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# Causal link between humid heatwaves and ischemic heart disease: assessing hospitalizations and economic burden across 955 Chinese counties

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## Abstract

**Background** Humid heatwaves might cause more massive destruction to human health systems, especially the cardiovascular system. However, there is no systematic approach for identifying humid heatwaves and assessing their impacts on human health and health-related economic burden. This study aims to elucidate the relationship between short-term exposure to humid heatwaves and the relative risk of hospitalization for ischemic heart disease (IHD) and the hospitalization-related economic burdens.

**Methods** This study utilizes hospitalization data from the Chinese Multiple-County (CMC) Hospital Network with 6,843,511 IHD cases across 1309 counties from 2016 to 2022. We employed a pre-post analysis and a causal inferential propensity score matching aided difference-in-differences (PSM-DID) approach to assess the causal effect of each type of humid heatwaves on IHD hospitalization rate changes.

**Results** IHD hospitalizations increased by 2.92% (95% CI, 1.17%, 4.66%), 2.76% (95% CI, 1.07%, 4.45%), and 1.60% (95% CI, 0.08%, 3.12%) following independent humid heatwaves, light precipitation involved-, and moderate precipitation involved-humid heatwaves, with annual hospitalization-related economic burden reached $154 million (95% CI, $20, $249 million), $75 million (95% CI, $14, $136 million), and $81 million (95% CI, $31, $131 million), respectively. Chronic IHD and Angina were the most sensitive subtypes. Moreover, middle-to-old and male populations were afforded the most burdens.

**Conclusions** As humid heatwaves become more intense, older populations with IHD should be provided with more care and medical resources. Identifying strategies and implementing actionable adaptation measures to minimize disruptions in healthcare delivery following these extremely hot and humid events is crucial to reducing IHD hospitalizations.

**Keywords** Humid heatwave, Ischemic heart disease, Precipitation, Economic burden, Propensity score matching aided difference-in-differences (PSM-DID)

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## Background

As global climate change intensifies, multiple regions such as Southeast Asia, West Africa, and South America are experiencing prolonged hot and humid conditions [1]. While previous studies have established the fundamental associations between extreme heat exposure (i.e., heatwaves) and cardiovascular disease (CVD) [2–4], the reliance on a single temperature parameter for heatwave identification may underestimate the actual health risks under climate change, as high humidity can exacerbate heat stress by inhibiting sweat evaporation and elevating perceived temperature [5, 6]. Besides, the accumulation of water vapor in the hot and humid atmosphere increases the likelihood of subsequent precipitation [7], which may offer a cooling effect that interferes with the lag effect of heat exposure. These complicated meteorological interactions of temperature and humidity pose substantial challenges in quantifying the impacts of comprehensive heat stress. Our work not only revealed the health risks exerted by the independent humid heatwaves but also the effect of cooling breaks of compounded rainfall during hot and humid days. Therefore, employing temperature and humidity as primary indicators [8] to define humid heatwaves has great potential in accurately capturing the spatiotemporal health response of the public, which expands the current understanding of heat stress under climate change. Ischemic heart disease (IHD), which constitutes the major component of the disease burden of CVDs, includes chronic IHD, chronic stable angina, acute myocardial infarction (MI), and its associated heart failure [9]. Globally, there were 31.1 million incident IHD cases, 247 million prevalent IHD cases, 8.88 million IHD deaths, and 187 million disability-adjusted life years (DALYs) lost [10]. IHD is also a leading cause of death in China, which accounts for 43% of CVD deaths and 24.1% of DALYs [11, 12]. Because IHD is sensitive to extreme weather disasters [13, 14], the levels of IHD hospitalizations can serve as a quantitative indicator for understanding the health impacts, and the health-related economic burden of humid heatwaves.

Despite extensive studies that have confirmed the elevated mortality or hospitalization risks for IHD during extreme heat exposure [15, 16], systematic evaluation of the health-related economic burden attributable to these extreme weather events remains limited. This evidence gap challenges local governments, policymakers, and healthcare facilities in efficiently allocating economic and medical resources. Precise estimation of economic burden across IHD subtypes, age, and gender groups enables more targeted healthcare provision for highly vulnerable populations—a particularly crucial consideration in less developed regions with limited healthcare resources.

To fill this critical deficit, our study aims to employ a causal inferential study design, including pre-post analysis and propensity score matching aided difference-in-differences (PSM-DID) approach in 3425 hospitals across over 1300 Chinese counties through Chinese Multiple-County (CMC) Hospital Network dataset, to (1) investigate the sensitivity and temperoal evolution of IHD hospitalizations following the onset of humid heatwaves (both independent and precipitation involved); (2) identifying the vulnerable populations with respect to age group and gender; (3) estimate the humid heatwaves induced, IHD hospitalizations related potential economic burden in China over the years 2016–2022.

## Methods

### Data sources and IHD cases

Meteorological data were obtained from the Visual Crossing global weather database [17], and IHD clinical diagnoses [18] were collected from the CMC Hospital Network dataset. Specifically, the Visual Crossing global weather database combines the Integrated Surface Database (ISD) from the National Oceanic and Atmospheric Administration (NOAA) and historical records from thousands of ground stations, generating hourly level, high-resolution ($0.1° \times 0.1°$) meteorological metrics including but not limited to temperature and humidity [19]. For meaningful interpretation at the county scale, these metrics were converted to the daily average by area. The CMC Hospital Network dataset, initially established in 2016, documents all patient records from a collective of 3425 hospitals in 1309 counties across China. IHD hospitalizations were examined by the international classification of diseases, $10^{th}$ revision (ICD-10) codes [18], including angina (I20), myocardial infarction (I21, I22, I23), chronic ischemic heart disease (I25), other ischemic heart diseases (I24). We also aggregated demographic, socioeconomic, environmental, and health-related data (e.g., gross regional product (GRP), GRP growth rate, population, gender ratio, the elderly proportion, education attainment, green coverage, and number of hospitals) from the National Bureau of Statistics [20].

### Independent and precipitation-involved humid heatwaves

To evaluate the composite effects of extreme temperature and high humidity, as well as other factors comprising atmospheric pressure and solar energy, we developed a comprehensive meteorological humid heatwave index (for more details, see Additional file 1 methods: Text 1) [21–32], with assistance of which the humid heatwave is defined as a climate-related hazard persisting for three or more days exceeding the $90^{th}$ percentile threshold in local history based on the criteria from the World Meteorological Organization (WMO) and NOAA.

Based on the occurrence of subsequent rainfall (due to high humidity [33]), the humid heatwave is categorized into the independent and the precipitation-involved humid heatwaves. An independent humid heatwave is when the index exceeds the 90$^{th}$ percentile for three or more consecutive days without any subsequent precipitation [34]. In contrast,a precipitation-involved humid heatwave is recognized as a compound event where precipitation occurs within 1 week following the onset of a humid heatwave. This 1-week window period aligns with existing studies focusing on compound extreme climate hazards [35]. Besides,it also fits the observation window configuration in our PSM-DID framework discussed later. Additionally,based on the precipitation levels [36],precipitation-involved humid heatwaves are further categorized as follows: light precipitation involved (LPI,< 9.9 mm/day); moderate precipitation involved (MPI,9.9 ~ 16.9 mm/day); and extreme precipitation involved (EPI,over the 95$^{th}$ percentile (17.0 mm/day) of precipitation in history [36]). We did not provide detailed DID estimates for EPI humid heatwaves due to the very limited number of events. To further understand the mechanisms of cooling breaks that precipitation plays in precipitation-involved humid heatwaves,varying levels of independent precipitation events were additionally analyzed to capture the relative changes in ambient temperature and humidity after rainfalls (Additional file 1 results: Table 1). Moreover,the humid heatwave event was at the county level which followed the standard aggregation approach based on the weights of population density for the justification of hazard exposure [37, 38].

### Pre- and post-period and warning period

Considering the short duration of humid heatwave exposure and the potential IHD hospitalization risk in lag period, by tagging the start of the event day as day 0, the observation windows were set by weeks as follows (also refer to Additional file 1 results: Fig. 3):

(1) Warning: pre- vs. post-period as [− 6, −4] vs. [− 3, −1] days;
(2) Period 1: pre- vs. post-period as [− 10, −4] vs. [0, 6] days;
(3) Period 2: pre- vs. post-period as [− 17, −4] vs. [0, 13] days; and.
(4) Period 3: pre- vs. post-period as [− 24, −18] vs. [14, 20] days.

Note that a 3-day warning period immediately before the onset of the humid heatwave is particularly considered and removed from the pre-event timeline, aiming to avoid analyzing escalated hospitalization rates that might occur in the pre-period in the DID model. Otherwise, the relative risk induced by the humid heatwave would be underestimated. Typically, period 1 reflects the most threatening relative risk imposed by most humid heatwaves immediately after the onset, resulting from the highest heat intensity at their active periods. Period 2 indicates the overall relative risk during the first 2 weeks following the onset of humid heatwaves. For most categories of events, period 3 refers to the period in which the lag effect gradually diminishes to no statistical significance stage.

### Control county matching and selection

We employed a rigorous PSM framework for selecting control counties, pairing each humid heatwave-affected county with four controls. Firstly, any county directly adjacent to the affected county was excluded. Secondly, counties that were undergoing or had experienced humid heatwaves within 1 month before or after the study period were removed, aiming to avoid the potential interference from the previous humid heatwave on the subsequent event. Previous studies have also confirmed that heat stress on IHD typically lasts within 1 month [39]. Thirdly, we paired the affected and control counties that had the same local Köppen-Geiger climate type [40]. Moreover, to avoid auto-correlations, both global and local Moran's $I$ were examined and we excluded counties with local Moran's $I$ exceeding 0.5 [41] (More details can be found in Additional file 1 methods: Text 2). After expelling candidate counties through geographic location, interval requirement, spatial autocorrelation, and local climate type, we utilized PSM to select control counties that mirrored the conditions of the affected counties but excluded the impact of humid heatwaves [42]. Covariates included county-scale socioeconomic (GRP per capita, growth rate, and employment rate), demographic (population density, gender ratio, and percentage of population with bachelor's or higher degree), environmental condition (green coverage), and healthcare attributes (number of hospitals per 100,000 population, averaged healthcare expenditure), as well as daily air pollutants [43–49] ($PM_{2.5}$, $PM_{10}$, and $O_3$) are considered as confounding factors to balance. We calculated the standardized mean differences (SMD; Additional file 1 results: Fig. 1) and the histograms of propensity score distributions (Additional file 1 results: Fig. 2) of balanced covariates before and after PSM. The |SMD|< 10% and the consistent distributions of propensity scores indicate the effective matching between humid heatwave-affected and non-exposed control counties.

### Hospitalization-related economic burden

Given the relative change of cause-specific hospitalization rate from the statistical analysis (PSM-DID) and followed the commonly adopted assumption [50] that the excess relative risk of IHD hospitalization rates was identical across all affected counties that experienced humid heatwaves in China. We estimated the hospitalization-related economic burden by considering each county's population demographic and exposure characteristics. Then, these county-scale burdens were summed up to compute the hospitalization-related burden at the national scale. Mathematically, the potential economic burden is estimated as:

$$B = \sum_{i=1}^{N_c} \sum_{j=1}^{N_G} R_0 AF_{i,j} N_{i,j} C \chi (1 + \alpha)$$

where subscript $i$ and $j$ respectively refer to the $i$ county and $j$ population group with $N_c$, $N_G$ the corresponding summations. $R_0$ is the reported IHD incidence rate in China. $AF_{i,j} = \frac{n\sum(RR-1)D}{n\sum(RR-1)D+T}$ is the event-frequency and population-group dependent attributable fraction to humid heatwaves, with $n$, $D$, $T$, $RR$, $RR-1$, and $\sum(RR-1)D$ being the number of events, the length of observation window (i.e., periods 1–3), the total study period, relative risk, excess relative risk, and cumulative excess relative risk, respectively. $N_{i,j}$ is the population size therefore the product $R_0 AF_{i,j} N_{i,j}$ refers to the number of hospitalizations attributed to humid heatwaves. $C$ is the direct cost per IHD hospitalization that encompasses healthcare goods, services, and consumption of other medical resources [51] so $R_0 AF_{i,j} N_{i,j} C$ accounts for the total economic burden for $j$ age group in $i$ county. Further given the purchasing power parties (PPP) $\chi$ that consider the absolute purchase power difference in different currencies [52], and the inflation rate [53] $\alpha$ over the years, we derive the explicit function of economic burden ($B$) which is consistent with the previous study [54].

### Statistical analyses

We conducted a pre-post analysis to estimate the overall relative change in IHD hospitalization rate following the onset of humid heatwaves in affected counties. The pre-post estimates refer to the temporal health outcome attributed to the humid heatwave and other confounding factors (e.g., air pollution, economic prosperity, healthcare facilities). Then we employed a causal inferential study design, utilizing a rigorous PSM-DID approach [55] to compare the hospitalization rate relative change in humid heatwave-affected counties with matched control counties. After PSM, the confounding factors among affected and control counties are balanced therefore the DID estimates exclusively represent the health impact triggered by the humid heatwaves. Note that for the pre-post analysis, the primary predictor was the indicator (hospitalization rates) of pre- vs. post-event status. In the PSM-DID approach, we evaluated the relative risk difference in IHD hospitalizations using a binary interaction term between the county type (affected = 1 or control = 0) and the period (pre-period = 1; post-period = 0). A county-level generalized linear mixed-effect model was adopted, which treated the geographic location as a random effect and the daily total IHD hospitalizations as the dependent variable. We incorporated county-specific population size as an offset on a logarithmic scale to account for the difference in population among analyzed counties. Temporal fluctuations such as holidays and day-of-week cycles were also considered. For the mathematical model descriptions, see Additional file 1 methods: Text 3.

Regarding the pre-post analysis, it captures the temporal changes in hospitalization rates in affected counties before and after the humid heatwaves. Estimates given by pre-post analysis were just utilized for reference, as both humid heatwaves and confounding factors (such as the local economy and air pollutants) contributed to the captured hospitalization risks. In contrast, PSM-DID analysis yielded the primary findings of health risks (i.e., relative changes in hospitalization rates) that were solely attributed to humid heatwaves. This causal inference is achieved by a double-difference framework. By applying the rigorous inclusion/exclusion criteria and propensity score matching, confounding factors between humid heatwave-affected counties and non-exposed controls were balanced ($|SMD| < 10\%$). Furthermore, the parallel trends preceding the hazard occurrence indicate that there were no statistically significant temporal effects between humid heatwave-affected counties and non-exposed controls. Thus, all the relative changes in hospitalization rates were the causal impacts exerted by humid heatwaves.

To explore variations in our findings across different IHD sub-categories and demographic groups, we conducted stratified analyses for each IHD category, gender, and age group. Sensitivity analyses were performed using the $95^{th}$ percentile of the meteorological humid heatwave index to ensure the robustness of our primary findings. All statistical tests were reported with $P$-values and confidence intervals (CIs) to measure statistical significance and uncertainty. The analyses used R version 4.1.3, Matlab R2023a, and ArcGIS Pro 3.2.

## Results

### Study population and exposure characteristics

From 2016 to 2022, in total, 10,553 county-specific humid heatwaves were identified in the CMC Hospital Network covered counties (i.e., 1309 administrative counties)

**Table 1** Baseline disaster and population characteristics of the Chinese Multiple-County (CMC) Hospital Network in 2016–22

| Characteristics | *N* (%) |
|---|---|
| Disaster characteristics | |
| Study population characteristics | |
| Baseline disaster and population characteristics of the Chinese | 6,843,511 |
| Angina | 2,589,772 (37.8) |
| MI | 794,234 (11.61) |
| Chronic ischemic heart disease | 3,316,109 (48.46) |
| Other ischemic heart diseases | 143,396 (2.10) |
| Gender | |
| Male | 3,648,523 (53.31) |
| Female | 3,194,988 (46.69) |
| Age group | |
| 18–44 | 228,031 (3.29) |
| 45–64 | 2,484,319 (35.82) |
| Over 65 | 4,223,639 (60.89) |
| Employment status | |
| Unemployment | 575,858 (8.41) |
| Employment | 4,197,730 (61.34) |
| Retired | 2,069,923 (30.25) |

LPI and MPI humid heatwave refers to the compound humid heatwave in which shower/light precipitation and moderate precipitation are involved within the 7-day window

*LPI* light precipitation involved, *MPI* Moderate precipitation involved, *MI* Myocardial infarction

through the comprehensive meteorological index, of which 3375 (32.0%) independent humid heatwave events, 3328 (31.5%) LPI, 3203 (30.5%) MPI humid heatwave events, and 647 (6.0%) EPI heatwave were characterized (Table 1), mainly affecting the eastern and southern-eastern of mainland China (Fig. 1). These counties experienced 6,843,511 IHD cases, the average duration of an independent humid heatwave was 10.68 days. Most IHD cases occurred in middle-aged to elderly populations, with 52.31% male and 61.34% employed. IHD cases were classified into four sub-types: angina (37.8%), MI (11.61%), chronic IHD (48.46%), and other IHD diseases (2.10%). Furthermore, humid heatwaves related IHD hospitalization cases in a sequential observation period are shown in Figs. 2A,B, and the majority of IHD hospitalizations were attributed to chronic IHD (49.58–50.27%) and angina (36.00–36.38%) in each window period.

## Cause-specific IHD hospitalization changes following humid heatwaves

Overall, IHD hospitalization rate was 2.39% (95% CI, 1.27%, 3.51%) higher in affected counties during the first week (period 1, days 0–6) following a humid heatwave, with DID estimates showing a 2.03% increase (95% CI, 0.27%, 3.79%) (Additional file 1 results: Table 2). Specifically for different types of humid heatwaves, the hospitalization rate changes decreased with the escalating level of precipitation involved during the effective period of humid heatwaves (Table 2). Independent humid heatwaves imposed the most harmful impact on human health, with DID estimates of 2.92% (95% CI, 1.17%, 4.66%), 1.73% (95% CI, 0.58%, 2.89%), and 0.38% (95% CI, −0.09%, 0.86%) during the first, the first two, and the third weeks. In comparison, LPI and MPI humid heatwaves possessed comparatively lower stresses, with hospitalization rate excess increase respectively 2.76% (95% CI, 1.07%, 4.45%) and 1.60% (95% CI, 0.08%, 3.12%) during the first week and then gradually diminished with time.

Concerning the responses of subcategories of IHD hospitalizations, chronic IHD associated with recurrent conditions demonstrated the most positive change stressed by humid heatwaves over the observation time (Period 2 independent 2.25%, [95% CI, 0.06%, 4.44%]; MPI 1.10%, [95% CI, 0.30%, 1.90%]; Fig. 2B). In comparison, angina was almost on par with the chronic IHD in the first week (independent 2.21% [95% CI, 1.08%, 3.34%]; MPI 1.32% [95% CI, 0.60%, 2.04%]), but exhibited a notable decline in the overall impact during the first 2 weeks (independent 1.57% [95% CI, 1.12%, 2.03%]; LPI 0.92% [95% CI, 0.43%, 1.41%]; MPI 0.41% [95% CI, 0.11%, 0.71%]). In contrast, MI and other IHD hospitalizations had no statistically significant evidence (95% CI) following the onset of humid heatwaves.

During the 3-day warning period preceding the onset of humid heatwaves, the overall IHD hospitalization rate increased by 0.90% (95% CI, 0.76%, 1.04%) in the affected counties, while DID estimates attributed a 1.10% (95% CI, 0.85%, 1.35%) overall increase to humid heatwaves (Additional file 1 results: Table 2). Though shifts were less significant, these observations highlighted the necessity of considering the warning period in the PSM-DID framework.

## Gender and age stratification analyses

IHD hospitalizations showed strong disparities in gender and age factors under humid heatwaves. Particularly for the total IHD hospitalization cases, the rate increase attributed to the independent humid heatwaves lasted for 2 weeks for men (2.48% [95% CI, 0.80%, 4.16%]), whereas the adverse impact was only remarkable in the first week for women (2.15% [95% CI, 0.22%, 4.08%]) (Fig. 3A). Regarding age groups, middle-aged to older populations experienced a higher risk of IHD hospitalizations within 2 weeks of exposure to the independent humid heatwaves (middle age 1.61% [95% CI, 0.04%, 3.18%]; the elderly 3.29% [95% CI, 0.39%, 6.19%]), while no significant changes were observed

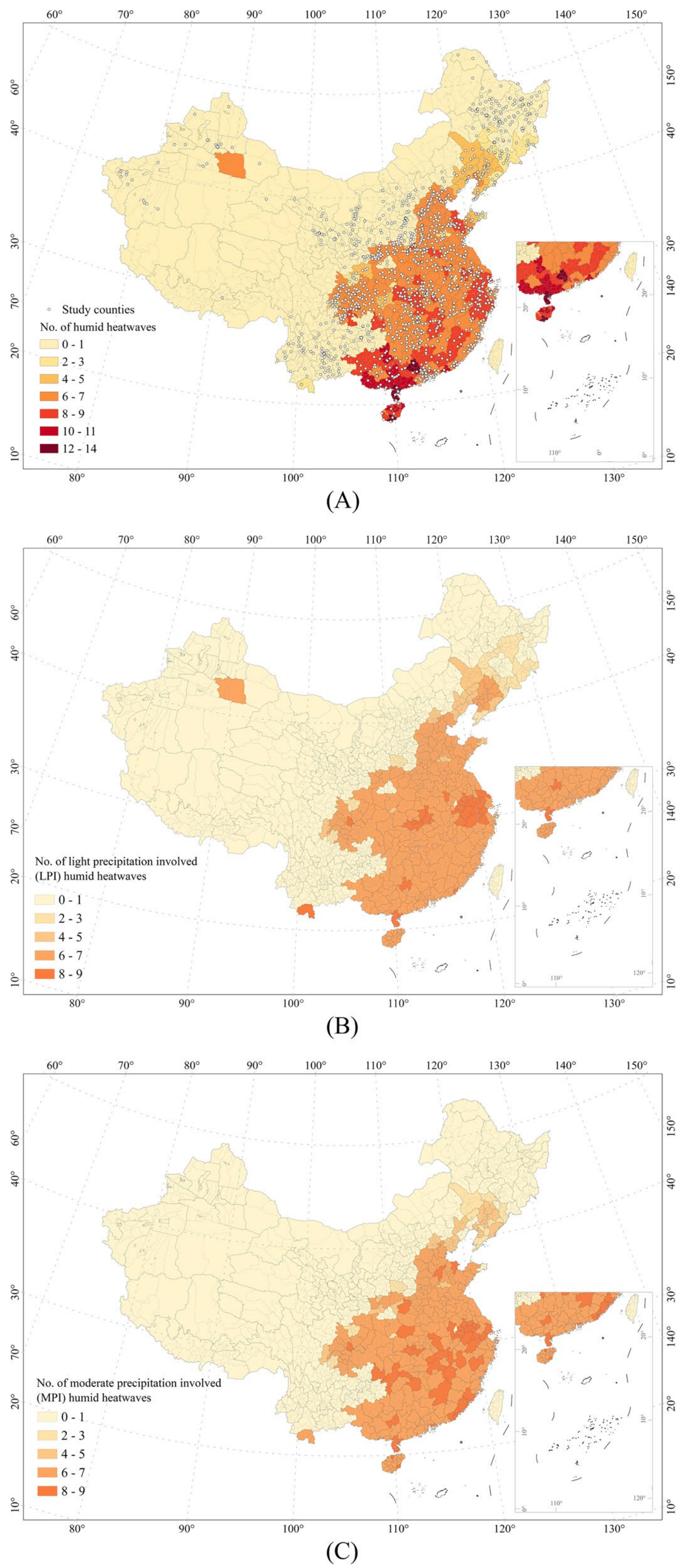


**Fig. 1** Distributions of humid heatwaves in CMC Hospital Network from 2016 to 2022. **A** Independent humid heatwave. **B** LPI humid heatwave. **C** MPI humid heatwave

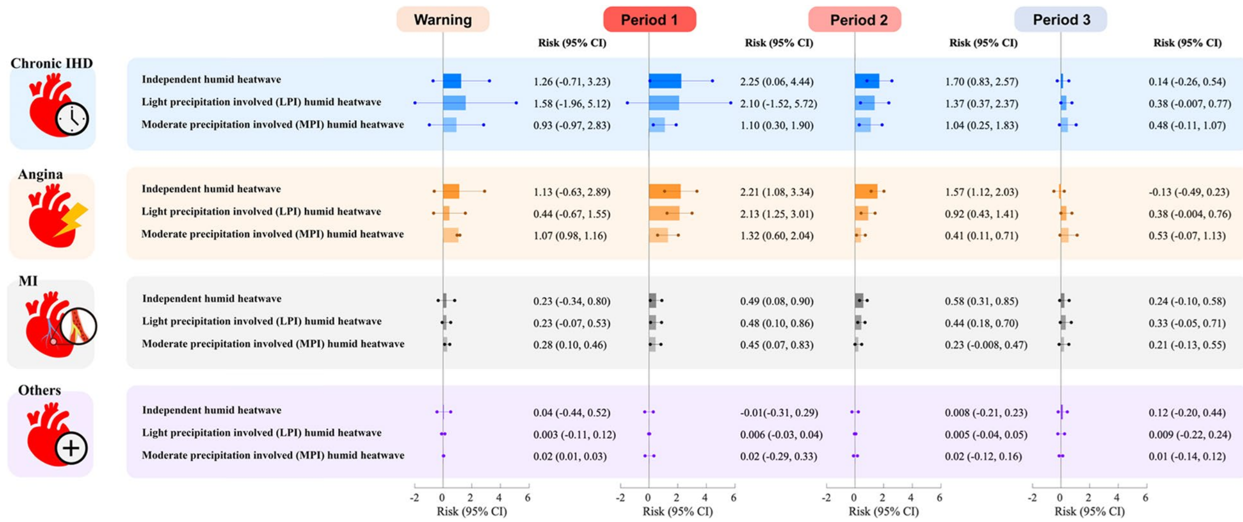


**Fig. 2** Association between short-term exposure to humid heatwaves by sub-categories of IHD in different window periods. LPI and MPI humid heatwave respectively refers to the compound humid heatwave that shower/light precipitation and moderate precipitation is involved within the 7-day window. Period 1 indicates days 0–6 (post-period [from event start day 0]) vs days −4 to −10 (comparison pre-period); Period 2 indicates days 0–13 (post-period [from event start day 0]) vs days −4 to −17 (comparison pre-period); Period 3 indicates days 14–20 (post-period [from event start day 0]) vs days −18 to −24 (comparison pre-period); Warning indicates days −3 to 0 (warning-period [from event start day 0]) vs days −4 to −6 (comparison pre-period). The primary predictors were an indicator of whether a county was affected or control, time (pre- versus post-disaster), and the interaction between the two. All models included the disaster-specific match groups as fixed effects and were adjusted for county population, holiday, and day of week. IHD—ischemic heart disease; MI—myocardial infarction; CI—confidence interval; LPI—light precipitation involved; MPI—moderate precipitation involved

in the younger population (Fig. 3B). The IHD hospitalizations for both age- and gender-specific population groups decreased with observation time, with no statistical meaningful impact (95% CI) captured in the third week by the PSM-DID analysis.

### Humid heatwave-induced hospitalization related economic burden

From 2016 to 2022, the yearly averaged potential economic burden of IHD hospitalizations attributable to independent humid heatwaves, LPI, and MPI humid heatwaves reached 154 million US dollar (USD) (95% CI 20, 249 million), 75 million USD (95% CI 14, 136 million), and 81 million USD (95% CI 31, 131 million), respectively (Fig. 4A–C). The eastern and southeastern coastal regions, as well as a few large metropolitan clusters in the central and northern plain areas, were afforded the pivotal economic burden triggered by humid heatwaves. The trend for each event type showed slight fluctuations over the 7 years (Fig. 4D). Moreover, the middle-aged and the elderly groups suffered from the majority of the adverse impacts induced by humid heatwaves, collectively constituting around 90% IHD hospitalization-related economic burden, while the burden on the younger demographic was relatively minimal. Additionally, the humid heatwaves induced burdens on males (66.06%) were also comparatively higher than females (33.94%) (Fig. 5). Moreover, parallel trends for independent and precipitation-involved humid heatwaves were examined before implementing the DID analysis (Fig. 6).

### Sensitivity analyses

Sensitivity analyses employing the 95th$^{th}$ percentile distribution of the comprehensive meteorological index as threshold to define the humid heatwave events (Additional file 1 results: Table 3) produced slightly larger DID estimates than our primary analysis: IHD hospitalization had DID estimates of 2.82% (95% CI, 0.83%, 4.81%), 2.74% (95% CI, 1.03%, 4.45%), and 1.57% (95% CI, 0.10%, 3.04%) for the independent humid heatwave, LPI, and MPI humid heatwaves during the first week (period 1), respectively. These slightly increased magnitudes were attributed to the more extreme scenario in which the 95$^{th}$ was more server than the 90$^{th}$ humid heatwaves. Nevertheless, consistent trends of these IHD hospitalization rate changes were captured in the sequential observation windows. These results supported the robustness of both our humid heatwave identification approach and PSM-DID causal inferential framework.

## Discussion

We found a significant increase in total IHD hospitalizations in the first 2 weeks following the onset of an independent humid heatwave, while the risk of IHD gradually

**Table 2** Association between short-term exposure to humid heatwaves and the risk of IHD hospitalizations

| Period | All IHD cases | Affected counties, relative change (95% CI) | Diff-in-Diff (95% CI) (affected *RR*/control *RR*) |
|---|---|---|---|
| Independent humid heatwave (*N* = 3375) | | | |
| Warning | 73,976 | 0.79 (0.64, 0.94) | 1.28 (1.01, 1.55) |
| Period 1 | 169,106 | 2.53 (1.56, 3.51) | 2.92 (1.17, 4.66) |
| Period 2 | 337,179 | 1.57 (0.89, 2.25) | 1.73 (0.58, 2.89) |
| Period 3 | 163,921 | − 0.10 (− 1.14, 0.94) | 0.38 (− 0.09, 0.86) |
| LPI humid heatwave (*N* = 3328) | | | |
| Warning | 74,937 | 0.85 (− 0.62, 2.32) | 0.69 (− 1.11, 2.49) |
| Period 1 | 174,991 | 2.39 (1.29, 3.50) | 2.76 (1.07, 4.45) |
| Period 2 | 347,502 | 0.80 (0.06, 1.55) | 0.69 (− 0.61, 1.99) |
| Period 3 | 168,302 | − 1.23 (− 2.36, − 0.10) | 0.21 (− 1.03, 1.44) |
| MPI humid heatwave (*N* = 3203) | | | |
| Warning | 69,123 | 1.02 (0.58, 1.45) | 1.60 (− 0.98, 4.18) |
| Period 1 | 162,229 | 1.89 (0.86, 2.92) | 1.60 (0.08, 3.12) |
| Period 2 | 323,559 | 0.15 (− 0.55, 0.86) | 0.31 (− 0.73, 1.37) |
| Period 3 | 156,717 | 0.12 (− 0.94, 1.18) | 0.32 (− 1.01, 1.65) |

The relative changes (95% CI) in affected counties refer to the result given by the pre-post analysis, whereas the Diff-in-Diff (95%) corresponds to the estimates given by the PSM-DID framework. LPI and MPI humid heatwave, respectively, refer to the compound humid heatwave in which shower/light precipitation and moderate precipitation are involved within the 7-day window. Warning indicates days − 3 to 0 (warning-period [from event start day 0]) vs. days − 4 to − 6 (comparison pre-period); Period 1 indicates days 0–6 (post-period [from event start day 0]) vs. days − 4 to − 10 (comparison pre-period); Period 2 indicates days 0–13 (post-period [from event start day 0]) vs. days − 4 to − 17 (comparison pre-period); Period 3 indicates days 14–20 (post-period [from event start day 0]) vs. days − 24 to − 18 (comparison pre-period). The primary predictors were whether a county was affected by the events or not, time (pre- versus post-disaster), and the interaction between the two. All models included the disaster-specific match groups as fixed effects and were adjusted for county population, holiday, and day of the week. *IHD* ischemic heart disease; *CI* confidence interval; *Diff-in-Diff* difference-in-differences; *LPI* light precipitation involved; *MPI* moderate precipitation involved; *RR* relative risk

decreased when light-to-moderate precipitation occurred during the humid heatwave effective period. Collectively, the estimated average potential healthcare burdens related to IHD hospitalizations were approximately $154 million (95% CI $20, $249 million), $75 million (95% CI $14, $136 million), and $81 million (95% CI $31, $131 million) for independent humid heatwaves, LPI humid heatwaves, and MPI humid heatwaves, respectively.

Our work expands upon the existing evidence by systematically assessing how short-term exposure to humid heatwaves could elevate the IHD hospitalization risk. While previous studies revealed the association between heatwaves and overall mortality of cardiovascular disease, there remains insufficient statistical evidence regarding the impact of high temperature on cause-specific IHD hospitalizations [3, 56, 57]. Additionally, extensive studies simply defined heatwaves through a single temperature parameter with less attention paid to the intricate interplay of extreme temperature and high humidity in the broader meteorological context [58, 59]. This neglect extends to the often overlooked influence of precipitation during hot and humid days. As precipitations could remarkably reduce the ambient temperature (Additional file 1 results: Table 1), compared to independent humid heatwaves, precipitation involved LPI and MPI humid heatwaves had less influence on IHD hospitalizations, particularly among middle-aged and the elderly populations with chronic IHD and angina.

This study also emphasizes the urgent need to establish an effective early warning system and implement proactive adaptation strategies to address the escalating challenges posed by global warming, not restricted to China [60] but also other nations and/or regions grappling with prolonged hot and humid days such as those in southeast Asia [61], central and south America [62] and equatorial regions of Africa [1]. An early warning system is essential as it furnishes actionable information to the public, advising them to take measures (e.g., staying indoors or seeking cooler shelters), bolstering preparedness for heat stress, and ensuring prompt emergency responses [63]. However, only about half of the 193 WMO member countries have established multi-hazard early warning systems [64]. Significant gaps remain in weather observation networks, particularly in Africa, parts of Latin America, and Pacific and Caribbean island states. In Central America, countries have developed protocols that include vulnerable groups more comprehensively in preparedness efforts and have established National Emergency Committees and legal frameworks to support these warning systems [65]. These findings suggest policymakers should accelerate warning strategies in their climate change mitigation plans, especially in climate change scenarios.


**Fig. 3** Association between short-term exposure to humid heatwaves and the risk of IHD hospitalizations and its sub-categories by gender and age group. **A** IHD hospitalizations by sex (male vs female); **B** IHD hospitalizations by age (young-age, middle age vs old age). Independent humid heatwave indicates humid heatwave without the effect of any precipitation; LPI and MPI humid heatwave respectively indicates the compound humid heatwave that shower/light precipitation and moderate precipitation is involved within the 7-day window; Extreme precipitation indicates independent extreme precipitation without the humid heatwave. Warning indicates days −3 to 0 (warning-period [from event start day 0]) vs. days −4 to −6 (comparison pre-period); Period 1 indicates days 0–6 (post-period [from event start day 0]) vs. days −4 to −10 (comparison pre-period); Period 2 indicates days 0–13 (post-period [from event start day 0]) vs. days −4 to −17 (comparison pre-period); Period 3 indicates days 14–20 (post-period [from event start day 0]) vs. days −24 to −18 (comparison pre-period). IHD—ischemic heart disease; CI—confidence interval; LPI—light precipitation involved; MPI—moderate precipitation involved

Our study indicated the vulnerability and gender disparities in humid heatwave-related IHD hospitalizations. Notably, different sub-categories of IHD, particularly chronic IHD and angina, showed a significant association with humid heatwaves. This finding aligns with those reported by Liu et al. and Saucy et al. in a meta-analysis and a Swiss study [3, 66], which suggests an urgent need for awareness among individuals with chronic IHD of the potential for extreme weather to trigger disease recurrence. Additionally, understanding the mechanisms behind the observed decrease in plasma volume and increased concentration of red blood cells and other

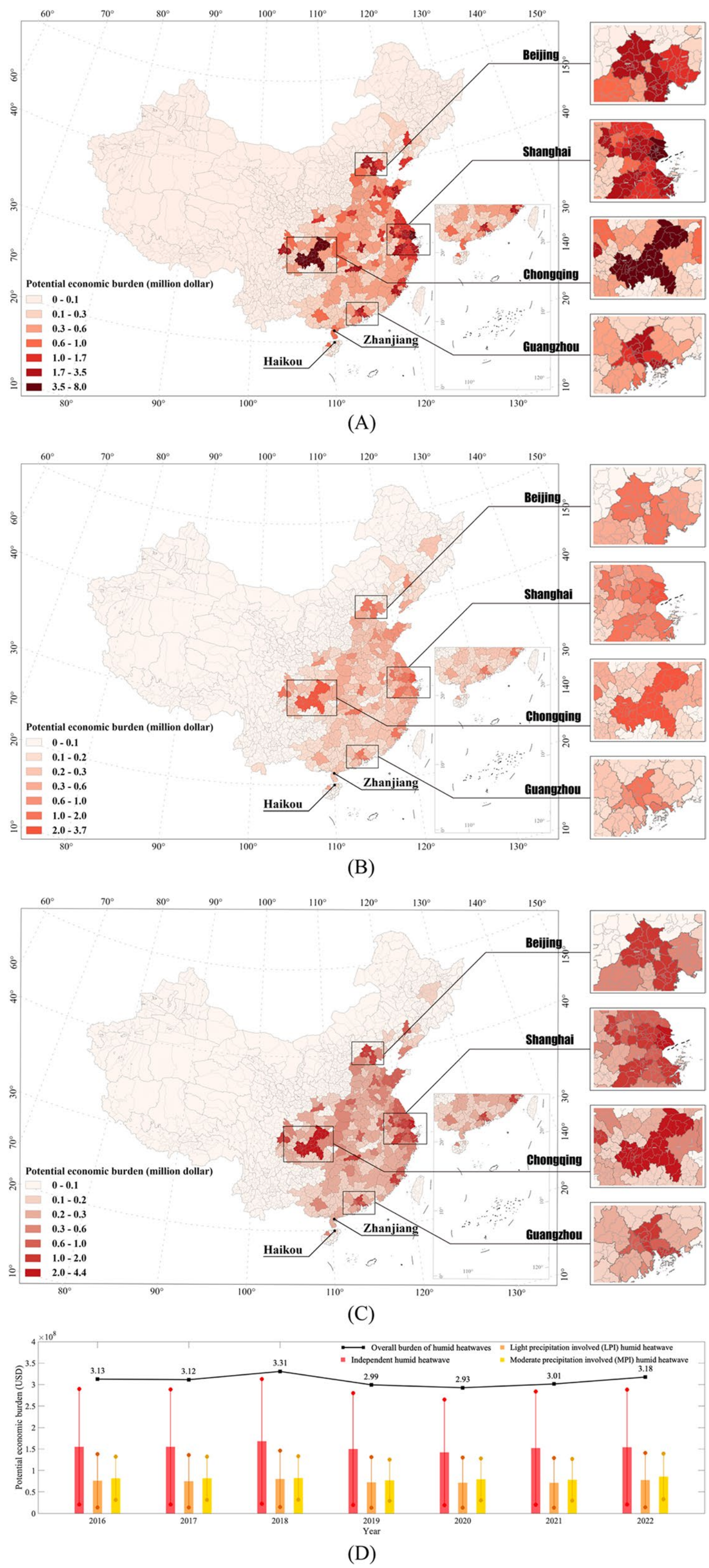


**Fig. 4** IHD hospitalization-related potential economic burden in CMC Hospital Network. **A** Independent humid heatwave. **B** LPI humid heatwave. **C** MPI humid heatwave. **D** Total economic burden by year

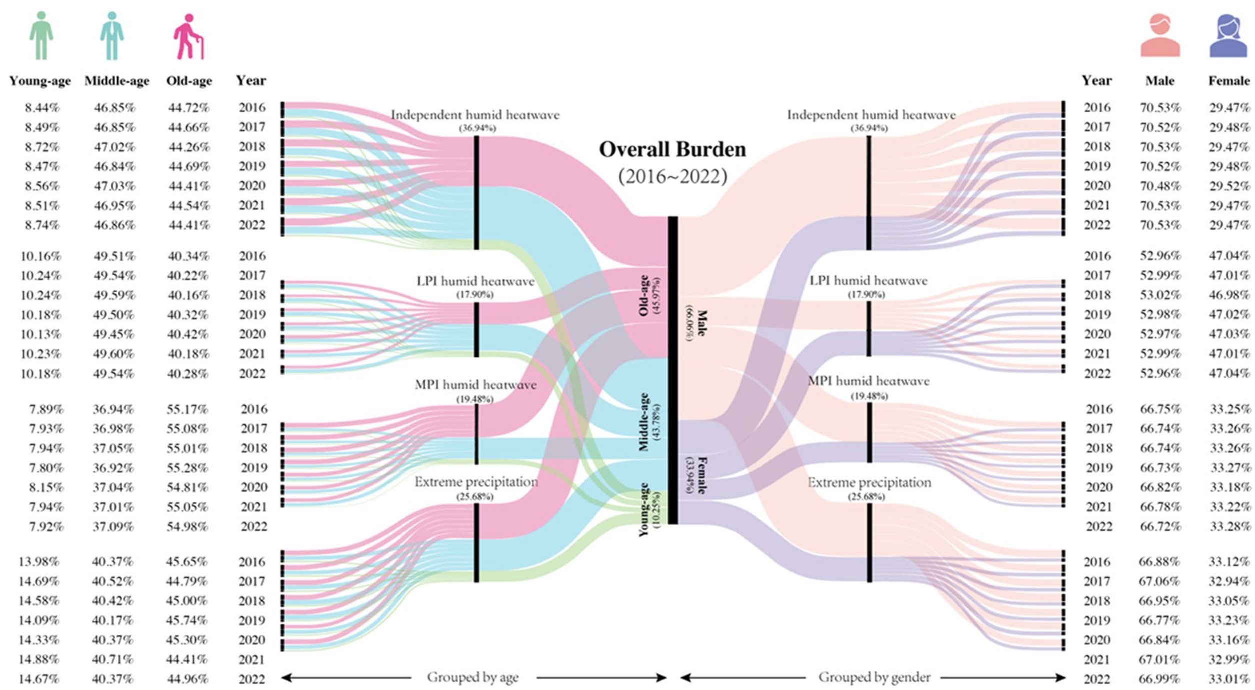


**Fig. 5** Percentages of overall potential IHD hospitalization economic burden due to the extreme weather disasters by gender and age group. LPI—light precipitation involved; MPI—moderate precipitation involved

blood constituents, which contribute to elevated blood viscosity and cholesterol concentration, thus potentially causing thromboembolism and heightened risk of ischemic heart disease in males, older population, and low-income groups, could be crucial [67]. Furthermore, heat-induced increases in heart rate and cardiac contractility could escalate myocardial oxygen consumption, potentially leading to fatal arrhythmias and angina [6].

This study separately examined the impacts of independent humid heatwaves and precipitation-involved compound humid heatwaves, offering a more precise estimation of the risk of IHD hospitalizations and addressing potential underestimations in previous research [5, 6, 68, 69]. Consecutive light-to-moderate precipitation events diminish the severity and duration of independent humid heatwaves, resulting in a relatively lower IHD risk with no significant risk increases after 1 week of the event onset in precipitation-involved humid heatwaves. Moreover, to highlight the adverse impacts difference of heat stress between humid heatwaves and conventional heatwaves (solely defined by temperature), we conducted supplementary analysis utilizing temperature thresholds only (Additional file 1 results: Table 4). Results show that for all subtypes of IHD diseases, independent humid heatwaves consistently exerted higher excess hospitalization risks than conventional heatwaves, with their peak hospitalization risks (i.e., Period 1) increased by 31.58%, 36.42%, and 6.5% for chronic IHD, angina, and MI diseases, respectively. However, the cooling effect of subsequent rainfall during MPI humid heatwaves led to a marked reduction in IHD hospitalizations, decreasing by 35.67%, 18.52%, and 2.17% for chronic IHD, angina, and MI, respectively in the first week. Our findings align with prior studies, though available evidence remains limited. Tang et al. conducted a single-city study demonstrating a significant correlation between extreme precipitation and ischemic stroke in China [70]. The analysis of two extreme compound events (humid heatwaves and extreme precipitation) was not conducted in this study due to the rarity of such events, but further research is necessary to better understand these potential compound interactions.

The estimated potential economic burden related to IHD hospitalizations demonstrated slight fluctuations from 2016 to 2022, with a noticeable concentration in the metropolis. This pattern suggests that the economic burden is influenced by both extreme weather events and varying socio-demographic and economic conditions. For instance, Beijing (39.90° N, 116.41° E), despite experiencing fewer humid heatwaves, exhibited a relatively high economic burden. In contrast, southernmost counties like Zhanjiang (21.27° N, 110.36° E) and Haikou (20.04° N, 110.21° E) showed lower economic burdens, attributed

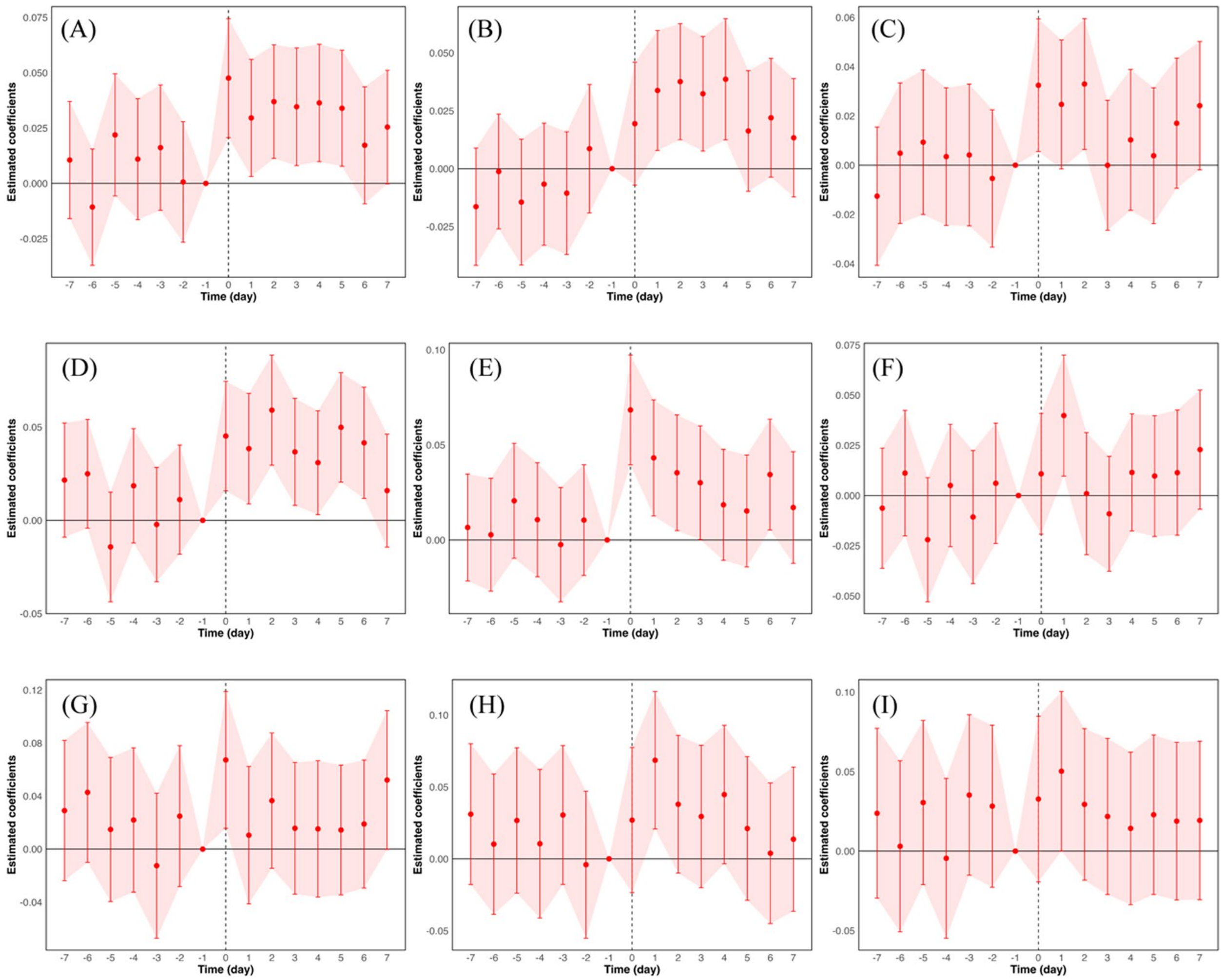

**Fig. 6** Parallel trend examination for subtypes of IHD under different types of humid heatwaves. Chronic IHD: **A** independent humid heatwaves; **B** light precipitation involved humid heatwaves; **C** moderate precipitation involved humid heatwaves; Angina: **D** independent humid heatwaves; **E** light precipitation involved humid heatwaves; **F** moderate precipitation involved humid heatwaves; MI: **G** independent humid heatwaves; **H** light precipitation involved humid heatwaves; **I** moderate precipitation involved humid heatwaves. Abbreviation: MI-myocardial infarction. Positive days refer to the post-period in observation window Period 1, whereas negative days are the corresponding pre-period. The warning period of 3 days are removed. Day 0 refers to the onset of the humid heatwave. Day −1 is for reference. Results showed that before humid heatwaves, there was no significant pre-hazard difference between humid heatwave affected and non-exposed control counties, while after hazard onsets, significant temporal trend divergence was observed for cause-specific hospitalization rates as the estimated coefficients with 95% confidence intervals completely above zero for a certain duration of days. Our parallel trends examination confirmed the validity of causal inference designed by the PSM-DID analytical framework

to smaller populations and lower socio-economic levels, despite more frequent humid heatwaves. Shanghai (31.14° N, 121.29° E), Chongqing (29.34° N, 106.33° E), and Guangzhou (23.06° N, 113.15° E) not only experienced more humid heatwaves, but also revealed higher economic burdens. Additionally, prior studies have highlighted direct costs of around USD 5000 per IHD hospitalization episode, with total IHD expenditures reaching USD 79.8 billion, marking it the largest cardiovascular-related expenditure in the USA [55, 71]. In comparison, our estimates suggest that the economic impact of IHD hospitalizations due to humid heatwaves is approximately USD 310 million, accounting for 1.86% of the total IHD-related economic burden of USD 16.7 billion in China [51]. Our findings align with previous research indicating a more significant economic impact on males and middle-to-older. This discrepancy can be explained by the increased vulnerability of these groups to extreme weather events [72] and the higher likelihood of males participating in outdoor work or recreational activities.

To our knowledge, this is the first national study to use pre-post and PSM-DID analyses to evaluate the impact of humid heatwaves (including both independent and precipitation-involved types) on public health concerning changes in IHD hospitalization rates. Compared to the extensively used Distributed Lag Non-Linear Models (DLNM), the PSM-DID framework has essential advantages as it offers stronger causal inference capabilities through its dual methodological framework. Our rigorous PSM matching strictly balanced the observable county characteristics between affected and control counties, while the difference-in-differences strategy accounts for the time-invariant confounding factors and common temporal trends. Besides, PSM-DID has simple configurations, with all the variables obtained from statistical attributes or measured data. While DLNM in principle can capture the health impacts brought by humid heatwaves, it requires additional artificial input model parameters such as the degree of freedom and spline functions, which to some extent enhance the complexity but do not offer additional insights for the health outcomes. Moreover, while DLNM can capture non-linear relationships and temporal dependencies after adjusting for the potential confounding factors, it primarily establishes associations rather than causal effects. This DLNM limitation persists due to potential unmeasured confounders and the inherent nature of time-series analyses. Given the increasing prevalence of extreme weather event-related IHD hospitalizations, the considerable IHD healthcare burden, and the substantial societal impacts, local governments should establish early warning systems to alert the public, disseminate relevant weather information, plant more trees to increase precipitation, formulate risk reduction strategies, and ensure continuity of healthcare services following such events. Our findings offer valuable insights for China and other nations in tailoring public health policies that enhance healthcare providers' ability to respond effectively.

### Study limitations

This study has some limitations. First, the potential for migration or spillover [73] effects in control counties cannot be dismissed despite adjusting for socioeconomic, geographic, and demographic factors. Besides, the difficulty in obtaining age-specific IHD incidence rates necessitated using all-age group data to estimate the economic burden. Finally, limited EPI humid heatwave events make analyzing this compound event's effects on IHD hospitalization risks challenging.

## Conclusions

Populations exposed to humid heatwaves experienced increased IHD hospitalizations, with an annual economic burden up to 310 million USD. Males and elderly individuals afforded most of the burden. Chronic IHD and Angina are the sensitive subcategories, while myocardial infarction and the others are less pronounced. As climate-related extreme weather events become more intense, implementing proactive adaptation strategies and maintaining the functions of the healthcare system following these extreme events are crucial to reduce their adverse impacts on public health.

Supplementary information.

### Abbreviations

| | |
|---|---|
| CIs | Confidence intervals |
| CMC | Chinese Multiple-County |
| CVD | Cardiovascular disease |
| DALYs | Disability-adjusted life years |
| DLNM | Distributed lag non-linear model |
| EPI | Extreme precipitation involved |
| GRP | Gross regional product |
| ICD | International classification of diseases |
| IHD | Ischemic heart disease |
| ISD | Integrated Surface Database |
| LPI | Light precipitation involved |
| MI | Myocardial infarction |
| MPI | Moderate precipitation involved |
| NOAA | National Oceanic and Atmospheric Administration |
| PPP | Purchasing power parties |
| PSM-DID | Propensity score matching aided difference-in-differences |
| RR | Relative risk |
| SMD | Standardized mean differences |
| USD | US dollar |
| WMO | World Meteorological Organization |

## Supplementary Information

The online version contains supplementary material available at https://doi.org/10.1186/s12916-025-04133-8.

Additional File 1 Methods: Texts 1-3. Text 1-Derivation of comprehensive meteorological index. Text 2-Calculation of global and local Moran's I. Text 3-Propensity score matching aided difference-in-differencesframework. Additional File 1 Methods: Figures S1-S4. Figure S1-Magnitude of $I_T$ increases with $T_{max}$ and $\overline{T}$. Figure S2-Magnitude of $I_H$ with respect to $\overline{T}$ and $RH$. Figure S3-Magnitude of $I_P$ with respect to $P$. Figure S4-Magnitude of $I_E$ with respect to $\overline{E}$. Additional File 1 Methods: Tables S1-S4. Table S1 Summarized specific requirements, constraints and demonstrations in derivation. Table S2 Values of $I_T$ at specific daily maximum and averaged temperature. Table S3 Composite temperature-related humidity indices in previous literature. Table S4 Values of $I_H$ at specific relative humidity and averaged daily temperature. Additional File 1 Results: Figures 1-3. Figure 1 Standardized mean differences of covariates before and after PSM. Figure 2 Histograms of Propensity score distributions before and after PSM. Figure 3 Observation windows for DID analysis. Additional File 1 Results: Tables 1-4. Table 1 Relative changes in ambient temperature and relative humidity following humid heatwaves and light-to-moderate precipitations. Table 2 Association between short-term exposure to overall humid heatwaves and the risks of overall IHD hospitalizations. Table 3 Sensitivity analysis for association between short-term exposure to humid heatwaves and the risk of IHD hospitalizations. Table 4 Association between short-term exposure to conventional heatwavesby sub-categories of IHD in different window periods.

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**Authors' contributions**
TW, HXS, and ZYZ designed the study. TW, HXS analysed and interpreted the data. ZSL, HJF, TJM, FD, WH, MX, and HNY reviewed the clinical codes. HXS and TW conducted the statistical analyses and wrote the first draft of the manuscript. SB, MR, GL, MHR, and SZS critically revised the manuscript for important intellectual content and approved the final version. The corresponding author (ZYZ) attests that all listed authors meet authorship criteria and that no others meeting the criteria have been omitted.

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**Data availability**
No datasets were generated or analysed during the current study.

## Declarations

**Ethics approval and consent to participate**
The institutional review board at Peking University (YS2024116) approved this study with a waiver of participant consent.

**Consent for publication**
All authors have approved the manuscript for publication.

**Competing interests**
The authors declare no competing interests.

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