temperature is 36.91°C . There are 32,488 hospital-day units with temperatures below -6°C , and 17,178 hospital-day units with temperatures over 30°C . The socioeconomic characteristics are summarized in panel D of Table 1.

III. EMPIRICAL STRATEGY

We use the nonparametric temperature bin model to examine the contemporaneous effects of temperature on hospital workload, which allows us to identify the nonlinear impact of temperature (Deschenes and Greenstone 2011, White and 2017, Agarwal et al. 2021, Cohen and Dechezlepretre 2022). Our baseline specification is as follows:

$$\ln Y_{i,t} = \beta_0 + \sum_{j=1}^{14} \beta_j \text{Temp}_{i,t}^j + \gamma X_{i,t} + \alpha_{i,w} + \pi_d + \epsilon_{i,t} \quad (1)$$

where i , t , w , and d denote hospital, date, week-of-year, and day-of-week, respectively. Y_{it} represents the outcome of interest, which measures hospital workload. Our baseline primarily employs the number of hospitalizations through the ED in hospital i on day t to measure the hospital workload. In subsequent analysis, we extend our analysis to additional outcomes such as healthcare costs and patient structures. We take the logarithm of the dependent variables to

⁷ Not all cities in our sample have complete documentation of socioeconomic characteristics at the city level in yearbooks. In case of missing values, we use the corresponding province-level (the higher administrative unit) characteristics as an approximation.

estimate the effects in percentage relative to the benchmark temperature. Furthermore, we assess the number of hospitalizations by disease categories, age, and sex to explore potential heterogeneity effects.

$Temp_{it}^j$ represents a series of dummy variables indicating whether the temperature at hospital i on day t falls within a specific j -th temperature bin. These temperature bins are ordered from the coldest to the hottest, with the estimator β_1 capturing the contemporaneous effects of the extremely low temperature ($< -6^\circ\text{C}$), and β_{14} reflecting the effects of the extremely high temperature ($> 30^\circ\text{C}$). We omit the modest temperature bin (12°C – 15°C) as a reference group in all regressions, so the estimates of all other bins are interpreted as the effects relative to a day of temperature range of 12°C – 15°C . In other words, the coefficient β_j measures the change in daily ED workload when the temperature on a given day falls within the j -th temperature bin, compared with when the temperature is between 12°C and 15°C .

$X_{i,t}$ is a vector of control variables for hospital i on day t . In our primary specification, we control for daily precipitation conditions, as precipitation can influence both ambient temperature and inpatient visits. $\alpha_{i,w}$ and π_d represent the hospital-year-week fixed effects and day-of-week fixed effects, respectively. Including hospital-year-week fixed effects helps control for all time-varying shocks that occur within each hospital on a weekly basis. This includes confounders such as time-invariant hospital characteristics (i.e., location of hospital), time-variant hospital characteristics (i.e., rank of hospital), and common shocks affecting all hospitals during the same year-week periods (i.e., national holidays). Day-of-week fixed effects control for the unobserved systematic difference of weekends and weekdays. Standard errors in the baseline model are two-way clustered at the hospital level and year-week level, allowing for serial correlation within a hospital and spatial correlation within a week-year. $\epsilon_{i,t}$ is the error term.

To check the robustness, we use five sets of alternative methods. First, we check the robustness with alternative fixed effect choices, including hospital fixed effects, week-of-year fixed effects, and hospital-year-month fixed effects. Second, we report the standard errors of our estimates using different clustering approaches. Third, we estimate the model with different sets of control variables. Our primary model controls only for local precipitation and includes the hospital-week-of-year fixed effects. In robustness checks, we add more socioeconomic characteristics to the specification, including hospital fixed effects and week-of-year fixed effects, to control for local economic development level, economic structure, healthcare infrastructure, and electronic usage conditions.⁸ Fourth, we revisit our primary specification while modifying how we measure climate factors. In our baseline model, the hospital-centered daily temperature is calculated as a squared inverse distance-weighted average temperature from all weather stations in our dataset. To check the robustness, we re-estimate our baseline using different ways of constructing the hospital-centered temperature measure. For example, one of our robustness checks is using the nearest

⁸ Level of economic development is measured by GDP per capita, economic structure is measured by share of the agriculture sector and share of the industrial sector in GDP, and health infrastructure is measured by the number of hospitals, beds, and physicians.

station's climate data to represent the hospital-centered weather factors. Additionally, we adjust the weight or geographical range used in computing hospital-centered weather factors. The detailed alternative computations are introduced in Appendix A. Last, we conduct a placebo test by randomly reshuffling climate conditions across hospitals and over time.

Temperature may not only have contemporaneous effects on hospital workload on the same day but also exert delayed influences. To estimate the lagged impacts of temperature on hospital workload, we apply a distributed lag model (Deschenes and Moretti 2009, Deschenes and Greenstone 2011, White 2017):

$$\ln Y_{it} = \beta_0 + \sum_{j=1}^{14} \sum_{\tau=0}^T \beta_{j,t-\tau} Temp_{i,t-\tau}^j + \gamma X_{i,t,\tau} + \alpha_{i,w} + \pi_d + \epsilon_{i,t} \quad (2)$$

where T lags for each temperature bins are included in the model to capture the potential delayed effects. Building on previous empirical studies suggesting that the impact of temperature on population health can last up to 30 days (Deschenes and Moretti 2009, White 2017), we consider lags ranging from 1 to 30 days to investigate the dynamic cumulative effects of temperature.

Similar to the denotation in the previous model, $Temp_{i,t-\tau}^j$ represents whether the temperature at hospital i on day $t - \tau$ falls within the j -th temperature bin. The coefficient $\beta_{j,t-\tau}$ represents the effects of temperature (falling within the j -th temperature bin) during time period $t - \tau$ on hospital workload in time period t . The cumulative effect of temperature is therefore calculated as a linear combination of the coefficients of all the j -th bins from day t to $t - \tau$, i.e. $\sum_{\tau=0}^T \beta_{j,t-\tau}$.

i , t , w , and d are identically denoted as in the model for contemporaneous effects. The cumulative effect model controls for the same fixed effects and applies the same ways of clustering standard errors as in the previous model. The covariates $X_{i,t,\tau}$ controlled in the cumulative effect model include additional T lags for precipitation (i.e., $\sum_{\tau=0}^T \gamma_{t-\tau} Precip_{i,t-\tau}$).

IV. BASELINE RESULTS

A. Contemporaneous Effects

We begin by examining the relationship between temperature and hospital workload using the temperature bin model demonstrated in equation (1), with 12°C–15°C as the benchmark. By controlling for hospital-year-week fixed effects and day-of-week fixed effects, the model conservatively estimates the impact of daily mean temperature on the number of ED admissions. The results are summarized in Figure 1, where each dot represents the estimated coefficients β_j from equation (1), indicating the difference in ED admissions when the temperature on that day falls in the j -th bin, relative to the benchmark temperature. The estimations are ordered by the temperature range of bins from the lowest to the highest. The 95% confidence interval (CIs) are plotted in yellow. We connect the dots and their corresponding 95% CIs across bins to visually

represent the change in ED admissions as temperature increases or decreases toward the extreme high or low ends. The corresponding coefficient estimates are provided in column 1 of Table 2.

The contemporaneous effect of temperature on hospital workload displays a nearly linear pattern, with temperature having a monotonic, positive impact on the number of ED admissions. The workload of ED increases to a high volume during the extremely hot days. Specifically, for a day with mean temperature exceeding 30°C, the number of ED admissions increases when daily mean temperature is higher, reaching an increase by 7.7%, compared with a benchmark temperature of 12°C –15°C. During the extreme cold days, the workload of EDs shrinks to a smaller scale. Compared with the benchmark, on days with a mean temperature below –6°C, the number of ED admissions decreases by 12.3%. The variation in workload among EDs increases as the temperature moves toward both extreme hot and extreme cold. Relatively, the variation in workload during extreme cold days (with a daily mean temperature < 0°C) exceeds twice the variation during extreme hot days (with a daily mean temperature > 30°C). This suggests that the hospitals face larger uncertainty of patient inflow when the temperature becomes extreme.

The contemporaneous effects observed in this study align with findings in the existing literature that use regional-level hospital admission rates as outcomes. Along with White (2017), Karlsson and Ziebarth (2018), Agarwal et al. (2021), Gould et al. (2024), and Aguilar-Gomez, Graff-Zivin, and Neidell (2024), our results suggest an increase in hospital admission on the hottest days. Contemporaneous effects of extremely hot days with a temperature exceeding 30°C are larger than those observed by White (2017) in California (3.4%) and by Karlsson and Ziebarth (2018) in Germany (2.9%) when the temperature exceeded 80°F (27°C), and lower than those observed by Agarwal et al. (2021) in the PRC (7.3%) when the temperature exceeded 27°C.

In contrast with the U-shaped relationship between mortality and extreme temperatures found in most studies (Deschenes and Greenstone 2011, Barreca 2012, Barreca et al. 2016), but in line with studies on morbidity and extreme temperature, which often show a near-linear relationship, we observe negative contemporaneous effects during extremely cold days. Specifically, our study finds a 12.3% decrease in hospital admissions on days with temperatures below –6°C, which is a larger effect compared with the 10°F (–12°C) threshold observed by Karlsson and Ziebarth (2018). White (2017) also finds negative contemporaneous effects in California when temperatures drop below 40°F (4°C), with a 6.1% decrease, which is smaller than our estimate.

Agarwal et al. (2021) report positive but statistically insignificant contemporaneous effects on hospital admissions for patients enrolled in the Urban Resident Basic Medical Insurance (URBMI) or Urban Employee Basic Medical Insurance (UEBMI) insurance schemes, regardless of the hospitalization channel (outpatient or ED). We replicate this model using the number of patients through all channels in our sample and find similar statistically insignificant contemporaneous effects as Agarwal et al. (2021) (see Appendix Figure 1). Additionally, we conduct heterogeneity analysis by type of insurance and find hospital admissions of patients enrolled under the different types of insurance (URBMI, UEBMI, New Cooperative Medical Scheme [NMCS], other insurance,

entirely out-of-pocket payment) and find similar linear-shaped contemporaneous effects of temperature. We discuss these results in Section V.

B. Robustness Check

We conduct five sets of robustness check. First, we estimate the temperature–hospital workload relationship with different fixed effects, including hospital fixed effects, week-of-year fixed effects, and hospital-year-month fixed effects. Second, we check the robustness when we cluster the standard error at hospital level only. Third, we re-estimate the models after controlling for local socioeconomic characteristics. Fourth, we conduct the robustness checks by using alternative measures of hospital-centered temperature to take the place of the squared inverse distance-weighted average temperature from all weather stations at the location of the hospitals. Fifth, we conduct a placebo test by randomly reshuffling climate conditions across hospitals and over time.

Appendix Table 2 summarizes the estimations of models with varied specifications and alternative ways of clustering standard errors. In each column, we report two types of standard errors: the parentheses present the standard error two-way clustered at the hospital and year-week level, and the bracket indicates the standard errors clustered at the hospital levels. In columns (1) to (5), we report the estimations of specifications controlling for different sets of fixed effects. In column (1), we check the robustness by controlling for hospital fixed effects and year-week fixed effects. Column (2) checks the robustness by controlling for hospital-by-year-week fixed effects. In column (3), the robustness is checked by a specification with hospital fixed effect and year-week fixed effect, adding the day-in-week fixed effect controlling the unobservables, which varies among weekdays. Column (4) reports the estimations of our primary model, which controls for the hospital-by-year-week fixed effects and the day-in-week fixed effect. Column (5) checks the robustness by controlling for hospital-by-year-month fixed effects.

The results using different sets of control variables are summarized in Appendix Table 3. Column (1) shows the temperature-healthcare utilization relationship for the model when we only include temperature bins, controlling for hospital-by-year-week fixed effects and day-in-week fixed effects, and with two-way clustered standard errors. Column (2) shows the results for the baseline model, where daily hospital-centered precipitation is added compared with the model used in the first column. Columns (3) to (6) include a set of city-year-level socioeconomic characteristics to the specification with hospital fixed effects and year-week fixed effects. To be specific, in column (3), we add GDP per capita to measure the effect of economic development level, and in column (4) we further add the share of the agriculture sector and the share of the industrial sector in GDP to control for the effect of economic structure. In column (5), we add the number of hospitals, beds, and physicians in the city where the hospital is located to control for the overall level of healthcare infrastructure in the neighborhood of the hospital. In column (6), we further consider electricity usage to control for the engineering-oriented impact. The positive relationship of high temperature and hospital workload are consistent across all models. The negative effects of mild low temperature become statistically insignificant as we add more control variables; however, the

statistically significant negative relationship between extreme low temperature and hospital workload remains robust.

We then provide estimations using different ways of constructing hospital-centered temperature, and report results in Appendix Table 4. Column (1) provides estimations using alternatively weighted hospital-centered temperature, and column (2) provides estimations using the temperature from the nearest weather station. Columns (3) to (6) provide estimations using hospital-centered temperature computed from restricted sets of weather station according to distances between stations and hospitals. The coefficients using each measurement of temperature are consistent with and have similar magnitude to our primary results, suggesting good robustness. And column (7) shows the results for the placebo test. None of the coefficients are statistically significant, which suggests that the results of this paper are not driven by unobserved factors or coincidence.

C. Other Measures of Temperature

We further investigate the impact of extreme temperature by examining the contemporaneous effects of alternative temperature measures, including daily apparent temperature, highest temperature, and lowest temperature. The estimated coefficients are reported in columns (2) to (4) of Table 2, which are generally consistent in sign and significance with the contemporaneous effects estimated using daily mean temperature. The impact of extreme temperature measured by apparent temperature on hospital workload is slightly more moderate than that measured by the ambient temperature. Compared with a day with a mean apparent temperature of 12°C–15°C, there are 6.4% more ED admissions on a day with a mean apparent temperature exceeding 30°C, and 11.5% fewer ED admissions on a day with a mean apparent temperature below –6°C. Using daily highest temperature and lowest temperature to identify the impact of extreme temperature events, we find that, when the highest temperature on a day reaches 36°C and above, the number of ED admissions is 9% higher than that on a day with a highest temperature between 12°C and 15°C. At the other end, ED admissions decrease by 9% on a day with the lowest temperature below –9°C. The results suggest a larger magnitude of impact of extreme heat on hospital workload.

We additionally include the temperature difference within a day into our primary model with contemporaneous effects of daily mean temperature. We categorize the difference of temperature within a day into four groups—less than 5°C, 5°C–8°C, 8°C–11°C, and above 11°C. The group of temperature difference less than 5°C is taken as the reference group. As shown in column (5) of Table 2, after controlling for the daily difference, the impact of temperature on ED admissions is of moderately less magnitude, and still statistically significant, and maintains a close-to-linear pattern. The estimated coefficients for each temperature difference group are positive and statistically significant (illustrated in Appendix Figure 2), increasing in magnitude when temperature difference becomes larger. When temperature difference within a day exceeds 11°C, ED admissions increase by 27%, compared with a day with a temperature up to 5°C.

D. Cumulative Effects

We then study the cumulative effect of the extreme temperature below 0°C and above 30°C. We first consider a lagging period of a month, as frequently considered in the previous literature on extreme temperature (Deschenes and Moretti 2009, White 2017). As depicted in panel A of Figure 2, the cumulative effect of extreme temperature on ED admissions is statistically insignificant over a period of 30 days, on both the hottest and the coldest end. Over a period of a week, the extreme hot temperature over 30°C cumulatively leads to an increase by 10.9% in ED admissions, which is of greater magnitude compared with the corresponding contemporaneous effect of extreme heat. The extreme cold temperature below -6°C cumulatively leads to a decrease by 18.7% in ED admissions, although this is of no statistical significance. The variation of cumulative impact of low temperature on ED admission is relatively larger than the cumulative impact of high temperature, over a lagging period of both a month and a week.

The above results show that the cumulative effect of extreme temperature on ED admissions has a larger magnitude and is more statistically significant over a lagging period of a week and diminishes over a 1-month period. The variation of the impact across EDs increases, whereas the magnitude of coefficient decreases. This leads us to consider the change in cumulative effect of extreme temperature over a lagging period varying from 1 to 30. The results are depicted in panels C and D of Figure 2. The negative cumulative effects of extreme low temperature expand as the cumulative period extends to a 25-day period, reaching an approximately 25% decrease in the number of admissions, and then shrinks gradually as the cumulative period continues to extend. The positive cumulative effects of extreme high temperature expand as the cumulative period extends to a 10-day period, and then die out quickly as the cumulative period extends to 30 days.

Our findings on extremely high temperature are similar to the findings of Agarwal et al. (2021) and Karlsson and Ziebarth (2018), which both suggest an statistically insignificant positive cumulative effect on the hottest days > 27°C. The results differ from those of White (2017), who find a positive cumulative effect of the hottest days. The dying-out pattern of the cumulative effects of the highest temperature when cumulative periods extend is consistent with the findings of Agarwal et al. (2021) and White (2017). Agarwal et al. (2021) find the cumulative effects of extremely high temperature become statistically insignificant at the level of 10% soon, when the cumulative periods extends to 5 days, whereas White (2017) find the statistically significant cumulative effect of extremely high temperature when the cumulative periods reach 50 days. For the coldest temperature, the results of cumulative effects are different from estimations in previous literature on city-level hospital admissions. We find negative but statistically insignificant cumulative effects in a period of 31 days, different from the positive and statistically significant effects found by White (2017) and the positive but statistically insignificant effects found by Agarwal et al. (2021). White (2017) suggest an 11% increase in hospital admissions on days with a temperature below 40°F (4°C) and Agarwal et al. (2021) suggest a statistically insignificant 9% increase on days with a temperature below -6°C.

E. Financial Burden

Additionally, we examine the impact of temperature on healthcare expenditure. Three measurements are used in estimation: average daily expenditure per patient in a hospital, average total expenditure per patient during their hospital stay, and aggregated total expenditure in a hospital. All measurements are averaged or aggregated for patients hospitalized on the same day.

As illustrated in Figure 3, per patient daily expenditure and total expenditure increase slightly on extremely cold days, with statistically significant positive effects discerned for extremely high temperatures, which contrasts with the contemporaneous effects on hospital admissions. The aggregated total medical expenditure realized in a hospital throughout the stay of patients hospitalized on extremely hot days over 30°C increases significantly by 7.1%; for those hospitalized on extremely cold days, total medical expenditure aggregated at the hospital level decreases by 10.4% (the corresponding estimations are reported in columns (1) to (3) of Appendix Table 5). The signs of contemporaneous effects on total daily expenditure aggregated at the hospital level of the two extremes align with those of inpatient admission numbers. These findings indicate that the upswing in medical expenditure on the hottest days is attributed primarily to an increase in inpatient visits, whereas the extreme cold temperature only elevates medical expenditure for individual patients without imposing greater burdens on healthcare providers.

We then study the payment structure to see the share of the increasing expenditure between patients and public insurance during extremely hot days. As depicted in Figure 3, aggregated at hospital level, both insured payments and out-of-pocket payments increase during extreme hot days, and decrease during extreme cold days, taking a similar trend as total expenditure. The corresponding coefficients are reported in columns (4) to (7) of Appendix Table 5. We find a larger magnitude of coefficients for out-of-pocket payment (7.7% during the hottest days and 11.7% during the coldest days) compared with those for total expenditure; and a smaller magnitude of coefficients for insured payments (6.2% during the hottest days and 8.1% during the coldest days), compared with those for total expenditure.

Figure 4 depicts the impact of temperature on proportion of insured payment to total payment. Insured payment takes up less of a proportion for patients admitted during extreme hot days. The results suggest that the change in the monetary burden is taken on mainly by patients themselves, rather than by health insurance. Our findings are consistent with Li, Smyth, and Yao (2023), who suggest out-of-pocket payments are more affected than insured payments by extreme temperature.

V. HETEROGENEITY ANALYSIS

A. Tiers and Grades of Hospitals

In this section, we examine the heterogeneity of contemporaneous effects on hospitals with different tiers and grades. In the PRC, the hospitals are ranked from highest to lowest as tier 3, tier 2, and tier 1, and A, B, and unrated within each tier. Hospitals ranked higher have better scale, have more medical equipment, and are more advanced in treating severe diseases. Our sample includes majorly tier 3 and tier 2 hospitals graded A or unrated. For the few hospitals graded B, we recategorize them with the group graded unrated of the corresponding tier into one group in the following analysis.

Estimations of heterogeneity by tier and grade are shown in Figure 5. The corresponding coefficients are reported in columns (1), (4), (7), and (8) of Appendix Table 6. For hospitals ranked tier 3 and tier 2 grade A, we find contemporaneous effects similar to the baseline results. For hospitals ranked tier 2 grade B and unrated, which are the lowest ranked hospitals in our dataset, the contemporaneous effects of extreme temperature are not statistically significant. The magnitude of coefficient estimated for hospitals ranked tier 3 grade A (the highest rank) is smaller than that of hospitals ranked tier 2 grade A and tier 3 grade B and unrated. The results indicate that the workload of middle-ranked hospitals is more sensitive to changes in temperature. The highest-ranked hospitals also have increasing patient numbers and decreasing patient numbers during hot days and cold days, respectively, but the impact is not as large as for their middle-ranked counterparts.

B. Departments Within Hospitals

We then investigate the within-ED heterogeneity of contemporaneous effects by department. Patients admitted via EDs are assigned to different inpatient departments immediately after admission, which enables us to investigate the workload of each department. Based on official documentation released by the National Health Commission (NHC), we uniform the categorization of medical departments across hospitals and obtain in total 16 departments.⁹

Figure 6 shows the contemporaneous effects by department; the corresponding estimations are provided in Appendix Table 7. For Internal Medicine, Surgery, and Pediatrics, the contemporaneous effects of extreme high temperature are positive and statistically significant, with a magnitude of 3.8%, 5.2%, and 4.4%, respectively. For the coldest temperature, the number of ED admissions decreases most in Internal Medicine. In Surgery, the number of ED admissions decreases during cold days, although this is statistically insignificant, while the variation of admissions expands largely compared with other departments. Emergency, Intensive Care, and

⁹ Our categorization is based on the 2-digit level uniformed code of departments (www.nhc.gov.cn/cms-search/downloadFiles/77e5a71bc2fa4dc88236d582632ab7ea.pdf). The 16 departments defined in this study are (1) Internal Medicine, (2) Surgery, (3) Obstetrics and Gynecology, (4) Pediatrics, (5) Ophthalmology, (6) Otolaryngology, (7) Stomatology, (8) Dermatology, (9) Psychiatry, (10) Epidemiology, (11) Oncology, (12) Emergency, (13) Rehabilitation, (14) Intensive Care, (15) Traditional Chinese Medicine, and (16) Other. We include departments such as Dental and Occupational Diseases in "Other" owing to low patient numbers.

Traditional Chinese Medicine also see a marginal significant linear effect of temperature. The rest of the departments see only a slight change or even no change in ED admissions under extreme temperature.

At this point, we document that the impact of temperature on hospital workload is not uniform across departments. There could be several potential explanations for this. First, the magnitude of the deviation in the number of patients with different diseases varies, as the mortality of different diseases is impacted heterogeneously by temperature. Second, healthcare utilization of individuals with different characteristics is not uniformly sensitive to temperature condition. Third, expecting a change in cost or quality of treatment during extreme temperatures, patients may adjust their decisions regarding seeking healthcare services. In the section that follows, we uncover the change in patient structure during extreme temperatures to more comprehensively investigate the impact on hospital workload.

C. Location of Hospitals: Income Level and Winter Heating

In this subsection, we examine the heterogeneity contemporaneous effects based on the income level of cities and presence or absence of centralized winter heating. Heterogeneity by location matters because hospitals in cities with differing income levels and heating infrastructure may have varying capacities to manage the potential challenge of extreme weather events. Previous literature suggests that higher socioeconomic status enables individuals to afford energy-intensive measures to create mild indoor climates, potentially mitigating temperature-related health impacts (Dell, Jones, and Olken 2014, Yu, Lei, and Wang 2019, Carleton et al. 2022). Detailed estimations are provided in Appendix Tables 8 (for heterogeneity by city income level) and 9 (for heterogeneity by centralized winter heating), with corresponding visualizations in Figures 7 and 8.

The findings indicate significant heterogeneity in how extreme temperatures affect hospital workloads based on city income levels and heating infrastructure, with notable differences observed across age groups. For heterogeneity by income levels, hospitals in lower-income cities show larger fluctuations in total inpatient admissions during extreme temperatures compared with those in higher-income cities. On extremely hot days (above 30°C), inpatient admissions increase by 8.4% in low-income cities. The corresponding increase is 7% in high-income cities. Similarly, on extremely cold days (below -6°C), admissions decrease by 13.9% in low-income cities compared with a smaller decrease of 11% in high-income cities. These differences suggest that hospitals in lower-income areas experience a greater burden of temperature-induced changes in patient load.

Breaking down these results by age groups, we observe notable disparities. For patients aged 5 and below, the changes in admissions are significant in low-income cities but insignificant in high-income cities. Specifically, admissions below age 5 increase during extreme heat and decrease during extreme cold in low-income areas, whereas high-income cities show no statistically significant changes for this age group. By contrast, the pattern for older patients is different. On extremely hot days, admissions of older patients increase by 6.5% in high-income cities and by

4.4% in low-income cities. During extremely cold days, older people admissions decrease similarly across income levels, with reductions of 11.7% in high-income cities and 11.5% in low-income cities. This age-specific variation highlights how temperature impacts are distributed differently within populations depending on income level.

Heterogeneity by centralized winter heating also reveals significant differences in hospital workloads during extreme temperatures. In cities with centralized heating, total inpatient admissions decrease by 10.6% on extremely cold days, compared with a larger decrease of 16.4% in cities without heating. On extremely hot days, the increases in total admissions are comparable, with hospitals in cities with heating seeing a 7.8% increase and those in cities without heating experiencing an 8.3% increase. These results suggest that centralized heating substantially moderates the impact of cold temperatures on hospital workloads but has limited influence during heatwaves.

Disaggregating the heating results by age groups reveals further patterns. For patients aged 5 and below, admissions increase more in cities with heating during extremely hot days, in contrast with the smaller changes observed for total admissions in heated areas. This could indicate age-specific sensitivity to extreme heat in regions with heating infrastructure. For older patients, the changes in admissions are consistent across heating groups. During extreme heat, admissions increase similarly in both heated and non-heated cities. During extreme cold, the decrease is smaller in heated cities (10.6%) than in non-heated cities (16.4%).

VI. PATIENT STRUCTURE

A. Diagnosed Disease

We first examine the patient structure of disease. There is a large diversity of healthcare services within a hospital regarding different diseases. A shift in the patient structure of disease, even if the total amount is unchanged, will lead to a higher workload for some parts of a hospital, and a shortage for some healthcare resources, which cannot be shared or mitigated by other parts facing a lower workload. Separating ED admissions into 19 groups of main diagnosed diseases, our results reveal an increase in the number of ED admissions during high temperature, and a decrease during low temperature, but with various magnitudes and statistical significances across groups.

The results are depicted in Figure 9, and the corresponding estimations are presented in Appendix Table 10. For injury and respiratory diseases, the contemporaneous effects of extremely high temperature are positive and statistically significant, with magnitudes as large as 11.9% and 7.5%, respectively. Our findings stand with the existing literature suggesting that injuries, cardiovascular diseases, and respiratory diseases increase in high temperature (Dillender 2021, Fritz 2022). For low temperature, the contemporaneous effects for these two diseases are statistically significantly negative, also with large magnitudes, reaching -9.2% and -10.1%, respectively.

Hospital admissions of patients diagnosed with diseases of the nervous, digestive, and circulatory systems and neoplasms also decrease statistically significantly by approximately 10% on the coldest days, but do not statistically significantly increase during the hottest days. Hospital admissions for infectious diseases increase statistically significantly on the hottest days (by 2.5%) and decreases on the coldest days (by 3%) compared with a benchmark temperature day. This result is consistent with some clinical findings that morbidity of infectious disease decreases in low temperature (Burkart et al. 2021). Explaining this is outside the scope of this paper. For admissions related to the eye, the skin, musculoskeletal diseases, pregnancy, the perinatal period, genes, and mental illness, no statistically significant contemporaneous effects or slight contemporaneous effects are found. These results are consistent with the findings of studies focusing on morbidities (White 2017, Agarwal et al. 2021), which suggests hospital workload is slightly driven by diseases with morbidities less likely related to change in temperature, as compared with temperature-sensitive diseases such as injuries, cardiovascular diseases, and respiratory diseases.

Appendix Figure 3 displays the cumulative effects of the highest (panel B) and lowest (panel A) temperatures categorized by disease. Across most diseases, the cumulative effects of extreme high temperatures diminish as the cumulative timeframe extends, consistent with the overall trend. These findings suggest that the influence of extreme heat persists in increasing the workload associated with infectious diseases even over an extended period, thereby prolonging the hospital's exposure to the pressure caused by such diseases.

The cumulative effects of extreme cold temperature die out soon for respiratory diseases, though the contemporaneous effects for such diseases are statistically significant and of a large magnitude. For circulatory diseases, the decrease in cumulative effects of coldest temperatures becomes larger as the period extends. Other diseases have a similar pattern of not statistically significant cumulative effects.

B. Demographic Features

Age. We now examine the age structure of patients. We separate the number of ED admissions according to age into three groups: children aged 5 and below, the older people aged 65 and above, and the rest of the population. The first two groups stand for the babies and the older people, who may need special consideration in treatment. Panel A of Figure 10 depicts impacts on numbers of patients by age group, and panel B the change in proportions. The sign of contemporaneous effects across different age groups remains consistent; however, the significance and magnitudes of the coefficients differ notably. EDs experience an increase in pediatric patients on the hottest days and a decrease on the coldest days, with a smaller magnitude than for the middle-aged patients. There is a similar decrease in the number of old patients to that among patients aged 6–64; however, during extreme high temperature, the

increase in the number of old patients is not as large as that in the number of middle-aged patients.¹⁰ The corresponding results are reported in columns (1) to (3) of Appendix Table 11.

The results on the proportion of patients of different age groups further reveal the change in patient structure during extreme temperatures. On the hottest days, baby patients aged 5 and below make up a statistically significantly larger proportion, whereas old patients aged 65 and above make up a statistically significantly smaller proportion. On the coldest days, the proportion of middle-aged patients increases, whereas the proportion of old patients decreases statistically significantly. The results imply that, though the number of older patients during extreme high temperature increases, the proportion of this cohort drops, while baby patients take up a larger proportion, requiring more healthcare resources.

Sex. The results for numbers of male and female admissions are depicted in panel A of Figure 11, and the results for proportions of male patients are depicted in panel B of Figure 11. The corresponding results are reported in columns (4) to (5) of Appendix Table 11. The contemporaneous effects are less heterogeneous with regard to sex, as the sign and significance of all coefficients are consistent. The magnitude of effects at both extremes are larger for men than for women, showing that number of admissions of male patients increases more on the hottest days. On the cold days, the magnitude of impact on number of admissions of both sexes is similar. Overall, male patients make up a larger proportion during hot days, whereas on days with a temperature lower than 15°C there is no change in the structure of patients by sex. The findings are consistent at high temperature to the estimations with regard to morbidity in Agarwal et al. (2021). Agarwal et al. report a statistically significant increase in hospitalization of both sexes on extremely hot days, with women less influenced than men. Their estimations report no statistically significant effects on the coldest days, which differs from our estimations. The sex difference found in this paper is consistent with some existing literature that suggests older women show greater adaptability to extreme heat than men (van Steen et al. 2019, Navas Martin et al. 2023).

C. Insurance

We further consider the type of insurance the patients are enrolled in. Co-payment patterns differ among patients with different types of insurance, potentially leading to a variance in their sensitivity to climate change. In this section, we investigate in the structure of patients regarding their enrollments in the three major public health insurance schemes (UEBMI, URBMI, and

¹⁰ Additionally, we segment the ED admissions into 18 5-year groups, for more detailed analysis on age structure. The results for the more precise age groups are presented in Appendix Table 12. For all age groups, we find statistically significant positive effects during extreme hot temperature, and statistically significant negative effects during extreme cold temperature. The population aged 15–30 has the smallest significance of contemporaneous effects. Hospital workload is driven mainly by number of patients aged 50 and above, according to our estimations. Contemporaneous effects on hospital admissions of patients aged 50–65 are statistically significant and of large magnitude, exceeding the estimations for overall admissions of both hottest and coldest temperature. The number of visits of patients aged 65–80 decreases by around 9% on the coldest days, reaching the largest magnitude among all groups. However, the magnitudes of contemporaneous effects shrink when the age of patients reaches 80–85 and even become of less significance for patients aged 85 and above. Overall, the results are consistent with the findings using three age groups.

NMCS). The estimations are depicted in Figure 12, where panel A shows the impact of temperature on number of patients of each insurance type and panel B shows the impact of temperature on proportions of each insurance type. The corresponding coefficients are reported in Appendix Table 13.

Number of ED admissions for all three insurance types increases when temperature is high and decreases when temperature is low. The number of ED admissions enrolled in UEBMI increases and decreases by a larger magnitude during extreme temperature compared with the other two insurance types. The number of ED admissions insured by NCMS increases by only 1.9% on extreme hot days, and decreases by 5.1% on extreme cold days, which is only half the magnitude of the corresponding estimations for the total number of ED admissions. The proportions of NCMS enrollees and URBMI enrollees drop statistically significantly when the temperature exceeds 30°C, whereas the proportion of UEBMI drops statistically significantly when the temperature is below -6°C. The results suggest UEBMI enrollees are more sensitive to the change in temperature. As UEBMI generally has a higher premium rate and a lower deductible amount compared with URBMI and NCMS, our results imply that the change in hospital workload is driven mainly by the inflow of patients facing a smaller number of out-of-pocket payments. In Section VIII, we further examine the impact of temperature on healthcare expenditures as well as the co-payment structure.

D. Severity of Sickness

We use diagnosis-related group (DRG) points to measure the severity of sickness. Used to assign diseases into different reimbursement groups, DRG points reflect the average relative cost of a specific category of disease at city level. In our dataset, each patient has a DRG point recorded based on their diagnosis at the time of admission. For example, if a patient has a recorded DRG point of 0.5, it implies their diagnosed disease is expected to cost half of the average inpatient cost in the city of that year throughout their stay in hospital. Therefore, DRG can be recognized as a uniformed measurement of severity of sickness of each admission at city-year level. By using our fixed effect model, the variation of DRG points across city and year are captured by the hospital-year-week fixed effect, thus ensuring compatibility among hospitals.

We categorize the DRG points into six groups¹¹ and aggregate the number and proportion of admissions of patients with DRG points falling in each group at daily ED level. The estimated coefficient for the number of admissions of each severity group is depicted in panel A of Figure 13. The corresponding coefficients are reported in Appendix Table 14. The number of patients with not-very-severe diseases (with a DRG point less than 2) is sensitive to the change of temperature, whereas the number of patients with severe diseases (with a DRG point over 2) is not statistically significantly affected by the temperature. The number of admissions for patients with lower-than-average severity of sickness increases during extreme hot days, and decreases

¹¹ The cutoffs of the groups are 0.25, 0.5, 1, 2, and 4.

during extreme cold days statistically significantly, and with the largest magnitude (by around 10%), marking the most sensitive sickness groups.

The results for changes in the proportion of patients with various grades of sickness is depicted in panel B of Figure 13. The corresponding coefficients are reported in Appendix Table 15. We find patients with relatively milder diseases make up a greater proportion during extreme hot days, and a lesser proportion during extreme cold days. On the other hand, along with the findings that the number of patients with severe diseases is not statistically significantly influenced by extreme temperature, these patients take up a lower proportion during the hotter days and a larger proportion during the colder days. Overall, the structure of patients with regard to severity of sickness shifts to consisting of more severe and severest patients during the coldest days, while consisting of more relatively milder patients during the hottest days. This shift implies that the increase in hospital workload during extreme high temperature is mainly contributed to by the increase in the number of patients, rather than by the increase in the efforts and resources expected to be required for each individual patient.

Given the structure of sickness changes as the temperature varies, we further examine the efficiency and quality of treatments for patients hospitalized during extreme temperature. We follow the previous literature to measure efficiency by length of stay, and measure the quality by the in-hospital mortality rate (Rathlev et al. 2007, Lucas et al. 2009, Pearce et al. 2023). In our sample, most of the patients have at least one operation during their stay in hospital, so we take number of days between admission and the first operation as an additional measurement of efficiency. The results are depicted in Appendix Figure 4. Generally, we find the efficiency and quality of treatments are not statistically significantly affected by the temperature. For efficiency, the coefficients are statistically insignificant, suggesting that being admitted into hospital on days with either higher or lower temperature does not influence length of stay or day between admission and first operation. For in-hospital mortality rate, the coefficient of extreme low temperature is statistically significantly positive, whereas the coefficients of the other temperature bin remain statistically insignificant. However, given the previous results for structure of severity of sickness, indicating that patients are on average more severely sick during extreme cold days, the results on in-hospital mortality rate do not suggest a change in the quality of treatment.

VII. ADAPTATION

In this section, we explore the adaptation method of hospitals whose EDs face an expanding inpatient volume on extremely hot days. As suggested in the previous literature, additional medical personnel and a more flexible allocation of equipment can be solutions to hospital crowding (Hwang et al. 2011). Here, we examine whether hospitals could adjust the provision of healthcare services to suit the increase or decrease in demand on extreme temperature days by adjusting the number of physicians—the main providers of services.

We estimate the effect of extreme temperature on the number of physicians serving in the inpatient sector of the ED. As shown in Figure 14, we find the number of physicians in charge of ED-hospitalized patients increases as the temperature becomes higher. The corresponding

coefficients are reported in Appendix Table 16. We find the total number of physicians slightly increases, by 2.3%, during extremely high temperature, and decreases by 8% during extremely low temperature, with only slight significance. By further investigating physicians of different seniorities, we find that the number of senior physicians (chief doctors) is not affected by extreme temperatures, but the number of the most junior physicians (resident doctors) decreases by 8.8% on the coldest days and increases by 2.9% on the hottest days, statistically significantly. The variation in the number of physicians on cold days is relatively large compared with that on hot days. This suggests that, though there are on average fewer physicians really in charge of ED patients when admissions decrease, hospitals do not face the necessity to adjust their personnel allocation. Our results show that hospitals are taking active actions to increase the number of physicians (majorly junior ones) serving the expanding ED admissions during extremely hot days.

We then explore the heterogeneity in adaptation across different hospitals. Hospitals of various levels and local contexts may differ when practicing adaptation strategies. In the following analysis, we identify potential disparities in responding to contemporaneous temperature shock among hospitals of different tiers and grades, located in cities with different average incomes and centralized winter heating policies.

We estimated the impact of temperature on the total number of physicians and the number of physicians by seniority. The estimations shown in Figure 15 are for heterogeneity by hospital ranking. We find the total number of physicians increases only in tier 2 hospitals (by 3.2% and 4.9% for grade A and other grades, respectively). The estimated coefficient for the impact of extremely high temperature on the total number of physicians in tier 3 hospitals is not statistically significant. On extremely cold days with a temperature below -6°C , hospitals ranked tier 3 B and below reduce the number of physicians serving inpatients in the ED in response to the decreases in patient volume. Overall, though experiencing similar fluctuations in the number of inpatient admissions associated with temperature, tier 3 hospitals lack the flexibility in personnel adjustment. The estimations by seniority show a similar pattern. For tier 2 A hospitals, the number of the chief, attending, and resident physicians in the ED increases by 2.2%, 2.7%, and 3.8%, respectively, standing out among hospitals ranking in other tier-grade groups. Junior physicians are more flexible in adjusting during extreme temperature; however, for tier 3 A hospitals, even the number of resident physicians does not increase during extremely hot and cold days.

We then study the disparities in practicing adaptation in hospitals located in cities with different average incomes and centralized winter heating policies. The estimations are presented in Figures 16 and 17 for the two aspects, respectively. The average income level groups are defined in a similar way as in Section V. In EDs located in cities with high average income, the total number of physicians increases by 2.8% on extremely hot days with a temperature over 30°C and decreases by 8.4% on extremely cold days with a temperature below -6°C . The total number of physicians does not significantly change in EDs located in cities with middle and low-average income. The number of chief physicians is not impacted by extreme temperature, while the number of residence physicians significantly increases by 2.6% and 3.3% in EDs located in middle- and high-income cities.

Compared with EDs in regions with centralized winter heating, where the number of physicians is not significantly affected by extremely high temperature, EDs located in regions without centralized winter heating have 2.7% more physicians serving inpatients on a day with a temperature exceeding 30°C. There is also disparity in the magnitude of the impact of the extremely low temperature between these two groups. EDs in regions with centralized winter heating have 6.4% fewer physicians on days below -6°C, while the magnitude of the decrease in all physicians is 13.7% for EDs in regions without centralized winter heating. Similarly to the overall findings, the number of chief physicians changes slightly in response to extreme temperature, whereas the number of resident physicians increases by 3.4% and decreases by 14% on extremely hot and cold days in regions without winter heating.

VIII. CONCLUSION

This paper uses daily-level hospital-centered temperature and hospitalization records from hospitals across over 1,000 hospitals throughout the PRC from 2013 to 2022 to investigate the impact of extreme temperature on hospital workload. Focusing on EDs, we apply fixed effect models to examine the contemporaneous effect of daily temperature on the daily number of ED admissions, as well as the cumulative effect of temperature on the number of ED admissions over various cumulative periods.

Our results reveal that the number of hospital admissions at individual hospitals decreases by 12.3% during extremely cold days with temperature below -6°C and increases by 7.7% during extremely high temperature exceeding 30°C, compared with a benchmark temperature of 12°C–15°C. Taking the temperature of the previous 7 days into account, we find a cumulative decrease of around 18.7% on the coldest days and a cumulative increase of 10.1% on the hottest days. The cumulative effects diminish within a month. The magnitude of both contemporaneous and cumulative effects on hospital admission numbers are larger compared with estimations in previous literature. In addition, we explore the impact of extreme temperature by estimating the impact of daily highest temperature and daily lowest temperature. Our results show an increase in workload by 9% on extremely hot days with the highest temperature exceeding 36°C, and a decrease in workload by 9% on extremely cold days with the coldest temperature below -9°C. The impact of extremely high temperature is underestimated in the previous literature as the most extreme temperature is averaged away when using daily mean temperature. We also observe the monetarized impact of climate change: the total healthcare expenditure aggregated at the hospital level increases as the temperature gets higher. The increment is shared by patient and public insurance, while the former averagely take on more.

Beyond the overall impact of temperature on hospital workload, our results of heterogeneity analysis indicate that the impact of climate change on hospital workload will be larger for the middle-ranked hospitals, several specific departments, and cities with lower average income and without centralized winter heating. Accordingly, the patient structure also changes during extreme temperature, with children, male patients, and patients with respiratory diseases and injuries

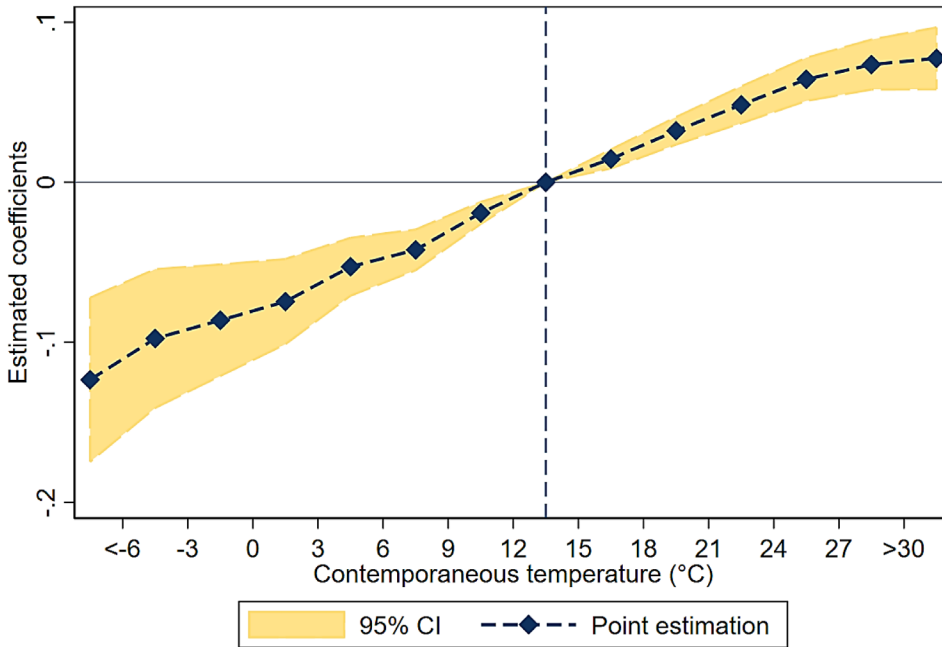
making up a larger proportion. The increase in admissions on extremely hot days consists mainly of mild severity of sickness, and the outcomes of these patients after their stays are not statistically significantly worsened.

Additionally, we examine the adaptation methods for hospitals to respond to the increasing volume of inpatient admissions on extremely hot days. Our results show that, during extremely high temperature, additional personnel are assigned to EDs to serve the increasing admissions. The adjustment happens mainly among junior physicians (i.e., resident doctors), in tier 2 hospitals, and in hospitals located in cities with higher average income and no centralized winter heating.

Departing from most of the literature about the relationship between climate change and health, this study investigates the impact of extreme temperature on the healthcare system from the perspective of hospitals. We would like to note that our results are conservative in measuring the change in hospital workload, as the data used in the analysis have information only on ED admissions; boarding patients and outpatients in EDs are not recorded. We solely study the impact of temperature on hospital workload, leaving the mechanisms unexplored. Comparing our findings with the previous literature about the impact of climate change on population health, the difference between the linear pattern we find and the J-shape pattern in the literature suggests that worsened health is only part of the mechanism through which climate change will influence realized healthcare utilization. Future research could try to specify other mechanisms such as unwillingness to travel outdoor or change in income and affordability of healthcare under climate change.

TABLES AND FIGURES

Figure 1: Contemporaneous Effects on Hospital Admissions

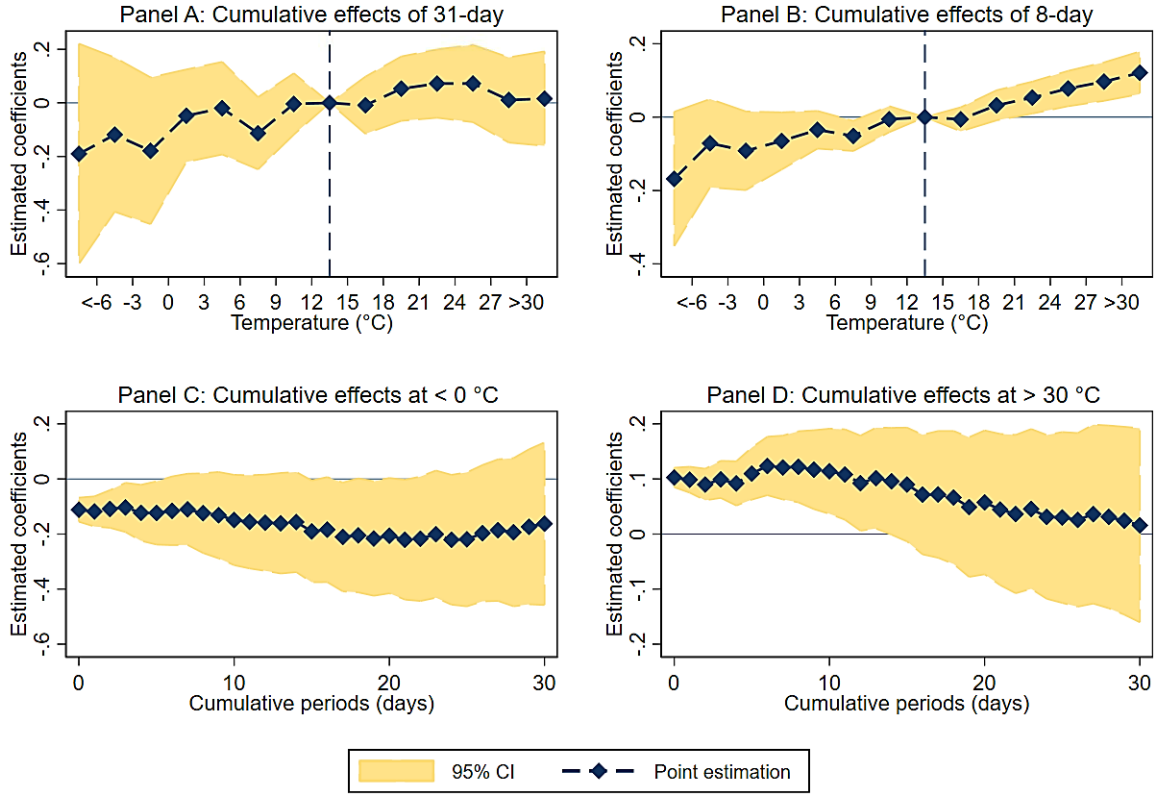


CI = confidence interval.

Notes: The figure presents contemporaneous effects on overall hospital admissions through emergency departments. Estimations of contemporaneous effects β_j are presented. Horizontal coordinates here show the median point of the corresponding temperature bin—for example, the horizontal coordinates of β_1 are -7.5°C , and are the same throughout the paper. Vertical dash line = benchmark temperature bin (12°C – 15°C).

Source: Authors' calculations.

Figure 2: Cumulative Effects on Hospital Admissions

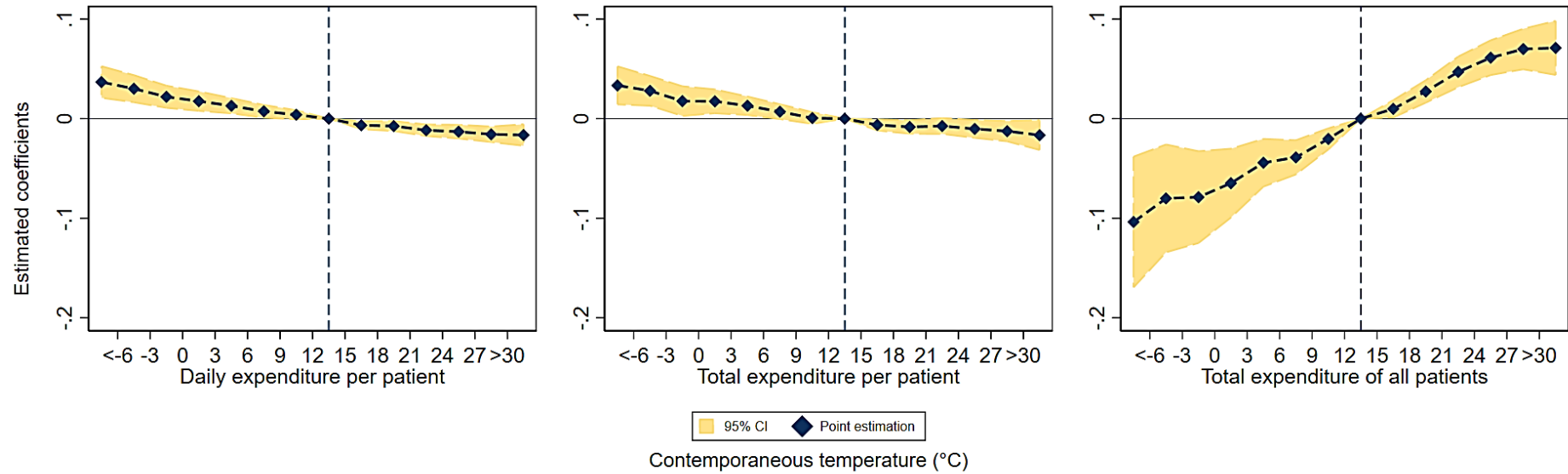


CI = confidence interval.

Notes: The figure presents cumulative effects on overall hospital admissions through emergency departments. Panels A and B correspond to joint estimations of $\beta_{j,t} \dots \beta_{j,t-\tau}$ of equation (5) with τ taking the value of 30 and 7, respectively. Panel C corresponds to joint estimations of $\beta_{1,t} \dots \beta_{1,t-\tau}$, $\beta_{2,t} \dots \beta_{2,t-\tau}$, $\beta_{3,t} \dots \beta_{3,t-\tau}$ with τ varying from 0 to 30, providing cumulative effects of various periods of the extreme cold temperature. Panel D corresponds to joint estimation of $\beta_{14,t} \dots \beta_{14,t-\tau}$ with τ varying from 0 to 30, providing cumulative effects of various periods of the extreme hot temperature. Vertical dash line in panels A and B = benchmark temperature bin (12°C–15°C).

Source: Authors' calculations.

Figure 3: Contemporaneous Effects on Healthcare Expenditure

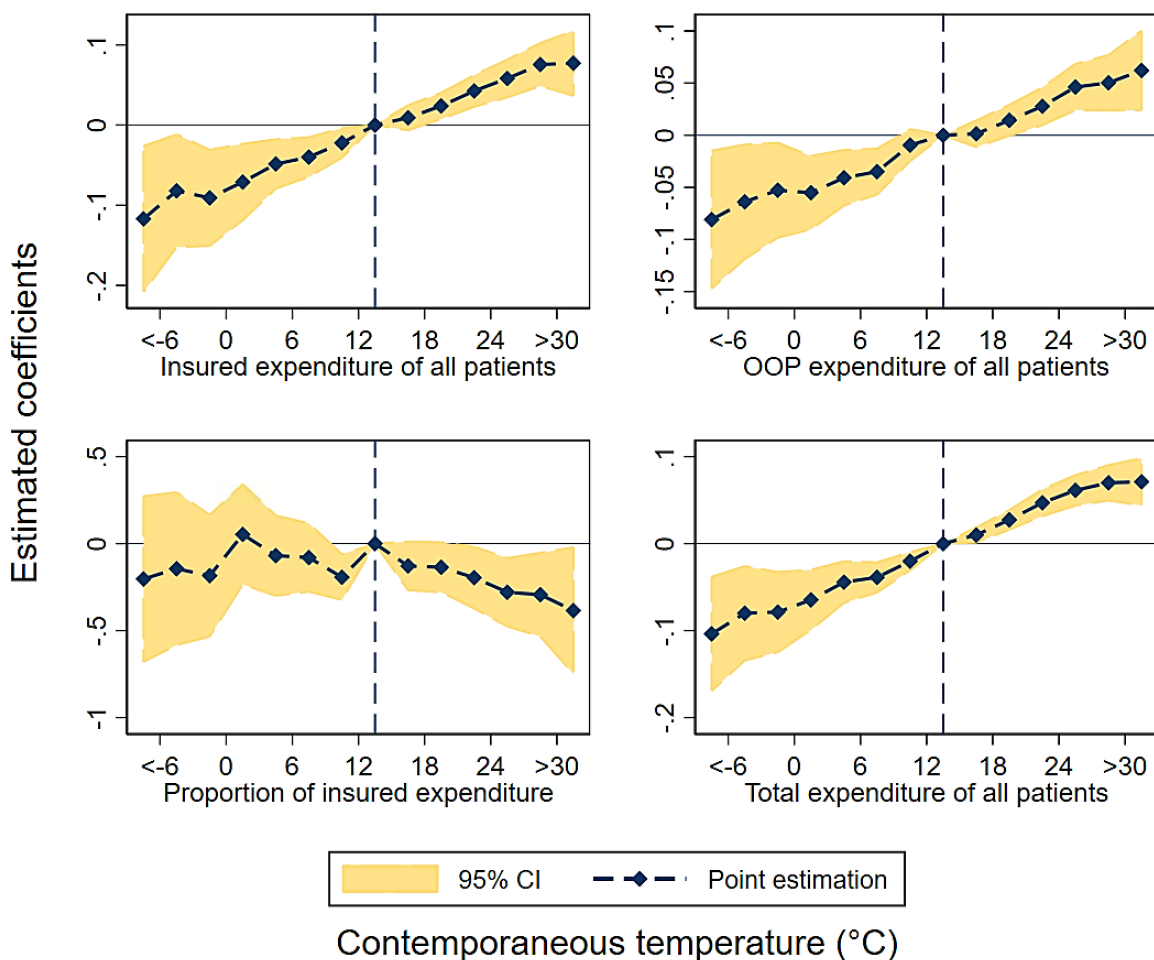


CI = confidence interval.

Notes: The figure presents contemporaneous effects on healthcare expenditure. Estimations of contemporaneous effects β_j are presented. Horizontal coordinates here show the median point of the corresponding temperature bin. Vertical dash line = benchmark temperature bin (12°C–15°C).

Source: Authors' calculations.

Figure 4: Contemporaneous Effects on Healthcare Expenditure Co-Payment

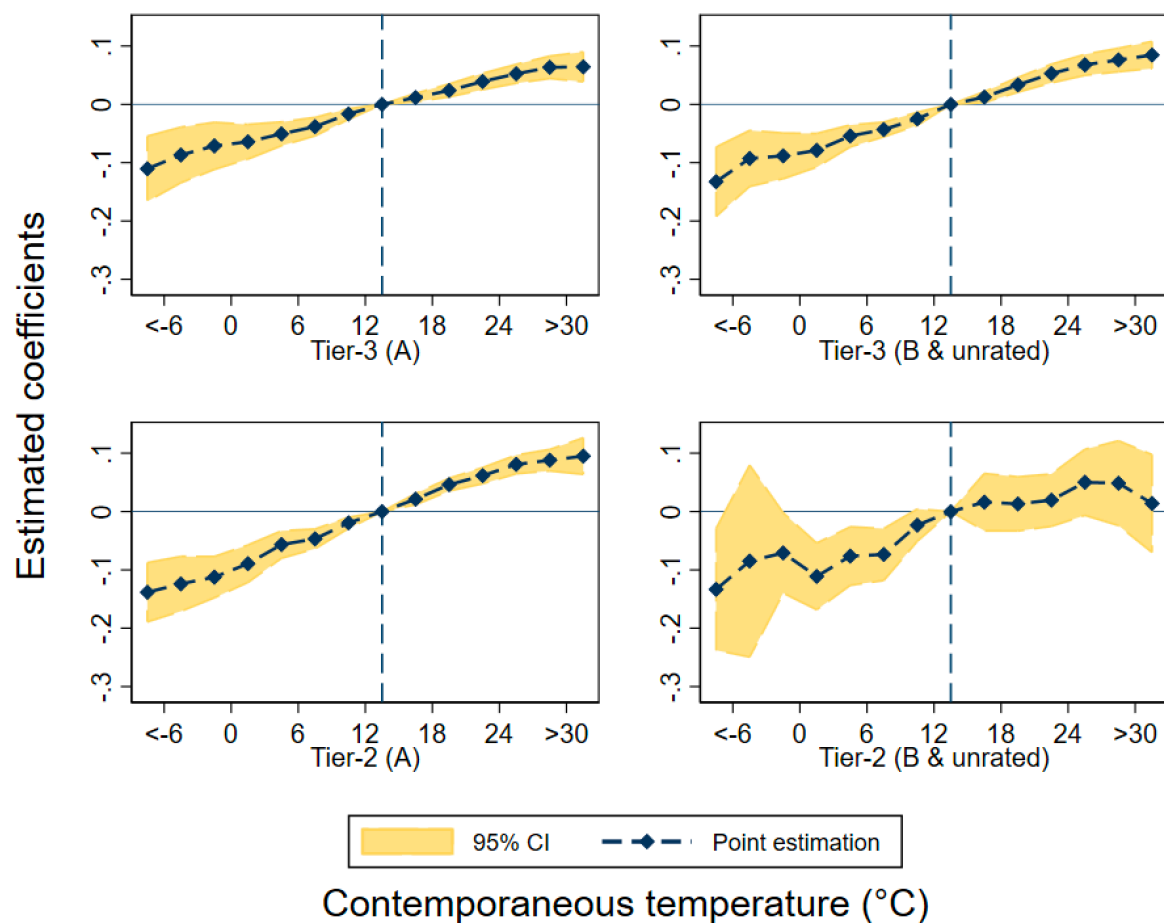


CI = confidence interval, OOP = out-of-pocket.

Notes: The figure presents contemporaneous effects on healthcare expenditure co-payment. The first row presents the average individual expenditure and the second row the expenditure of all patients in a hospital. The first column shows the effects on total expenditure, the second column shows the effects on OOP payments, and the third column shows the insured portion of the payment. Estimations of contemporaneous effects β_j are presented. Horizontal coordinates here show the median point of the corresponding temperature bin. Vertical dash line = benchmark temperature bin (12°C–15°C).

Source: Authors' calculations.

Figure 5: Contemporaneous Effect by Tiers and Grades of Hospitals

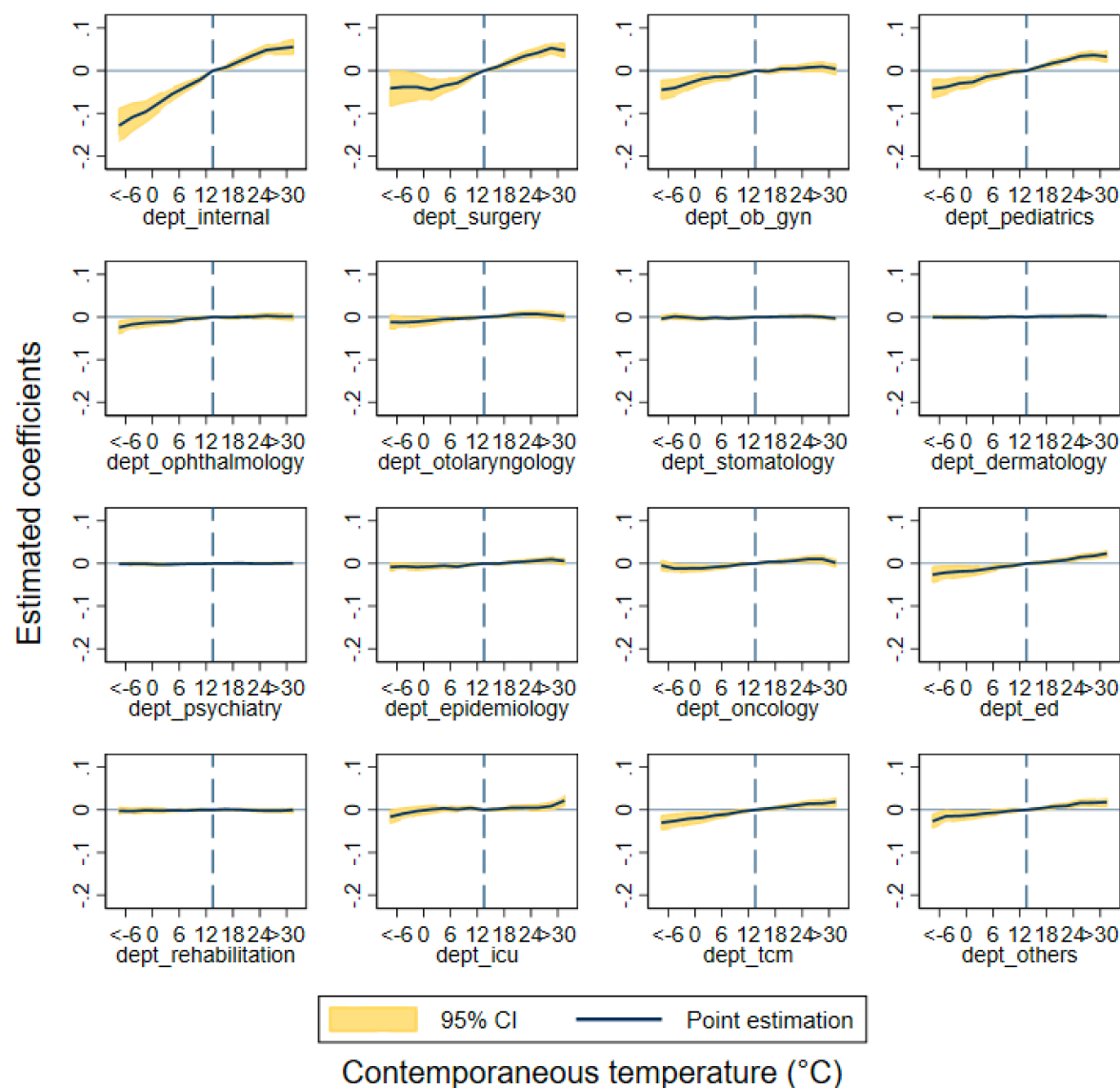


CI = confidence interval.

Notes: The figure presents contemporaneous effects on hospital admissions for hospitals of different tiers and grades (in parentheses). Estimations of contemporaneous effects β_j are presented. Horizontal coordinates here show the median point of the corresponding temperature bin. Vertical dash line = benchmark temperature bin (12°C–15°C).

Source: Authors' calculations.

Figure 6: Contemporaneous Effect by Departments

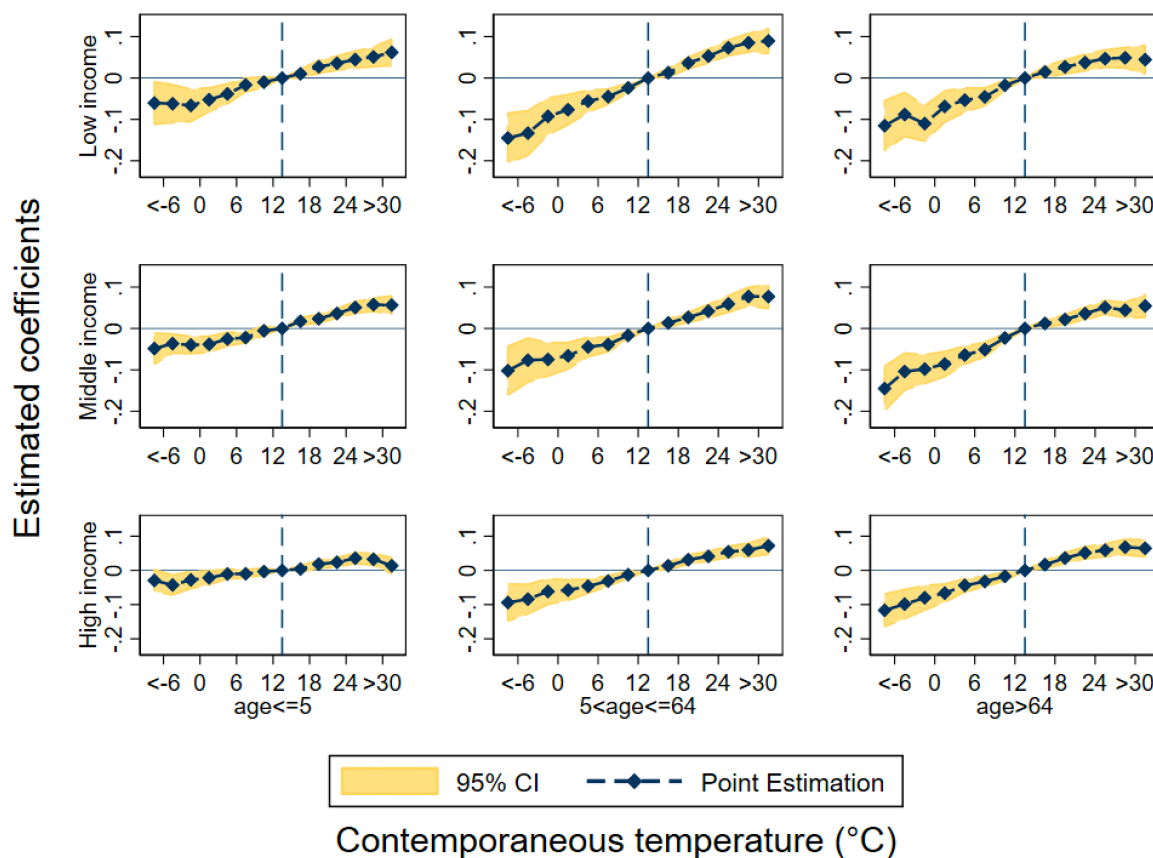


CI = confidence interval.

Notes: The figure presents contemporaneous effects on hospital admissions for 16 departments. Estimations of contemporaneous effects β_j are presented. Horizontal coordinates here show the median point of the corresponding temperature bin. Vertical dash line = benchmark temperature bin (12°C–15°C).

Source: Authors' calculations.

Figure 7: Contemporaneous Effects by City Average Income

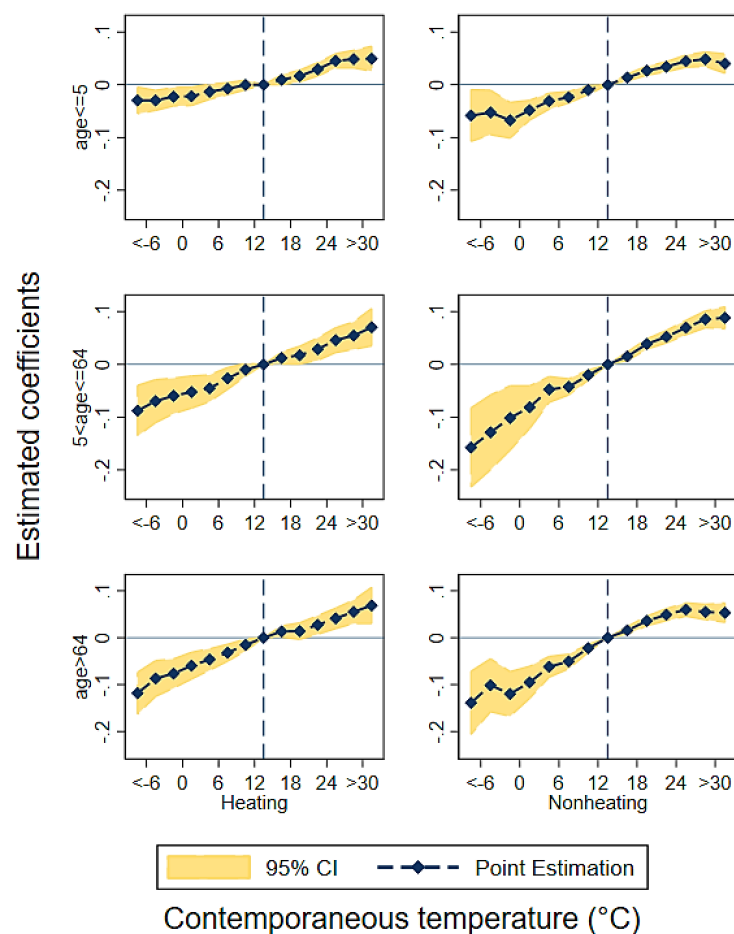


CI = confidence interval.

Notes: The figure presents contemporaneous effects on hospital admissions of different population with different levels of income. Estimations of contemporaneous effects β_j are presented. Horizontal coordinates here show the median point of the corresponding temperature bin. Vertical dash line = benchmark temperature bin (12°C–15°C).

Source: Authors' calculations.

Figure 8: Contemporaneous Effect by City Centralized Winter Heating

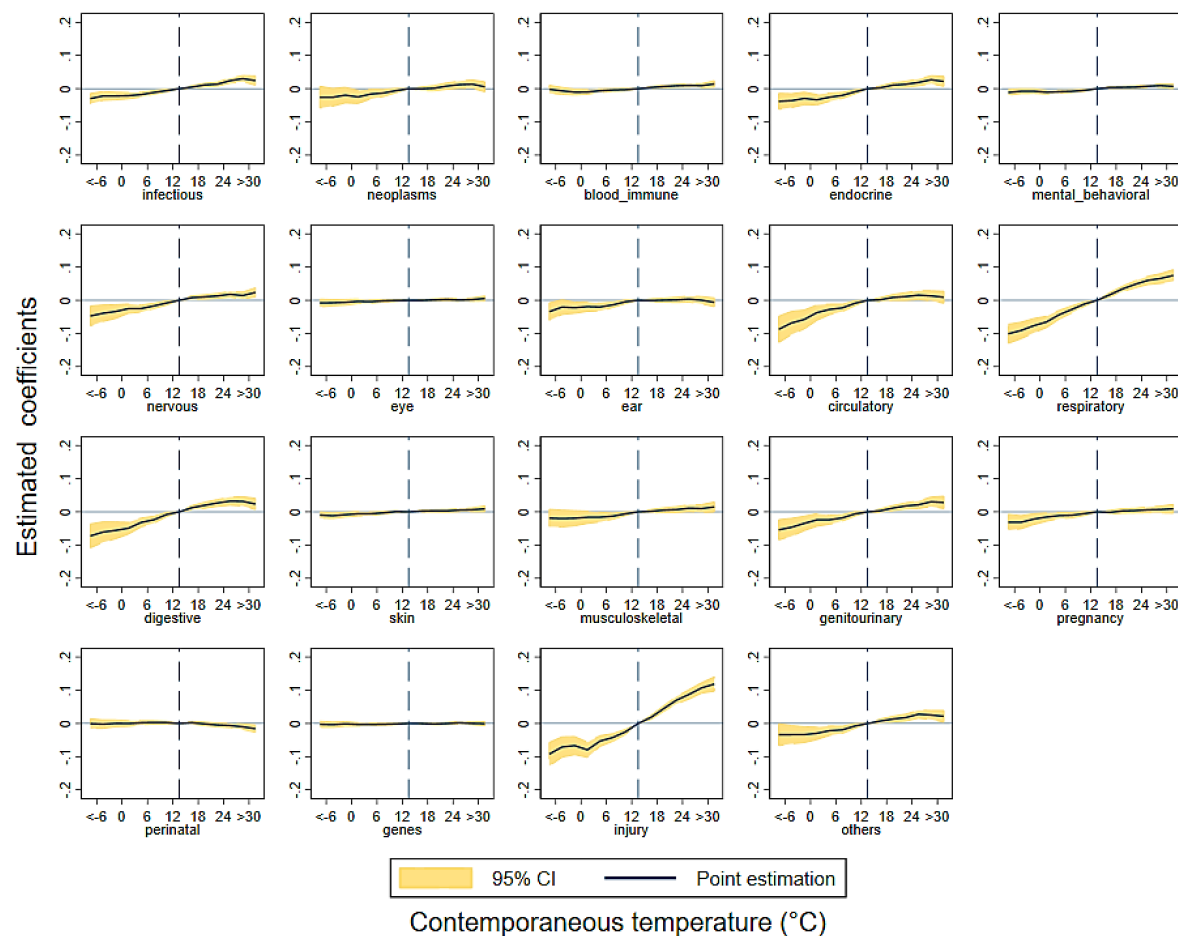


CI = confidence interval.

Notes: the figure presents contemporaneous effects on hospital admissions in areas with or without central heating. Estimations of contemporaneous effects β_j are presented. Horizontal coordinates here show the median point of the corresponding temperature bin. Vertical dash line = benchmark temperature bin (12°C–15°C).

Source: Authors' calculations.

Figure 9: Patient Structure: Diagnosed Diseases

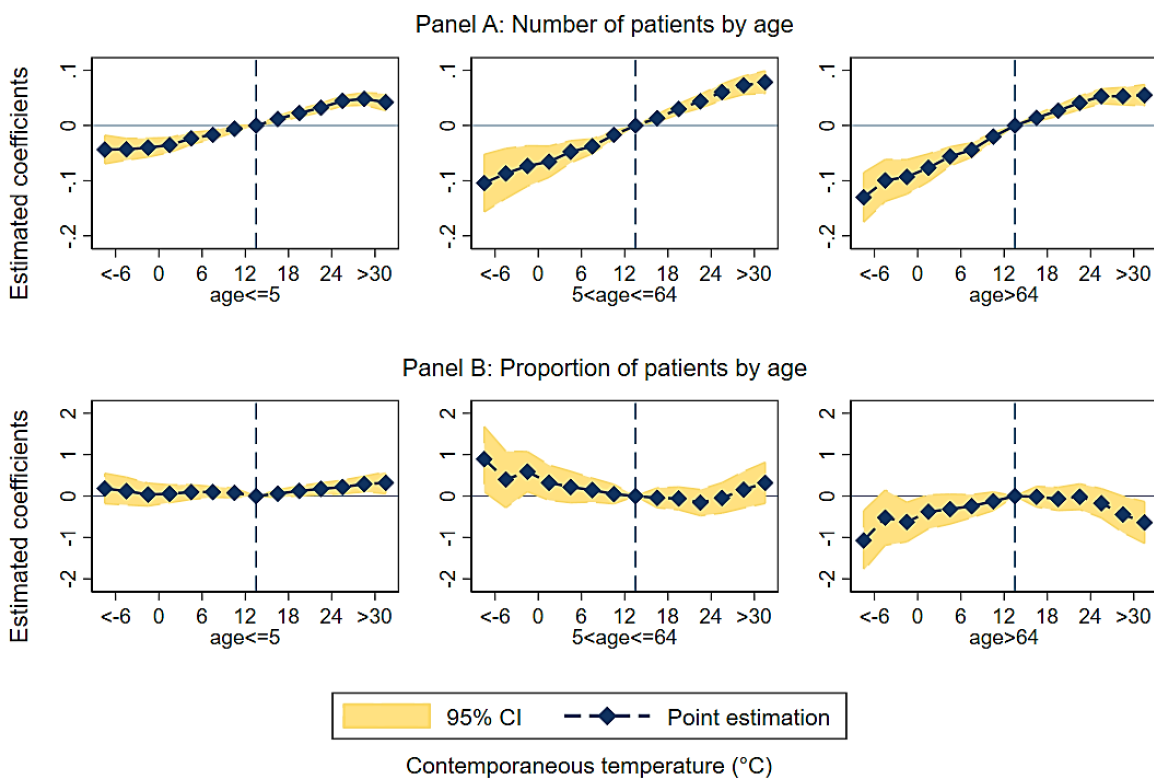


CI = confidence interval.

Notes: The figure presents contemporaneous effects on hospital admissions for 19 different alphabet-level categorized diseases based on International Classification of Diseases Version 10. Estimations of contemporaneous effects β_j are presented. Horizontal coordinates here show the median point of the corresponding temperature bin. Vertical dash line = benchmark temperature bin (12°C–15°C).

Source: Authors' calculations.

Figure 10: Patient Structure—Age

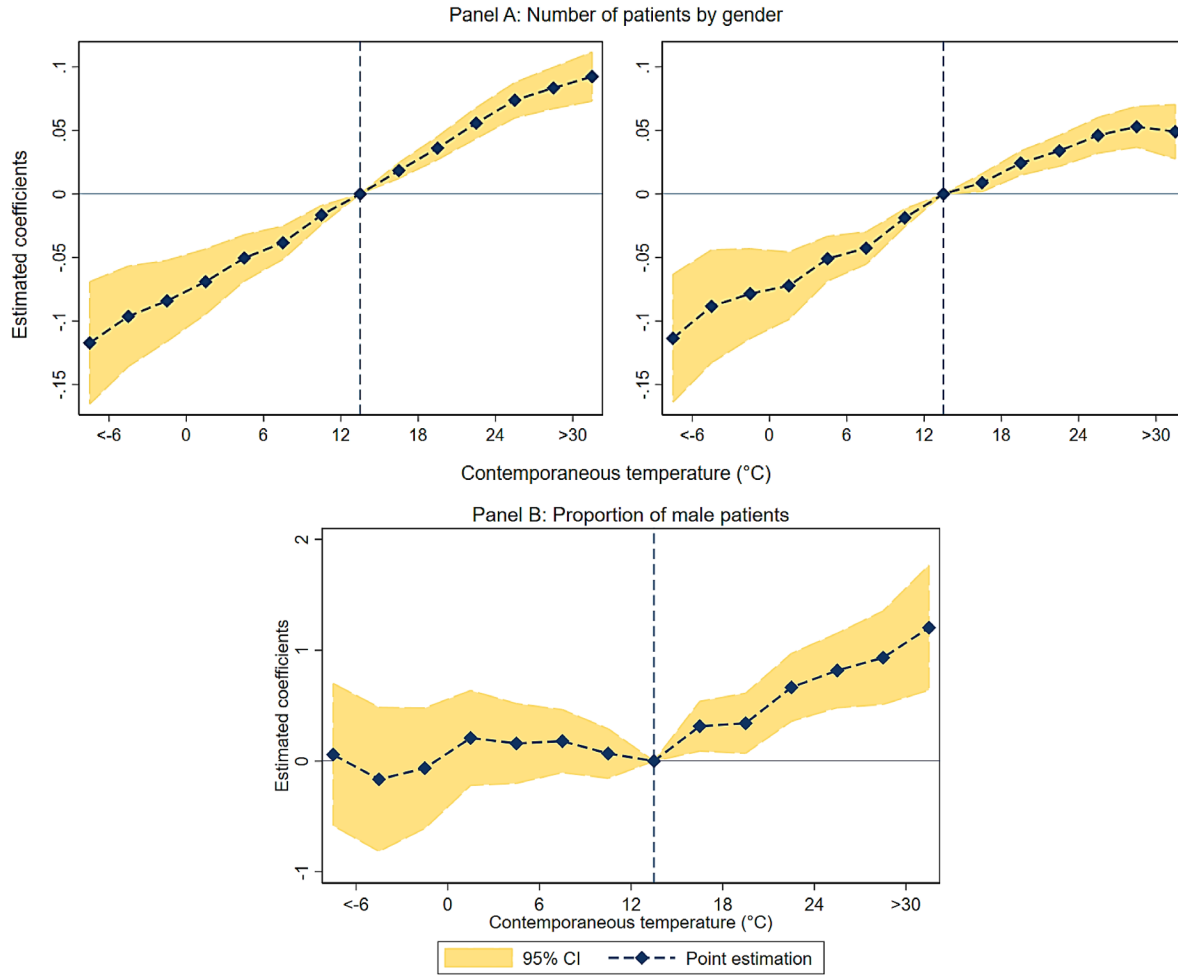


CI = confidence interval.

Notes: The figure presents contemporaneous effects on hospital admissions for age groups of 0–5, 6–64, and > 65. Panel A shows estimations for numbers of admissions and panel B shows estimations for proportion of admissions of each age group. Estimations of contemporaneous effects β_j are presented. Horizontal coordinates here show the median point of the corresponding temperature bin. Vertical dash line = benchmark temperature bin (12°C–15°C).

Source: Authors' calculations.

Figure 11: Patient Structure—Sex

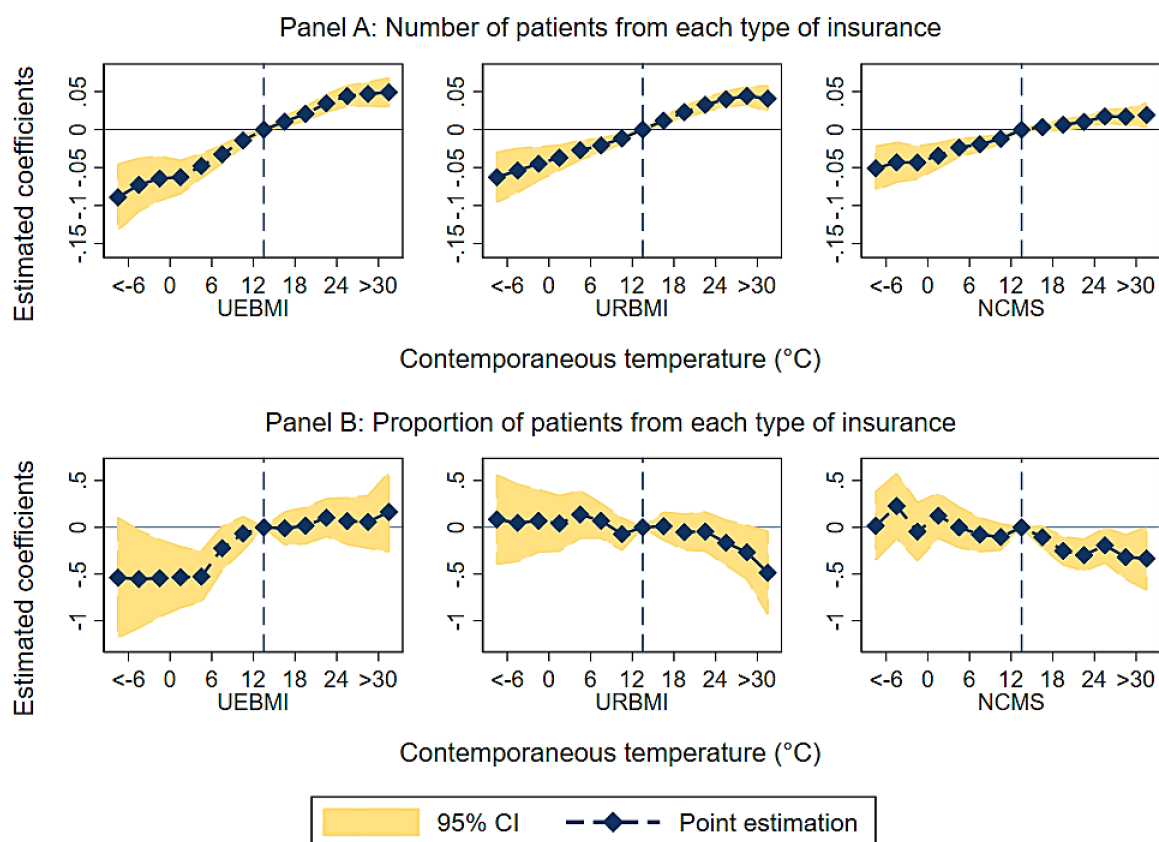


CI = confidence interval.

Notes: The figure presents contemporaneous effects on hospital admissions of male and female patients. Panel A show estimations for numbers of admissions, and panel B shows estimations for proportion of male patients. Estimations of contemporaneous effects β_j are presented. Horizontal coordinates here show the median point of the corresponding temperature bin. Vertical dash line = benchmark temperature bin (12°C–15°C).

Source: Authors' calculations.

Figure 12: Patient Structure—Type of Insurance

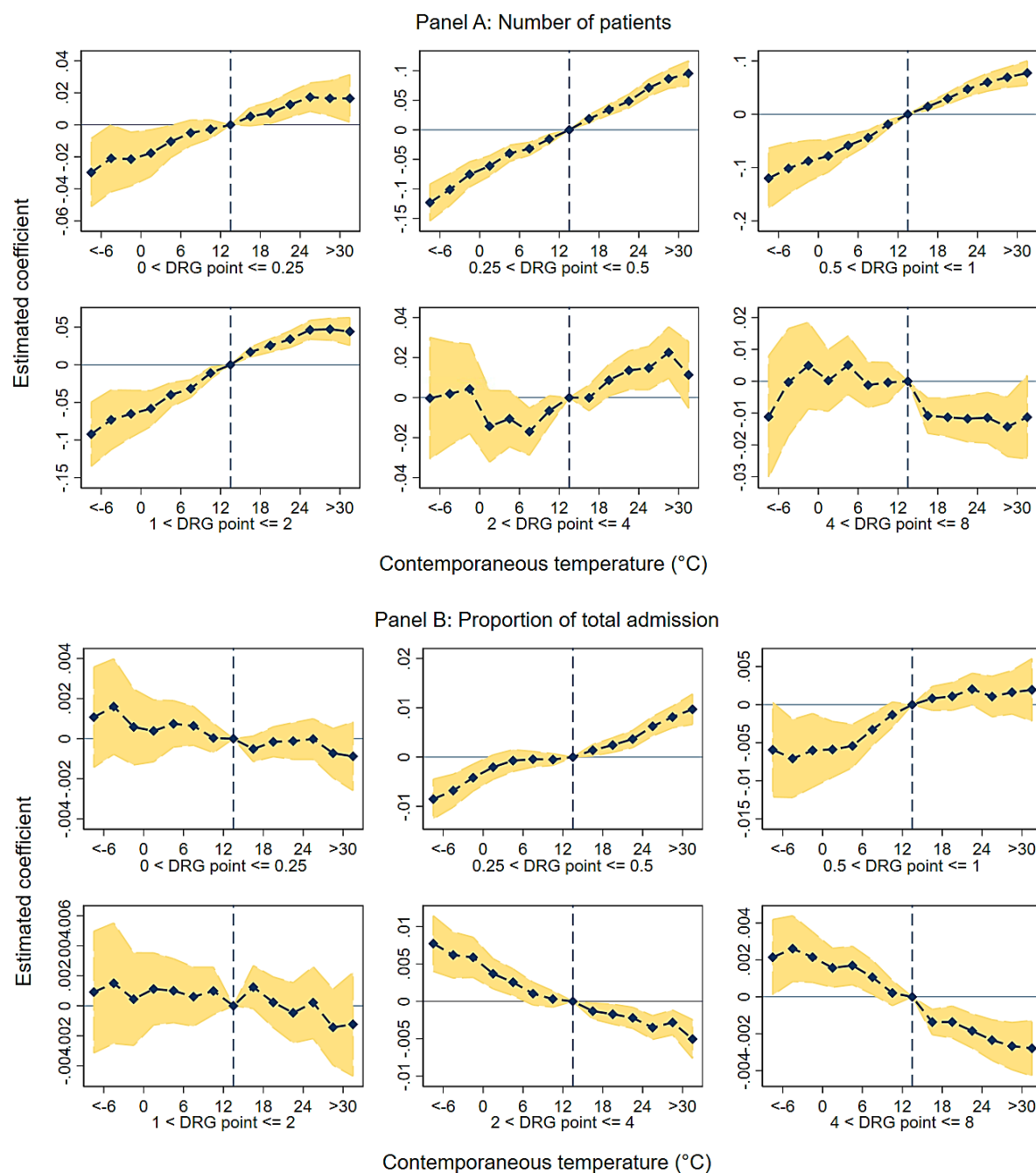


CI = confidence interval, NCMS = New Cooperative Medical Scheme, UEBMI = Urban Employee Basic Medical Insurance, URBMI = Urban Resident Basic Medical Insurance.

Notes: The figure presents contemporaneous effects on structure of hospital admissions by insurance type. In panel A, the dependent variables are logarithms of hospital-level daily number of admissions through emergency departments of one type of insurance among URBMI, UEBMI, and NCMS. In panel B, the dependent variables are proportions of admissions of the corresponding groups in panel A. Estimations of contemporaneous effects β_j are presented. Horizontal coordinates here show the median point of the corresponding temperature bin. Vertical dash line = benchmark temperature bin (12°C–15°C).

Source: Authors' calculations.

Figure 13: Patient Structure—Severity of Sickness

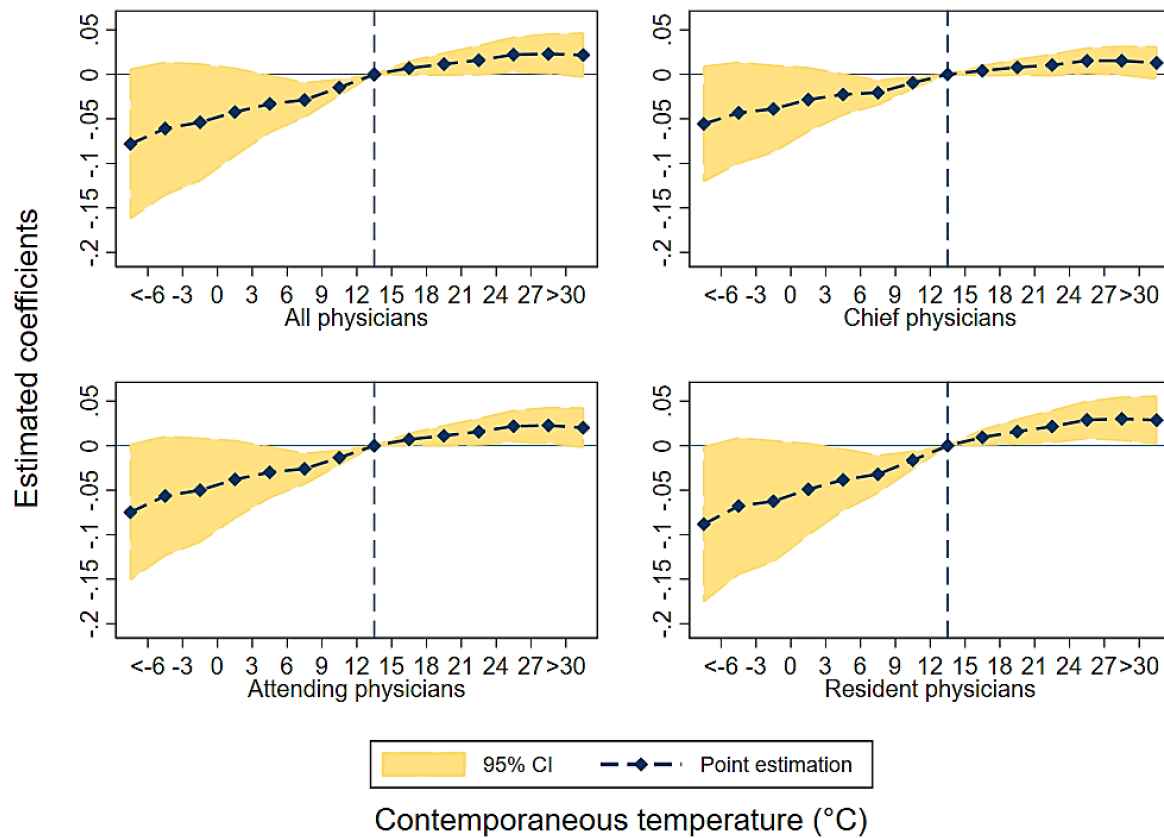


CI = confidence interval, DRG = diagnosis-related group.

Notes: The figure presents contemporaneous effects on hospital admissions for different severities of sickness. Severity is measured by DRG points, which is the ratio of average cost of a specific DRG disease group to the average cost of all patients at city level. Panel A shows the estimations for numbers of admissions, and panel B shows the estimations for proportion of admissions of each level of severity. Estimations of contemporaneous effects β_j are presented. Horizontal coordinates here show the median point of the corresponding temperature bin. Vertical dash line = benchmark temperature bin (12°C–15°C).

Source: Authors' calculations.

Figure 14: Adaptation by Adjusting Physicians Serving in Emergency Departments

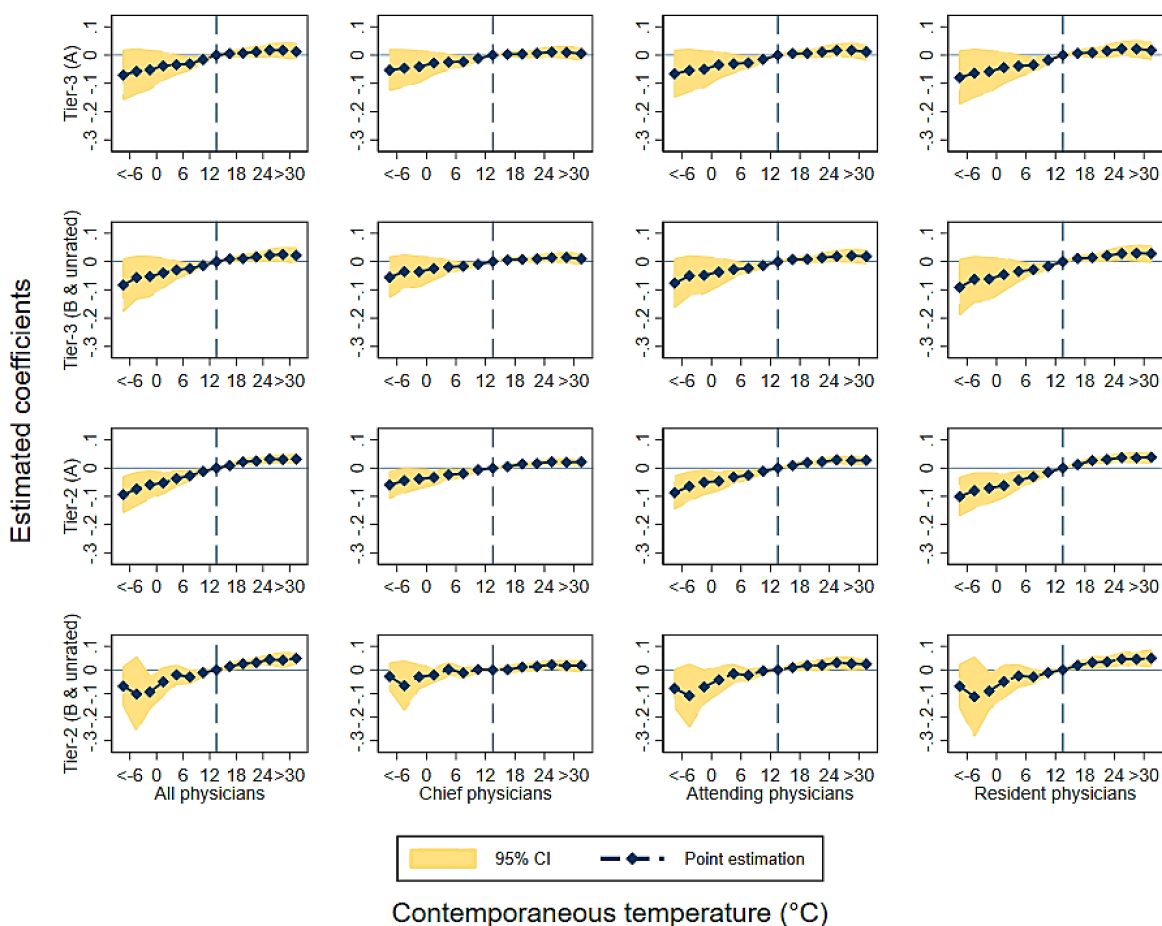


CI = confidence interval.

Notes: The figure presents contemporaneous effects on the number of physicians serving emergency department inpatients. Estimations of contemporaneous effects β_j are presented. Horizontal coordinates here show the median point of the corresponding temperature bin. Vertical dash line = benchmark temperature bin (12°C–15°C).

Source: Authors' calculations.

Figure 15: Adaptation by Level of Hospital

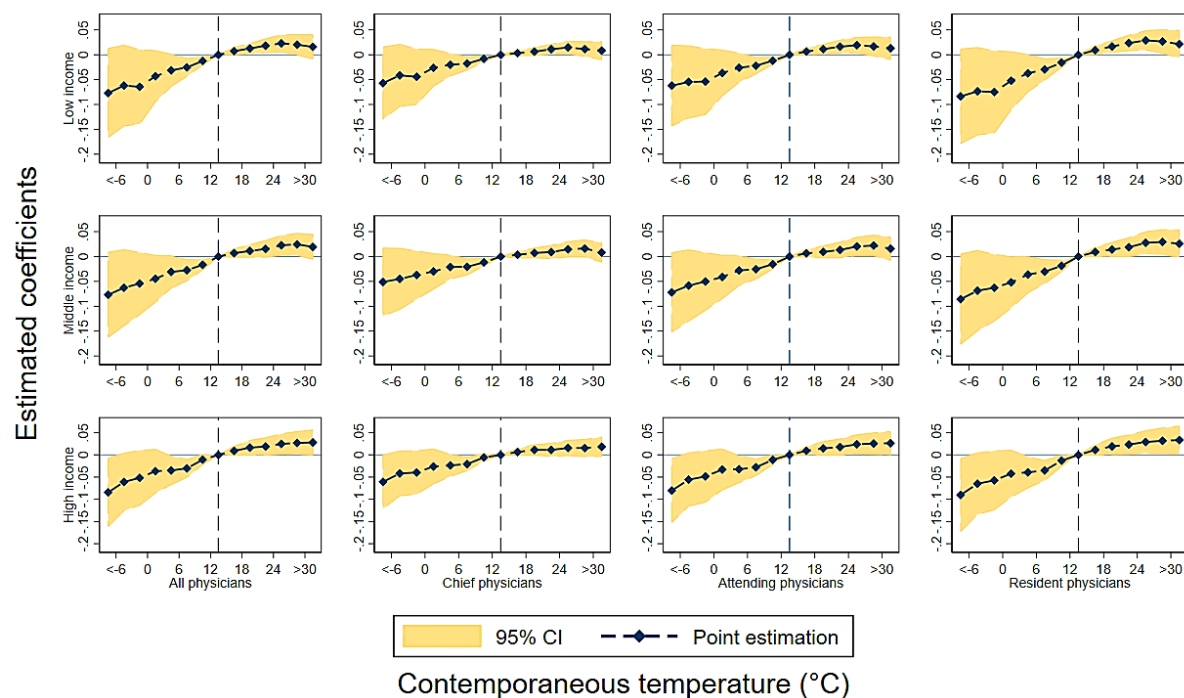


CI = confidence interval.

Notes: The figure presents contemporaneous effects on the number of physicians serving emergency department inpatients by seniority and level of hospital. From the left to the right are total number of physicians, chief physicians, attending physicians, and resident physicians. From the bottom to the top are tier 2 (B & unrated), tier 2 (A), tier 3 (B & unrated), and tier 3 (A) hospitals. Estimations of contemporaneous effects β_j are presented. Horizontal coordinates here show the median point of the corresponding temperature bin. Vertical dash line = benchmark temperature bin (12°C–15°C).

Source: Authors' calculations.

Figure 16: Adaptation by City Average Income

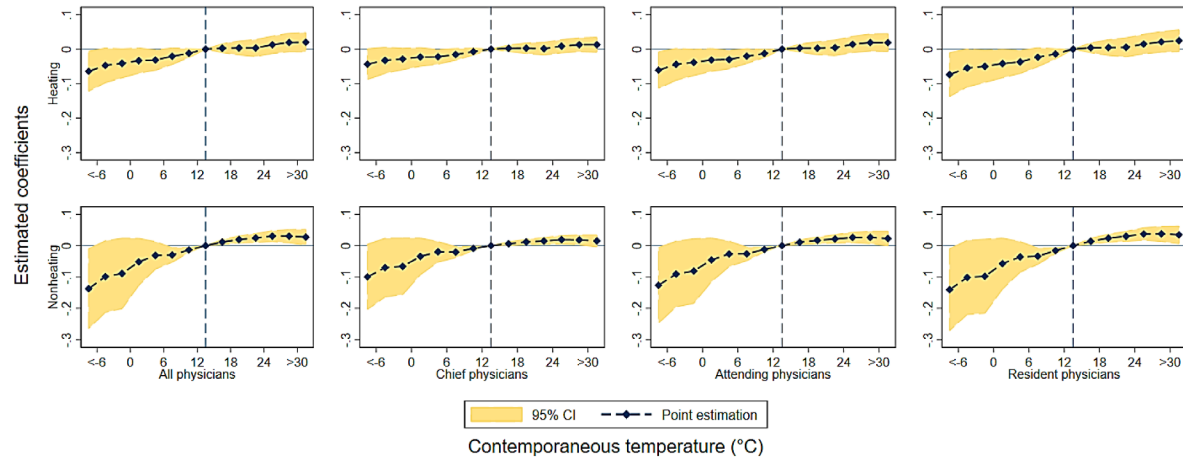


CI = confidence interval.

Notes: The figure presents contemporaneous effects on the number of physicians serving emergency department inpatients by seniority and city average income level where hospitals are located. From the left to the right are total number of physicians, chief physicians, attending physicians, and resident physicians. From the bottom to the top are cities with high, middle, and low average incomes. Estimations of contemporaneous effects β_j are presented. Horizontal coordinates here show the median point of the corresponding temperature bin. Vertical dash line = benchmark temperature bin (12°C–15°C).

Source: Authors' calculations.

Figure 17: Adaptation by Centralized Winter Heating



CI = confidence interval.

Notes: The figure presents contemporaneous effects on the number of physicians serving emergency department inpatients by seniority and centralized winter heating policy where hospitals are located. From the left to the right are total number of physicians, number of chief physicians, attending physicians, and resident physicians. From the bottom to the top are hospital locations where there is no/is centralized winter heating. Estimations of contemporaneous effects β_j are presented. Horizontal coordinates here show the median point of the corresponding temperature bin. Vertical dash line = benchmark temperature bin (12°C–15°C).

Source: Authors' calculations.

Table 1: Summary Statistics

	Number of Units (1)	Obs (2)	Mean (3)	Standard Deviation (4)	Min. (5)	Max. (6)
<i>Panel A: Hospital Admissions</i>						
Daily emergency department admissions	25,514,630	817,344	31.22	41.57	1	1,080
Age groups						
0–5	2,402,343	817,344	2.94	6.62	0	266
6–64	13,849,928	817,344	16.95	233.73	0	611
65+	9,262,359	817,344	11.33	16.12	0	412
Sex groups						
Male	13,447,957	817,344	16.45	22.14	0	567
Female	12,024,535	817,344	14.71	20.24	0	520
Expenditure per patient	–	814,611	12,666.13	111,44.57	0.01	1,280,536
Insured	–	814,611	8,200.11	9,132.89	0	656,013.4
Out-of-pocket	–	814,611	4,466.02	,7655.36	0	1,167,768
<i>Panel B: Hospital Characteristics</i>						
Number of hospitals	1,113	817,344	–	–	–	–
Tier 3	764	562,115	–	–	–	–
Tier 2	348	253,449	–	–	–	–
Tier 1	1	1,780	–	–	–	–
Number of physicians						
Chief	–	817,344	28.96	24.7	0	328
Attending	–	817,344	37.69	30.65	0	328
Residence	–	817,344	47.46	36.2	0	363

Continued on the next page

	Number of Units (1)	Obs (2)	Mean (3)	Standard Deviation (4)	Min. (5)	Max. (6)
<i>Panel C: Hospital-Centered Climate Factors</i>						
Precipitation	–	817,344	4.32	10.96	0	923.13
Temperature	–	817,344	15.28	10.61	-38.38	36.91
Temperature bins						
(,-6°C]	32,488	817,344	0.04	–	–	–
(-6°C,-3°C]	14,587	817,344	0.02	–	–	–
(-3°C,0°C]	23,663	817,344	0.03	–	–	–
(0°C,3°C]	36,818	817,344	0.05	–	–	–
(3°C,6°C]	50,950	817,344	0.06	–	–	–
(6°C,9°C]	61,870	817,344	0.08	–	–	–
(9°C,12°C]	62,421	817,344	0.08	–	–	–
(12°C,15°C]	71,298	817,344	0.09	–	–	–
(15°C,18°C]	79,464	817,344	0.10	–	–	–
(18°C,21°C]	84,313	817,344	0.10	–	–	–
(21°C,24°C]	99,010	817,344	0.12	–	–	–
(24°C,27°C]	104,656	817,344	0.13	–	–	–
(27°C,30°C]	78,515	817,344	0.10	–	–	–
(30°C,)	17,178	817,344	0.02	–	–	–

Continued on the next page

	Number of Units (1)	Obs (2)	Mean (3)	Standard Deviation (4)	Min. (5)	Max. (6)
<i>Panel D: City/County-Level Socioeconomic Characteristics</i>						
Gross domestic product per capita (CNY10,000)	267	694,974	6.58	5.56	1.32	48.60
% from agriculture sector	244	625,734	12.09	9.24	0.09	81.84
% from industrial sector	244	625,734	38.37	13.52	1.54	63.51
Population	267	694,974	455.01	340.27	16.20	3,404
Centralized winter heating	277	817,344	0.37	0.48	0.00	1.00
Number of hospitals	251	676,965	133.11	126.19	13.00	906.00
Number of beds	250	675,291	23,739.00	21,308.32	2,805.00	162,147
Number of physicians	251	676,965	13,077.14	12,602.23	1,605.00	94,417
Light index (county level)	797	815,300	4.69	9.11	0.00	69.01
Electricity usage	207	440,610	2,065,458.0 0	2,219,415.00	121,144.0 0	15,700,000
By urban residence	206	438,852	197,708.30	285,226.00	6,900.00	23,998,841

Notes: The table presents summary statistics for the samples defined in Section II.A (panels A and B), II.B (panel C), and II.C (panel D). Column (1) shows the number of hospital admissions in panel A, the number of hospitals in panel B, the number of daily hospitals with a centered temperature falling into each temperature bin in panel C, and the number of cities/counties with non-missing socioeconomic characteristics in Panel D. In all panels, column (2) shows number of observations (hospital-day) in the sample. Columns (3) to (6) show statistics for our hospital-day level sample in panels A to C, and statistics for city-level variables in panel D. In panel A, expenditure of specific healthcare items is not comprehensively documented, so the sum of expenditure on the listed four items is not equal to total expenditure. Panel B reports the number of hospitals in our sample and the number of physicians who serve in the inpatient sector in a hospital-day in our sample. Temperature bins in panel C are dummy variables, the mean of which shows the percentage of daily hospitals with a centered temperature falling into each bin.

Source: Authors' calculations.

Table 2: Contemporaneous Effects on Hospital Daily Admission

Y=Number of Patients	(1)	(2)	(3)	(4)	(5)
X=Mean Ambient Temperature	Mean	Mean	Max.	Min.	Mean
(, -9°C)	Ambient T	Apparent T	Ambient T	Ambient T	Ambient T
				-0.090*** (0.024)	
[-9°C, -6°C)	-0.123*** (0.026)	-0.115*** (0.020)	-0.100*** (0.025)	-0.073*** (0.020)	-0.109*** (0.026)
[-6°C, -3°C)	-0.098*** (0.022)	-0.100*** (0.017)	-0.089*** (0.022)	-0.067*** (0.016)	-0.085*** (0.022)
[-3°C, 0°C)	-0.086*** (0.018)	-0.090*** (0.015)	-0.076*** (0.019)	-0.051*** (0.013)	-0.074*** (0.018)
[0°C, 3°C)	-0.075*** (0.014)	-0.063*** (0.009)	-0.056*** (0.016)	-0.041*** (0.009)	-0.065*** (0.013)
[3°C, 6°C)	-0.053*** (0.009)	-0.053*** (0.007)	-0.043*** (0.011)	-0.031*** (0.006)	-0.045*** (0.009)
[6°C, 9°C)	-0.042*** (0.006)	-0.031*** (0.005)	-0.031*** (0.008)	-0.021*** (0.005)	-0.037*** (0.006)
[9°C, 12°C)	-0.019*** (0.003)	-0.016*** (0.003)	-0.016*** (0.004)	-0.014*** (0.003)	-0.017*** (0.003)
[15°C, 18°C)	0.015*** (0.003)	0.016*** (0.003)	0.017*** (0.004)	0.017*** (0.003)	0.012*** (0.003)
[18°C, 21°C)	0.032*** (0.004)	0.031*** (0.005)	0.032*** (0.005)	0.026*** (0.005)	0.026*** (0.004)
[21°C, 24°C)	0.048*** (0.006)	0.044*** (0.006)	0.048*** (0.006)	0.039*** (0.006)	0.039*** (0.006)
[24°C, 27°C)	0.064*** (0.007)	0.053*** (0.007)	0.062*** (0.006)	0.042*** (0.008)	0.052*** (0.007)
[27°C, 30°C)	0.074*** (0.008)	0.055*** (0.008)	0.075*** (0.007)	0.057*** (0.011)	0.058*** (0.008)
[30°C, 33°C)	0.077*** (0.010)	0.064*** (0.011)	0.086*** (0.007)		0.060*** (0.010)
[33°C, 36°C)			0.087*** (0.008)		
[36°C,)			0.090*** (0.011)		
Temp. diff.	No	No	No	No	YES
Precipitation	YES	YES	YES	YES	YES
Hospital-year-week FE	YES	YES	YES	YES	YES

Continued on the next page

Y=Number of Patients	(1)	(2)	(3)	(4)	(5)
X=Mean Ambient Temperature	Mean Ambient T	Mean Apparent T	Max. Ambient T	Min. Ambient T	Mean Ambient T
Day-of-week FE	YES	YES	YES	YES	YES
N	798,258	798,258	798,258	798,258	798,258
R-square	0.898	0.897	0.897	0.897	0.897

FE = fixed effects.

Notes: Dependent variable is logarithm of daily number of ED admissions. Column titles are temperature measurements used in estimation. Bin "[12°C,15°C]" is omitted, as it is the reference bin. In columns (1–3) and (5), coefficient reported at row "[−9°C,−6°C]" is coefficient for bin "(,−6°C)". In columns (1), (2), and (5), coefficient reported at row "[30°C,33°C]" is coefficient for bin "[30°C,)". In column (4), coefficient reported at row "[27°C,30°C]" is coefficient for bin "[27°C,)". All specifications estimate equation (1) by Ordinary Least Squares, controlling for precipitation, hospital-year-week fixed-effect, and day-of-week fixed-effect. Standard errors are two-way clustered at hospital level and year-week level. * Significant at 10% level, ** significant at 5% level, *** significant at 1% level.

Source: Authors' calculations.

REFERENCES

- Agarwal, Sumit, Yu Qin, Luwen Shi, Guoxu Wei, and Hongjia Zhu. 2021. "Impact of Temperature on Morbidity: New Evidence from China." *Journal of Environmental Economics and Management* 109 (20): 102495. <https://doi.org/10.1016/j.jeem.2021.102495>
- Aguilar-Gomez, Sandra, Joshua Graff-Zivin, and Matthew Neidell, M. 2024. "Hot and Crowded: Temperature, Healthcare Utilization and Patient Outcomes." Working Paper. Cambridge, MA: National Bureau of Economic Research.
- Asaro, Phillip, Lawrence Lewis, and Stewart Boxerman. 2007. "Emergency Department Overcrowding: Analysis of the Factors of Renege Rate." *Academic Emergency Medicine* 14 (2): 157–162.
- Barenbrug, A.W.T. 1974. *Psychrometry and Psychrometric Charts*. Cape Town: Cape and Transvaal Printers Ltd.
- Barreca, Alan. 2012. "Climate Change, Humidity, and Mortality in the United States." *Journal of Environmental Economics and Management* 63 (1): 19–34.
- Barreca, Alan, Karen Clay, Olivier Deschenes, Michael Greenstone, and Joseph Shapiro. 2015. "Convergence in Adaptation to Climate Change: Evidence from High Temperatures and Mortality, 1900-2004." *American Economic Review* 105 (5): 247–251.
- Barreca, Alan, Karen Clay, Olivier Deschenes, Michael Greenstone, and Joseph Shapiro. 2016. "Adapting to Climate Change: The Remarkable Decline in the US Temperature-Mortality Relationship over the Twentieth Century." *Journal of Political Economy* 124 (1): 105–159.
- Burkart, Katrin, Michael Brauer, Aleksandr Aravkin, William Godwin, Simon Hay, Jiawei He, Vincent Iannucci, Samantha Larson, Stephen Lim, Jiangmei Liu, Christopher Murray, Peng Zheng, Miageng Zhou, and Jeffrey Stanaway. 2021. "Estimating the Cause-Specific Relative Risks of Non-Optimal Temperature on Daily Mortality: A Two-Part Modelling Approach Applied to the Global Burden of Disease Study." *Lancet* 398 (10301): 685–697.
- Carleton, Tamma, Amir Jina, Michael Delgado, Michael Greenstone, Trevor Houser, Solomon Hsiang, Andrew Hultgren, Robert Kopp, Kelly McCusker, Ishan Nath, James Rising, Ashwin Rode, Hee Kwon Seo, Arvid Viaene, Jiakuan Yuan, and Alice Tianbo Zhang. 2022. "Valuing the Global Mortality Consequences of Climate Change Accounting for Adaptation Costs and Benefits." *Quarterly Journal of Economics* 137 (4): 2037–2105.
- Carter, Eileen, Stephanie Pouch, and Elaine Larson. 2014. "The Relationship Between Emergency Department Crowding and Patient Outcomes: A Systematic Review." *Journal of Nursing Scholarship* 46 (2): 106–115.
- Chan, David. 2018. "The Efficiency of Slacking off: Evidence from the Emergency Department." *Econometrica* 86 (3): 997–1030.

- Cohen, François, and Antoine Dechezlepretre. 2022. "Mortality, Temperature, and Public Health Provision: Evidence from Mexico." *American Economic Journal-Economic Policy* 14 (2): 161–192.
- Colmer, Jonathan. 2021. "Temperature, Labor Reallocation, and Industrial Production: Evidence from India." *American Economic Journal-Applied Economics* 13 (4): 101–124.
- Dell, Melissa, Benjamin Jones, and Benjamin Olken. 2014. "What Do We Learn from the Weather? The New Climate-Economy Literature." *Journal of Economic Literature* 52 (3): 740–798.
- Deschenes, Olivier. 2014. "Temperature, Human Health, and Adaptation: A Review of the Empirical Literature." *Energy Economics* 46: 606–619.
- Deschenes, Olivier, and Enrico Moretti. 2009. "Extreme Weather Events, Mortality, and Migration." *Review of Economics and Statistics* 91 (4): 659–681.
- Deschenes, Olivier, and Michael Greenstone. 2011. "Climate Change, Mortality, and Adaptation: Evidence from Annual Fluctuations in Weather in the US." *American Economic Journal-Applied Economics* 3 (4): 152–185.
- Dillender, Marcus. 2021. "Climate Change and Occupational Health: Are There Limits to Our Ability to Adapt?" *Journal of Human Resources* 56 (1): 184–224.
- Ebi, Kristie, Anthony Capon, Peter Berry, Carolyn Broderick, Richard de Dear, George Havenith, Yashushi Honda, R. Sari Kovats, Wei Ma, Arunima Malik, Nathan Morris, Lars Nybo, Sonia Seneviratne, Jennifer Vanos, and Ollie Jay. 2021. "Hot Weather and Heat Extremes: Health Risks." *The Lancet* 398 (10301): 696–708.
- Ellis, Cameron, and Meghan Esson. 2021. "Crowd-out and Emergency Department Utilization." *Journal of Health Economics* 80 (21): 102542.
<https://doi.org/10.1016/j.jhealeco.2021.102542>
- Fotheringham, A. Stewart, and Morton O'Kelly. 1989. *Spatial Interaction Models: Formulations and Applications*. Boston, MA: Kluwer Academic Publishers.
- Fritz, Manuela. 2022. "Temperature and Non-Communicable Diseases: Evidence from Indonesia's Primary Health Care System." *Health Economics* 31 (11): 2445–2464.
- Gould, Carlos, Sam Heft-Neal, Alexandra Heaney, Eran Bendavid, Christopher Callahan, Mathew Kiang, Joshua Graff-Zivin, and Marshall Burke. 2024. "Temperature Extremes Impact Mortality and Morbidity Differently." Working Paper Series. Cambridge, MA: National Bureau of Economic Research.
- Graff-Zivin, Joshua, and Matthew Neidell. 2014. "Temperature and the Allocation of Time: Implications for Climate Change." *Journal of Labor Economics* 32 (1): 1–26.

- Hoot, Nathan, and Dominik Aronsky. (2008. "Systematic Review of Emergency Department Crowding: Causes, Effects, and Solutions." *Annals of Emergency Medicine* 52 (2): 126–136.
- Hwang, Ula, Melissa McCarthy, Dominik Aronsky, Brent Asplin, Peter Crane, Catherine Craven, Stephen Epstein, Christopher Fee, Daniel Handel, Jesse Pines, Niels Rathlev, Robert Schafermeyer, Frank Zwemer, Jr., and Steven Bernstein. 2011. "Measures of Crowding in the Emergency Department: A Systematic Review." *Academic Emergency Medicine* 18 (5): 526–537. <https://doi.org/10.1111/j.1553-2712.2011.01054.x>
- Iniguez, Carmen, Doninic Roye, and Aurelio Tobias. 2021. "Contrasting Patterns of Temperature Related Mortality and Hospitalization by Cardiovascular and Respiratory Diseases in 52 Spanish Cities." *Environmental Research* 192 (5): 110191. <https://doi.org/10.1016/j.envres.2020.110191>
- Intergovernmental Panel on Climate Change (IPCC). 2023. "Summary for Policymakers." Climate Change 2023: Synthesis Report.
- Joseph, Anton, Sethna Saverymuttu, S.Z. Al-Sam, Martin Cook, and James Maxwell. 1991. "Comparison of Liver Histology with Ultrasonography in Assessing Diffuse Parenchymal Liver Disease." *Clinical Radiology* 43 (1) 26–31.
- Karlsson, Martin, and Nicolas Ziebarth. 2018. "Population Health Effects and Health-Related Costs of Extreme Temperatures: Comprehensive Evidence from Germany." *Journal of Environmental Economics and Management* 91: 93–117.
- Li, Xue, Russel Smyth, and Yao Yao. 2023. "Extreme Temperatures and Out-of-Pocket Medical Expenditure: Evidence from China." *China Economic Review* 77 (35): 101894. <https://doi.org/10.1016/j.chieco.2022.101894>
- Liao, Hua, Chen Zhang, Paul Burke, Ru Li, and Yi-Ming Wei. 2023. "Extreme Temperatures, Mortality, and Adaptation: Evidence from the County Level in China." *Health Economics* 32 (4): 953–969.
- Lucas, Ray, Heather Farley, Josph Twanmoh, Andrej Urumov, Nils Olsen, Bruce Evans, and Hamed Kabiri. 2009. "Emergency Department Patient Flow: The Influence of Hospital Census Variables on Emergency Department Length of Stay." *Academic Emergency Medicine* 16 (7): 597–602.
- Mullins, Jamie, and Corey White 2019. "Temperature and Mental Health: Evidence from the Spectrum of Mental Health Outcomes." *Journal of Health Economics* 68: 102240. <https://doi.org/10.1016/j.jhealeco.2019.102240>
- Mullins, Jamie, and Corey White. 2020. "Can Access to Health Care Mitigate the Effects of Temperature on Mortality?" *Journal of Public Economics* 191 (15): 104259. <https://doi.org/10.1016/j.jpubeco.2020.104259>

- National Bureau of Statistics (NBS). 2024. *Report on National Economic and Social Development in 2023*. Beijing: NBS.
https://www.stats.gov.cn/sj/zxfb/202402/t20240228_1947915.html
- National Health Commission (NHC). 2024. *People's Republic of China Health and Healthcare Statistics Yearbook*. Beijing: NHCC.
www.nhc.gov.cn/mohwsbwstjxxzx/tjzxtjsj/tjsj_list.shtml
- Navas Martin, Miguel Ángel, José Antonio Lopez Bueno, Fernando Follos, José Manuel Vellon, Isidro Miron, María Yolanda Luna, Gerardo Martinez, Julio Diaz, and Cristina Linares-Gil. 2023. "Adaptation to Heat and Social Health Inequalities according to Gender, Age and Territory: A Review of Studies Conducted in Spain (1983-2018)." *Revista De Salud Ambiental* 23 (1): 49–55.
- Pearce, Sabrina, Tyara Marchand, Tara Shannon, Heather Ganshorn, and Eddy Lang. 2023. "Emergency Department Crowding: An Overview of Reviews Describing Measures, Causes, and Harms." *Internal and Emergency Medicine* 18 (4): 1137–1158.
- Rathlev, Niels, John Chessare, Jonathan Olshaker, Dan Obendorfer, Supriya Mehta, Todd Rothenhaus, Steven Crespo, Brendan Magauran, Kathy Davidson, Richard Shemin, Keith Lewis, James Becker, Linda Fisher, Linda Guy, Abbott Cooper, and Eugene Litvak. 2007. "Time Series Analysis of Variables Associated with Daily Mean Emergency Department Length of Stay." *Annals of Emergency Medicine* 49 (3): 265–271.
- Rode, Ashwin, Tamma Carleton, Michael Delgado, Michael Greenstone, Trevor Houser, Solomon Hsiang, Andrew Hultgren, Amir Jina, Robert Kopp, and Kelly Mccusker. 2021. "Estimating a Social Cost of Carbon for Global Energy Consumption." *Nature* 598 (7880): 308–314.
- Salas, Renee, and Ashish Jha. 2019. "Climate Change Threatens the Achievement of Effective Universal Healthcare." *The BMJ* 366. DOI: [10.1136/bmj.l5302](https://doi.org/10.1136/bmj.l5302)
- Sartini, Marina, Alessio Carbone, Alice Demartini, Luana Giribone, Martino Oliva, Anna Maria Spagnolo, Paolo Cremonesi, Francesco Canale, and Maria Luisa Cristina. 2022. "Overcrowding in Emergency Department: Causes, Consequences, and Solutions—A Narrative Review." *Healthcare* 10 (9): 1625. <https://doi.org/10.3390/healthcare10091625>
- Steadman, Robert. 1984. "A Universal Scale of Apparent Temperature." *Journal of Climate and Applied Meteorology* 23 (12): 1674–1687.
- Van Steen, Yvette, Anna-Maria Ntarladima, Rick Grobbee, Derek Karssenberg, and Ilonca Vaartjes. 2019. "Sex Differences in Mortality After Heat Waves: Are Elderly Women at Higher Risk?" *International Archives of Occupational and Environmental Health* 92 (1): 37–48.

- Weinberger, Kate, Kipruto Kirwa, Melissa Eliot, Julia Gold, Helen Suh, and Gregory Wellenius. 2018. "Projected Changes in Temperature-related Morbidity and Mortality in Southern New England." *Epidemiology* 29 (4): 473–481.
- Wellenius, Gregory, Melissa Eliot, Kathleen Bush, Dennis Holt, Rebecca Lincoln, Andy Smith, and Julia Gold. 2017. "Heat-Related Morbidity and Mortality in New England: Evidence for Local Policy." *Environmental Research* 156: 845–853.
- White, Corey. 2017. "The Dynamic Relationship between Temperature and Morbidity." *Journal of the Association of Environmental and Resource Economists* 4 (4): 1155–1198.
- Woodworth, Lindsey. 2020. "Swamped: Emergency Department Crowding and Patient Mortality." *Journal of Health Economics* 70 (17): 102279.
<https://doi.org/10.1016/j.jhealeco.2019.102279>
- World Health Organization (WHO). 2020. "Factors Influencing Health Status and Contact with Health Services." International Classification of Diseases, 10th Revision, Clinical Modification. Version for 2019. <https://icd.who.int/browse10/2019/en#/XXI>
- WHO. 2024. *World Health Statistics 2024: Monitoring Health for the SDGs*. Geneva: WHO.
- Yardley, Jane, Ronald Sigal, and Glen Kenny. 2011. "Heat Health Planning: The Importance of Social and Community Factors." *Global Environmental Change-Human and Policy Dimensions* 21 (2): 670–679.
- Yu, Xiumei, Xiaoyan Lei, and Min Wang. 2019. "Temperature Effects on Mortality and Household Adaptation: Evidence from China." *Journal of Environmental Economics and Management* 96: 195–212.

Hospital Workload and Adaptation Under Climate Change

Evidence from the People's Republic of China

This paper estimates temperature impacts on hospital workload at emergency departments in the People's Republic of China between 2013 and 2022. The results show that mean temperature is directly associated with inpatient admissions in emergency departments. Internal medicine, surgery, and pediatrics experience more substantial increases in workload during extreme heat. Men, children, and patients with injuries or respiratory diseases make up a larger proportion of total admissions on extremely hot days. This research highlights the need for the healthcare system to increase personnel and adjust resource allocation in response to climate change.

About the Asian Development Bank

ADB is a leading multilateral development bank supporting inclusive, resilient, and sustainable growth across Asia and the Pacific. Working with its members and partners to solve complex challenges together, ADB harnesses innovative financial tools and strategic partnerships to transform lives, build quality infrastructure, and safeguard our planet. Founded in 1966, ADB is owned by 69 members—50 from the region.



ASIAN DEVELOPMENT BANK

6 ADB Avenue, Mandaluyong City

1550 Metro Manila, Philippines

www.adb.org