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Received: February 17, 2024; Accepted: September 27, 2024

The association between daily temperature extremes and human biomarkers: heterogeneous effects of occupation and season

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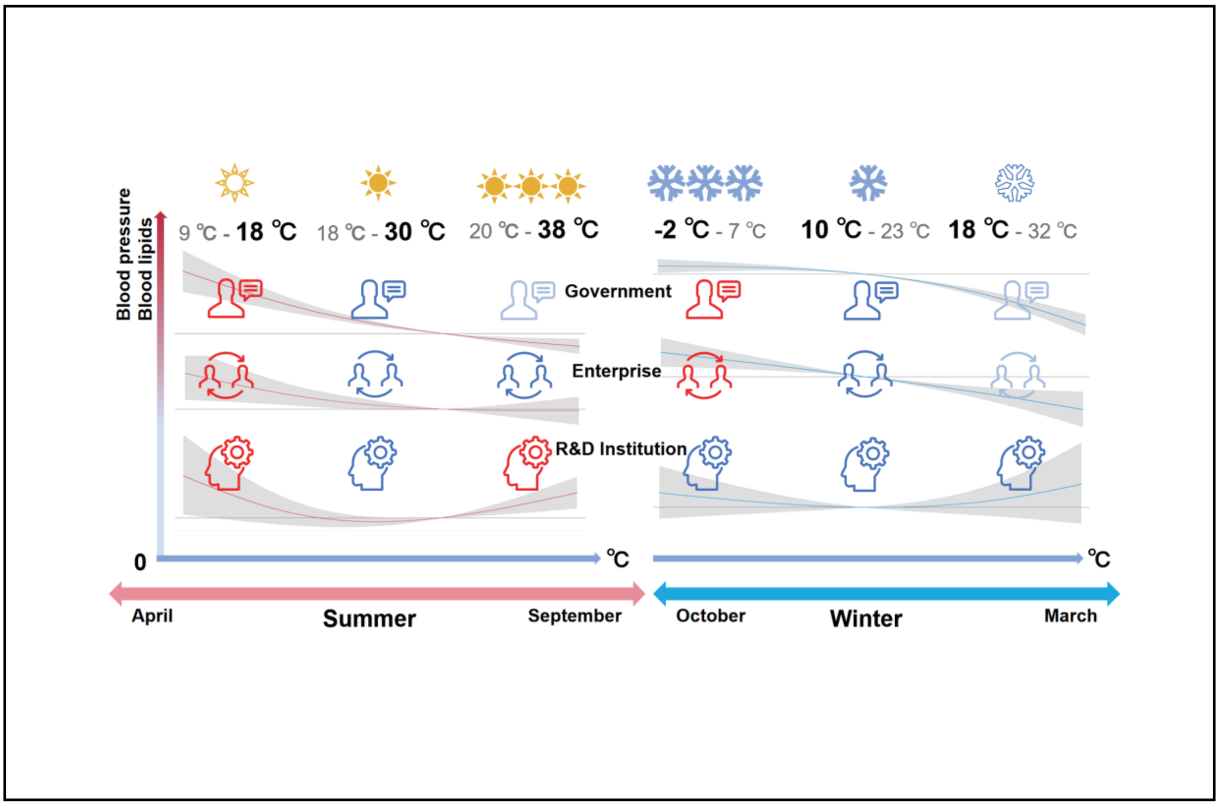
Graphical abstract



Blood pressure and lipid responses to extreme temperatures in winter and summer across different populations.

Public summary

- Government staff demonstrate the highest risk of exacerbated blood pressure and lipid levels under extreme cold across all seasons, while employees benefit from mild winters and researchers show minimal winter temperature sensitivity.
- Summer daily maximum and winter daily minimum temperatures, being more influential than daily averages, better predict individual susceptibility.
- Humans demonstrate greater adaptability during the winter-to-summer transition, whereas the summer-to-winter shift poses significantly higher health risks.

Citation: Zhao Y, Yang C M, Li Y N, et al. The association between daily temperature extremes and human biomarkers: heterogeneous effects of occupation and season. *JUSTC*, **2025**, 55(3): 0306. CSTR: 32290.14.JUSTC-2024-0019. DOI: 10.52396/JUSTC-2024-0019

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Cite This: *JUSTC*, **2025**, 55(3): 0306 (14pp)   Read Online   Supporting Information

Abstract: The impact of extreme temperatures on the health of individuals in different organizations remains uncertain. We employed stratified analyses to examine the impacts of summer (April–September) daily maximum temperatures and winter (October–March) daily minimum temperatures on blood pressure and lipid profiles across government staff, company employees, and researchers. We examined 209,477 physical examination records from a physical examination center in the First Affiliated Hospital of USTC from 2017 to 2021. Employing a segmented regression model within the framework of generalized linear regression (GLM), we examined the causal impact of extreme temperatures on health outcomes. Additionally, sensitivity analyses were conducted via distributed lag nonlinear models (DLNMs), with a focus on observing the long-term effects over a period of 21 days. Our findings indicate that government staff face increased health risks during extremely low temperatures, regardless of the season. Compared with participants experiencing median temperatures, government staff exposed to extremely low temperatures (below the 10th percentile, below 24 °C) in the summer presented maximum increases of 2.32 mmHg (95% CI: 1.542–3.098) in diastolic blood pressure and 6.481 mmHg (95% CI: 5.368–7.594) in systolic blood pressure. In winter, government staff exposed to temperatures below the 10th percentile (below 1 °C) demonstrated maximum increases of 0.278 mmol/L (95% CI: 0.210–0.346) in total cholesterol, 0.153 mmol/L (95% CI: 0.032–0.274) in triglycerides, and 0.077 mmol/L (95% CI: 0.192–0.134) in low-density lipoprotein. Conversely, warm winters benefit company employees, whereas researchers exhibit lower sensitivity to temperature changes in winter. The maximum temperatures in summer and minimum temperatures in winter had greater impacts on individuals. Small temperature fluctuations impact health more than large changes do. Notably, both the maximum and minimum temperatures were better predictors of health outcomes than the daily average temperature was. Blood pressure consistently displayed significant associations with temperature across all three groups, with extremely low temperatures increasing the risk and extremely high temperatures reducing it. However, the relationship between temperature and blood lipids is complex.

Keywords: extreme temperature; stress response; organizational members; temperature fluctuation; subtropical

CLC number: R195.4   **Document code:** A

1 Introduction

The increasing frequency of extreme climate events has led to attribution studies on environmental factors in public health[1]. Extreme temperatures, which are influenced by climate change, have become a significant risk factor for individual health[2]. A climate extreme (extreme weather or climate event) is defined as "the occurrence of a value of a weather or climate variable above (or below) a threshold value near the upper (or lower) end of the range of observed values of the variable[3]". Similarly, in climatological research, the air temperature is "extreme" when it reaches or is higher (lower) than an assumed threshold value[4]. However, temperature thresholds are context-specific and vary by geographic region, time period, latitude, climate characteristics, and season[5]. Therefore, employing relative thresholds[6], such as designating the temperature at the 90th percentile within a specific region and time period, is a recommended method for defining extreme temperatures.

Existing methods mainly determine extreme temperatures on the basis of daily average temperatures. In the field of atmospheric science, research has utilized relative thresholds of daily mean temperatures as criteria for assessing heatwaves[7]. In a study focused on Sweden, extreme cold was defined as the number of days colder than the 2nd percentile of the 26-day moving average of daily mean temperatures, whereas extreme heat was defined as the number of days hotter than the 98th percentile of the 2-day moving average of daily mean temperatures[8]. Similar studies have also estimated extreme temperatures on the basis of relative thresholds of daily mean temperatures[9,10].

However, the use of daily mean temperatures as a measure

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DOI: 10.52396/JUSTC-2024-0019
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of extreme temperatures may weaken the influence of the daily maximum (minimum) temperature because of the averaging algorithm. For example, during summer, the daily minimum temperature often occurs during the nonactive period from late evening to early morning[11], when the impact of the minimum temperature on human activities is minimal. This study aims to explore the impact of extreme temperatures on health by considering the maximum and minimum temperatures of the day. The difference between daily maximum temperatures is greater than that between daily average temperatures[12], making it more conducive to observing the impact of daily maximum temperatures on health. Additionally, weather forecasts typically report maximum and minimum temperatures, which directly influence people's perceptions of weather conditions. Heatwave warnings in summer and cold wave warnings in winter are often related to the maximum and minimum temperatures[13]. Therefore, it is necessary to consider the maximum and minimum temperatures of the day to avoid overlooking deviations caused by seasonal climatic characteristics. The maximum and minimum temperatures are more likely to attract people's attention and trigger preventive behaviors[14]. Additionally, both the maximum and minimum temperatures elicit physiological stress responses in the body[15,16], which can lead to worsened vascular conditions such as blood pressure and blood lipid levels[17]. By examining the daily maximum and minimum temperatures, we can assess health changes effectively following these stress responses. Moreover, if the daily maximum and minimum temperatures can induce stress responses, it is reasonable to assume that extreme average temperatures would also have a similar effect. Hence, in our sensitivity analysis, we also examined the traditional indicator of daily average temperature, and the conclusions remained unchanged.

The literature has paid little attention to temperature variations across seasons. In prior research, the seasonal impacts of temperature on absolute blood pressure levels have been documented[18]. There is growing evidence indicating seasonal fluctuations in blood lipid levels[19]. Seasonal differences are often overlooked in the clinical management of hyperlipidemia[20]. Ignoring seasonal variations when observing the effects of extreme temperatures on blood pressure and blood lipids can introduce biases. Assessing health risks linked to extreme temperatures throughout the year can aid in crafting more accurate health management strategies. Understanding seasonal impacts offers targeted guidance for preventing and treating cardiovascular diseases. This study aims to compare extreme temperatures during different seasons, indicating greater sensitivity to maximum temperatures in summer and greater susceptibility to minimum temperatures in winter. A similar study to this one differentiated between summer and winter in the definitions of heatwaves (HWs) and cold spells (CSs), but seasonal factors should already be considered in the definition of HWs and CSs[21]. In another study closely aligned with the present research, a combination of relative and absolute thresholds was employed, utilizing daily minimum temperatures in summer and daily maximum temperatures in winter as metrics for calculating extremely high and low temperatures, respectively[22]. These results indicate that both low and high temperatures increase the risk of mortality. The rise in heat-related mortality due to global warming is unlikely to be compensated for by decreases in cold-related mortality, highlighting the incomplete adaptation of the population to heat. Furthermore, this approach diverges from the methodology employed in this paper, and we subsequently demonstrate the superiority of our approach.

The location of this study is located in China's subtropical monsoon climate zone, which experiences four distinct seasons, with extreme temperatures observed in summer and winter. We divided the entire year into two periods: summer (April–September) and winter (October–March). Maximum temperatures occur during summer working hours[11], leading to adverse health effects such as increased abnormal newborns due to heat exposure and heatwaves[23], making them better predictors of disease occurrence. Existing study suggests that cold-related mortality risk is greater than heat-related risk in subtropical regions[24]. Therefore, using minimum temperatures in winter provides a better measure of the impact of extreme temperatures on health. We subsequently compared the minimum temperatures in summer and maximum temperatures in winter and found that the maximum temperatures in summer and the minimum temperatures in winter remained the best predictive indicators.

Numerous studies have shown that demographic characteristics, including sex[25], age[26], and education level[10], contribute to diverse health outcomes in extreme-temperature environments. However, we often overlook the influence of an individual's organization on their microlevel health. An individual's health is influenced not only by their own behaviors but also by external factors from societal entities such as workplaces and organizations[27]. The type of various occupation (government staff, corporate employees, and researchers) dictates the duration of exposure to extreme temperatures, and the working environment during such conditions is also a critical factor in cardiovascular disease. Therefore, examining the impact of extreme temperatures on individual health from a meso-level perspective while considering different organizational characteristics is essential. Varying job tasks within organizations result in individuals experiencing different levels of exposure. The extent of exposure directly affects the physiological stress that individuals face under extreme temperature conditions. For example, the use of cooling devices such as air conditioning effectively mitigates physiological strain during heatwaves[28]. Additionally, towns with a higher prevalence of winter heating systems present a weaker association between mortality rates and lower temperatures[29]. Furthermore, diverse groups perceive risk differently, and changes in adaptive behaviors can be attributed to increased exposure levels and individual risk perceptions[30]. Awareness of heat warnings and risk perception also contribute to the differential vulnerability associated with high temperatures[31]. Government staff, employees, and researchers demonstrate varying degrees of susceptibility to heat-related effects. Importantly, the impact of heat exposure on health varies between and within populations, as individual factors cannot be measured by arbitrary thresholds or cutoff values[32]. Moreover, tolerance and sensitivity to low temperatures are influenced by economic and social conditions and climate characteristics among different populations[33].

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Previous research on the health effects of extreme temperatures has focused predominantly on topics such as mortality rates[34] and adverse pregnancy outcomes[35]. This study employs medical examination data to investigate nuanced health indicators, such as blood pressure and lipid responses, which may not be readily apparent but are crucial for accurately assessing human capital losses and enabling targeted interventions.

Regions with prominent seasonal temperature variations often exhibit stronger short-term correlations between daily temperatures and mortality rates[36]. The distinctive seasonal patterns in our city prompted us to examine the relationship between temperature fluctuations and health. Temperature variability (TV) is measured primarily by two indicators: intraday TV, which represents the temperature range between day and night, and interday TV, which quantifies temperature changes between consecutive days[37]. Previous investigations on temperature fluctuations typically control for average temperature[38], as the mean temperature level might affect the effects of temperature variability on health[39]. However, our findings reveal that the highest summer temperatures and lowest winter temperatures demonstrate superior predictive capacity compared with the mean daily temperatures. By observing changes in adjacent maximum or minimum temperatures during summer or winter, we can capture not only the synergistic effect between fluctuations and high temperatures[40] but also the modifying impact of winter low-temperature exposure on temperature variability. Consequently, this study focuses primarily on the influence of interday temperature fluctuations on the health of different population groups.

2 Methods and data

We collected data from a physical examination center in the First Affiliated Hospital of USTC from September 2017 to September 2021, totaling 209,477 records. These records were matched with the daily maximum and minimum temperatures of the city. The dataset includes information on examination dates, participant gender, age, various physical indicator levels, and occupation. Among the participants, government staff (including government and public sector employees) accounted for 124,381 individuals (59.4%), company employees accounted for 66,690 individuals (31.8%), and research personnel accounted for 18,406 individuals (8.8%). Tables 1 and 2 report the descriptive results of the samples. This study was approved by the Ethics Committee of the First Affiliated Hospital of USTC (2024-RE-496). Given the retrospective design and de-identification of data, this study was exempt from informed consent.

Table 1. Descriptive results of the physical examination data.

Group	Reference range	Mean	S.D.	Min	Max	*N*
Government (Female: 41%)						
DP(mmHg)	60–89	76.04	11.64	37	144	123,951
SP(mmHg)	90–140	124.21	17.49	71	233	123,951
TC(mmol/L)	2.8–5.5	4.67	0.87	1.5	21.2	112,619
TG(mmol/L)	0.45–1.69	1.57	1.37	0.19	75.2	112,619
LDL(mmol/L)	1.7–3.12	2.72	0.77	0	21.85	112,619
Age(years)	>0	44.76	13.31	19	96	124,381
AQI(%)	0–500	64.64	32.65	11	256	124,381
Enterprise (Female: 40%)						
DP(mmHg)	60–89	75.64	11.56	41	151	66,487
SP(mmHg)	90–140	122.66	16.40	70	220	66,487
TC(mmol/L)	2.8–5.5	4.64	0.84	1.88	13.63	47,601
TG(mmol/L)	0.45–1.69	1.50	1.38	0.14	50.7	47,601
LDL(mmol/L)	1.7–3.12	2.70	0.75	0	8.77	47,601
Age(years)	>0	38.58	10.14	18	92	66,690
AQI(%)	0–500	72.09	36.63	11	256	66,690
R&D institution (Female: 41%)						
DP(mmHg)	60–89	76.15	11.68	37	148	18,345
SP(mmHg)	90–140	124.73	18.10	72	245	18,345
TC(mmol/L)	2.8–5.5	4.68	0.86	2.1	12.9	17,713
TG(mmol/L)	0.45–1.69	1.51	1.20	0.23	41	17,713
LDL(mmol/L)	1.7–3.12	2.75	0.77	0	8.1	17,713
Age(years)	>0	45.72	13.33	21	96	18,406
AQI(%)	0–500	60.72	24.94	11	271	18,406

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Table 2. Distribution of samples within each bin.

Group	The 1st bin	The 2nd bin	The 3rd bin	The 4th bin	The 5th bin	The 6th bin	The 7th bin	The 8th bin	The 9th bin
Government									
Summer	807	1,355	4,002	11,154	15,207	18,368	19,193	7,019	–
Winter	1,620	1,943	8,079	7,932	8,706	7,167	5,340	5,260	1,229
Enterprise									
Summer	911	931	3,182	6,065	7,334	6,733	4,887	809	–
Winter	702	1,844	5,113	6,561	5,610	8,041	5,613	1,963	391
R&D institution									
Summer	92	436	883	4,270	2,658	3,326	1,385	239	–
Winter	148	86	181	647	922	874	1,047	946	266

Blood pressure is measured noninvasively outside the body to measure diastolic (DP) and systolic (SP) pressures, whereas blood lipids are analyzed through blood tests to assess total cholesterol (TC), triglyceride (TG), and low-density lipoprotein (LDL) levels. Fig. S1 (in Supporting information) illustrates the process of case selection. The temperature data, including daily maximum, minimum, and mean temperatures, were sourced from the China Meteorological Administration and included measurements from all the meteorological stations in the city.

Owing to limitations in our data, we are unable to directly observe the continuous effects of temperature on individual blood pressure and lipid levels. Consequently, our study relies on cross-sectional observations of individuals. Through the analysis of large sample sizes at various time points, we indirectly evaluated the impact of temperature on individual blood pressure and lipids.

To assess the causal effects of daily maximum temperatures (and daily minimum temperatures) on different physiological indicators, we employ a parameter estimation strategy utilizing a generalized linear model (GLM) with a Gaussian distribution. Small sample sizes (for each day) may affect the validity of the estimates. However, the segmented regression model bins temperatures to ensure sufficient observational samples within each bin, thus mitigating estimation bias caused by missing data. The model is specified as follows:

$$
\begin{aligned}
Health_{id} = \sum_{j=1}^{T} \beta_j BinTemp_{jid} + \gamma_1 Age_i + \\
\gamma_2 Gen_i + \gamma_3 AQI_d + \mu_{\text{weat}} + \tau_{\text{year}} + \varepsilon_{id}, \qquad (1)
\end{aligned}
$$

where $Health_{id}$ represents the levels of various physiological indicators, such as DP, SP, TC, TG, and LDL, for individual i on day d. The variable $BinTemp_{jid}$ represents the classification of participant i on the basis of whether the maximum or minimum temperature encountered on day d of the health examination falls within interval j. A value of 1 is assigned if the temperature falls within the interval; otherwise, it is 0. Each bin has a width of 3 °C, with the median level as the midpoint. In our study, the first three bins collectively account for approximately 10% of the temperature distribution during summer or winter, whereas the last two bins encompass the remaining 10%. Thus, we define the first three bins as extremely low temperatures and the last two bins as extremely high temperatures. In many climates, the 10th and 90th percentiles of annual temperatures closely approximate the medians of winter and summer temperatures, respectively[41]. Since this study examines temperature independently during the summer and winter periods, the top and bottom 10% of the temperatures in each period can appropriately represent the extreme temperature conditions. To address collinearity concerns, we select the intervals containing the medians of the highest summer temperature and lowest winter temperature as the reference groups. The coefficient of interest, represented by β_j, elucidates the fluctuations in health outcomes among participants undergoing physical examinations on a specific day in response to temperature exposure relative to those in the reference group. Age_i and Gen_i represent the age and sex of the individuals, respectively. AQI_d is used to mitigate the influence of daily air quality on the outcome, and we also control for fixed effects of weather conditions μ_{weat} and years τ_{year}. Weather conditions are categorized into 17 types: blizzards, heavy snow, moderate snow, light snow, sleet, heavy rainstorm, rainstorm, heavy rain, moderate rain, light rain, showers, thunderstorms, sandstorms, fog, cloudy, and clear. ε_{id} denotes the random error term, and robust standard errors are utilized.

3 Results

The distribution of temperature exposure varies among different organizations in our sample, as illustrated in Fig. S2. Using the median values of 30 °C for the summer maximum temperatures and 5 °C for the winter minimum temperatures from the entire sample as reference points may introduce significant estimation bias due to these variations. Consequently, our estimates in the GLM are based on the median temperature distributions within each organization. Specifically, government staff have median values of 31 °C for the summer maximum temperature and 5 °C for the winter minimum temperature, whereas private sector employees have median values of 28 °C for the summer maximum temperature and 6°C for the winter minimum temperature. Furthermore, researchers have reported median values of 29 °C for the summer maximum temperature and 7 °C for the winter minimum temperature.

Importantly, weather, as an exogenous factor, should not be adjusted on the basis of the health condition of individuals not observed at the corresponding temperature. For sensitivity

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analyses within the distributed lag nonlinear model (DLNM) framework, we utilized the median summer maximum temperature of 30 °C and the median winter minimum temperature of 5 °C from the entire dataset as reference temperatures. This approach aimed to establish a more objective nonlinear relationship between extreme temperatures and health outcomes.

Before analyzing the blood pressure and lipid responses to extreme temperatures for each organizational group, we first observed the full sample. Table S1 (in Supporting information) shows the response of the full sample to extreme temperatures in summer and winter. Blood pressure is strongly consistent between summer and winter: extremely low temperatures increase the risk of high blood pressure, whereas extremely high temperatures reduce the risk. However, lipid levels exhibit more complex patterns.

The regression results in Tables 3 and 4 show that extremely low temperatures in summer increase the risk of worsened blood pressure and negatively impact TC levels. Relative to participants experiencing the median summer temperature, government staff exposed to the lowest three temperature bins (approximately below the 10th percentile, below 24 °C) demonstrated maximum increases of 2.32 (95% CI: 1.542–3.098) and 6.481 (95% CI: 5.368–7.594) mmHg in the DP and SP, respectively. Similarly, corporate personnel are projected to experience maximum increases of 1.957 (95% CI: 1.212–2.702) and 5.695 (95% CI: 4.619–6.771) mmHg in DP and SP, respectively, whereas researchers are estimated to experience corresponding increases of 3.433 (95% CI: 1.287–5.579) and 7.061 (95% CI: 3.966–10.156) mmHg, respectively. Government staff subjected to extremely low temperatures are anticipated to demonstrate a maximum increase of 0.14 (95% CI: 0.073–0.207) mmol/L in TC. Similarly, corporate personnel are projected to experience a maximum increase of 0.085 (95% CI: 0.009–0.162) mmol/L, whereas researchers are estimated to experience an increase of 0.34 (95% CI: 0.13–0.55) mmol/L.

There is variation in the effects on TG and LDL across different organizations. TG levels tend to increase by 0.183 (95% CI: 0.052–0.314) mmol/L for government staff during extremely low temperatures, whereas researchers experience a decrease of 0.302 (95% CI: 0.053–0.551) mmol/L during extremely high temperatures. LDL decreases by 0.096 (95% CI: −0.009–0.200) mmol/L in researchers during extremely high temperatures but increases by 0.053 (95% CI: −0.002–0.108) mmol/L in private sector employees. In winter, researchers generally show less sensitivity to temperature, except for a decreasing trend in the SP during extremely high temperatures. Extreme low temperatures still increase the risk of elevated blood pressure, whereas TC and LDL levels tend to decrease in private sector employees at extremely low temperatures.

4 Sensitivity analysis

4.1 Results of the DLNM

The binned regression model mentioned above captures the overall nonlinear relationship by performing linear regression

Table 3. Summer-specific associations between biomarkers and temperature extremes across three population groups.

	(1) DP	(2) SP	(3) TC	(4) TG	(5) LDL
Government staff					
[13 °C, 18 °C)	2.320***	6.481***	0.140***	0.183***	−0.0274
	(0.397)	(0.568)	(0.0344)	(0.0667)	(0.0294)
[18 °C, 21 °C)	1.718***	4.418***	0.0819***	−0.0378	0.0345
	(0.312)	(0.434)	(0.0247)	(0.0314)	(0.0224)
[21 °C, 24 °C)	1.620***	3.188***	0.0381**	0.0761**	0.000430
	(0.193)	(0.280)	(0.0164)	(0.0299)	(0.0142)
[24 °C, 27 °C)	0.936***	1.587***	0.0109	−0.00320	0.0117
	(0.137)	(0.198)	(0.0112)	(0.0167)	(0.0101)
[27 °C, 30 °C)	0.511***	0.583***	0.0105	0.00338	0.0118
	(0.119)	(0.173)	(0.00985)	(0.0144)	(0.00876)
[30 °C, 33 °C) Reference group	–	–	–	–	–
[33 °C, 36 °C)	−0.464***	−0.707***	−0.0102	0.0260*	0.0102
	(0.115)	(0.165)	(0.00931)	(0.0140)	(0.00839)
[36 °C, 40 °C)	−0.969***	−1.762***	−0.0203*	0.0878***	−0.000167
	(0.158)	(0.223)	(0.0123)	(0.0200)	(0.0111)
Control	Y	Y	Y	Y	Y
Weather fixed effects	Y	Y	Y	Y	Y
Year fixed effects	Y	Y	Y	Y	Y
N	76,930	76,930	73,359	73,359	73,359

(To be continued on the next page)

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(Continued)

	(1) DP	(2) SP	(3) TC	(4) TG	(5) LDL
Employees					
[12 °C, 18 °C)	1.957***	5.695***	0.0855**	0.0830	−0.0585*
	(0.380)	(0.549)	(0.0389)	(0.0887)	(0.0334)
[18 °C, 21 °C)	2.244***	4.305***	0.0376	−0.0738	0.0257
	(0.399)	(0.553)	(0.0387)	(0.0518)	(0.0360)
[21 °C, 24 °C)	1.370***	2.483***	0.0360*	0.0266	−0.00383
	(0.232)	(0.332)	(0.0210)	(0.0320)	(0.0188)
[24 °C, 27 °C)	0.495**	0.721***	0.0132	0.0193	0.000716
	(0.193)	(0.272)	(0.0166)	(0.0248)	(0.0150)
[27 °C, 30 °C) Reference group	–	–	–	–	–
[30 °C, 33 °C)	−0.710***	−1.008***	0.00124	0.00751	0.00481
	(0.185)	(0.259)	(0.0154)	(0.0260)	(0.0138)
[33 °C, 36 °C)	−0.854***	−1.006***	−0.0408**	0.0264	−0.00771
	(0.200)	(0.285)	(0.0163)	(0.0252)	(0.0148)
[36 °C, 40 °C)	−0.317	−0.595	0.0311	0.124**	0.0532*
	(0.398)	(0.554)	(0.0309)	(0.0519)	(0.0279)
Control	Y	Y	Y	Y	Y
Weather fixed effects	Y	Y	Y	Y	Y
Year fixed effects	Y	Y	Y	Y	Y
N	30,783	30,783	24,697	24,697	24,697
Researchers					
[12 °C, 19 °C)	3.433***	7.061***	0.340***	0.375	0.0788
	(1.095)	(1.579)	(0.107)	(0.261)	(0.0939)
[19 °C, 22 °C)	1.440***	2.090***	0.103**	0.0106	0.0401
	(0.544)	(0.784)	(0.0450)	(0.0500)	(0.0416)
[22 °C, 25 °C)	0.778*	1.380**	0.0423	0.00105	0.0134
	(0.440)	(0.623)	(0.0349)	(0.0374)	(0.0316)
[25 °C, 28 °C)	0.871***	1.349***	0.0172	0.00212	−0.0125
	(0.270)	(0.398)	(0.0209)	(0.0266)	(0.0191)
[28 °C, 31 °C) Reference group	–	–	–	–	–
[31 °C, 34 °C)	−0.270	−0.248	−0.00112	0.0253	−0.0220
	(0.284)	(0.413)	(0.0223)	(0.0274)	(0.0204)
[34 °C, 37 °C)	−0.154	−0.517	−0.0413	0.119***	−0.0654**
	(0.370)	(0.534)	(0.0293)	(0.0406)	(0.0263)
[37 °C, 40 °C)	0.0941	−0.654	−0.0944	0.302**	−0.0956*
	(0.669)	(0.973)	(0.0596)	(0.127)	(0.0535)
Control	Y	Y	Y	Y	Y
Weather fixed effects	Y	Y	Y	Y	Y
Year fixed effects	Y	Y	Y	Y	Y
N	13,240	13,240	12,935	12,935	12,935

Note: *, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively. Robust standard errors are in parentheses.

within each temperature interval (bin). However, the DLNM allows for direct polynomial fitting within each segment of a natural spline, resulting in a more precise characterization of the nonlinear relationship. Therefore, we employed a non-parametric estimation method using the DLNM to examine the nonlinear relationships between extreme temperatures and health indicators. The baseline model, as shown in Eq. (2), utilized quasi-Poisson distribution regression. We estimated

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the temperature–indicator association via a natural cubic B-spline with 8 degrees of freedom per year to account for monthly variations, taking the median temperature level as the reference point for calculating cumulative effects. Notably, for contemporaneous effects, we set the maximum lag order to 0; for long-term lag effects, we set it to 21 days.

$$g(\mu_t) = \alpha + \sum_{j=1}^{J} s_j(x_{tj};\beta_j) + \sum_{k=1}^{K} \gamma_k \varphi_{tk}, \tag{2}$$

where $\mu_t \equiv E(Y_t)$, $g(\cdot)$ represents the linking function, Y_t corresponds to the time series values of various indicators, $s_j(\cdot)$ describes the relationship between temperature x_{tj} and the dependent variable, and φ_{tk} incorporates additional variables such as participant age, gender, weather conditions, and air quality on the examination day.

Fig. 1 and Fig. 2 depict the relationships between the maximum temperatures in summer and minimum temperatures in winter and the corresponding health indicators, with the gray area indicating the 95% confidence interval. Extreme temperatures notably impact diastolic and systolic blood pressure, with the effect diminishing as temperatures move toward the comfort range[42]. Government staff face the highest risk during extremely low temperatures in summer and show an increasing trend in various indicators during extremely low temperatures in winter. Extreme high winter temperatures benefit private sector employees overall, but compared with other groups, their health is more vulnerable during this season. Researchers tend to exhibit increased blood lipid levels during extremely high summer temperatures, but not all indicators are significantly affected by temperature during winter.

4.2 Adjusting the summer/winter period

We restricted the summer period from May to September[43] and adjusted the winter period from November to March in the Northern Hemisphere[44]. This adjustment allowed us to distinguish between summer heat and winter cold temperatures by excluding certain low-temperature samples collected during the summer and high-temperature samples collected during the winter. After adjusting the time periods, the median maximum temperatures for government staff during the summer and minimum temperatures during the winter were 31 °C and 3 °C, respectively. For enterprise employees, the median maximum temperatures during summer and minimum temperatures during winter were 29 °C and 4 °C, respectively. Similarly, researchers reported median maximum temperatures of 29 °C during the summer and minimum temperatures of 4 °C during the winter. As depicted in Table S2, the results of the parameter estimation remained consistent with the findings obtained prior to the adjustment of the time periods.

Fig. S3 and Fig. S4 present the nonparametric estimation results following the adjustment of time periods, with median maximum temperatures in summer and minimum temperatures in winter at 30 °C and 4 °C, respectively. The DLNM results for each indicator remained consistent with the preadjustment trends regardless of the season. The impact of extremely low temperatures in summer decreased, with some in-

Table 4. Winter-specific associations between biomarkers and temperature extremes across three population groups.

	(1) DP	(2) SP	(3) TC	(4) TG	(5) LDL
Government staff					
[−9 °C, −5 °C)	0.0720	0.904**	0.278***	0.153**	0.0766***
	(0.295)	(0.411)	(0.0346)	(0.0618)	(0.0293)
[−5 °C, −2 °C)	−0.0245	0.521	0.0662***	0.00356	0.0409*
	(0.268)	(0.364)	(0.0250)	(0.0346)	(0.0219)
[−2 °C, 1 °C)	−0.449***	0.446*	0.0134	−0.000550	−0.00981
	(0.167)	(0.232)	(0.0151)	(0.0262)	(0.0132)
[1 °C, 4 °C)	−0.000374	0.364	0.0232	0.0400	−0.0128
	(0.166)	(0.231)	(0.0149)	(0.0264)	(0.0130)
[4 °C, 7 °C) Reference group	–	–	–	–	–
[7 °C, 10 °C)	−0.212	−0.754***	0.0104	0.0360	0.00826
	(0.176)	(0.248)	(0.0157)	(0.0288)	(0.0137)
[10 °C, 13 °C)	−0.368*	−1.521***	−0.0225	−0.0172	0.0201
	(0.194)	(0.273)	(0.0168)	(0.0290)	(0.0147)
[13 °C, 16 °C)	−1.766***	−3.798***	−0.0280	−0.0366	−0.00950
	(0.197)	(0.276)	(0.0171)	(0.0279)	(0.0150)
[16 °C, 21 °C)	−1.808***	−4.419***	0.0454*	0.108**	0.0752***
	(0.342)	(0.484)	(0.0276)	(0.0467)	(0.0252)
Control	Y	Y	Y	Y	Y
Weather fixed effects	Y	Y	Y	Y	Y
Year fixed effects	Y	Y	Y	Y	Y
N	47,021	47,021	39,260	39,260	39,260

(To be continued on the next page)

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(Continued)

	(1) DP	(2) SP	(3) TC	(4) TG	(5) LDL
Employees					
[−9 °C, −4 °C)	1.395***	2.323***	0.0345	0.0865	0.0352
	(0.443)	(0.600)	(0.0376)	(0.0626)	(0.0325)
[−4 °C, −1 °C)	1.512***	1.688***	−0.0230	0.0611	−0.0230
	(0.278)	(0.398)	(0.0259)	(0.0528)	(0.0223)
[−1 °C, 2 °C)	0.265	0.580*	−0.00702	−0.00830	−0.0114
	(0.217)	(0.302)	(0.0217)	(0.0308)	(0.0193)
[2 °C, 5 °C)	0.491**	0.685**	0.0232	0.0256	0.00756
	(0.195)	(0.271)	(0.0189)	(0.0295)	(0.0167)
[5 °C, 8 °C) Reference group	–	–	–	–	–
[8 °C, 11 °C)	0.649***	0.0413	−0.108***	0.0292	−0.0440**
	(0.192)	(0.269)	(0.0198)	(0.0307)	(0.0176)
[11 °C, 14 °C)	−0.282	−0.755***	−0.0637***	−0.0277	−0.0324*
	(0.202)	(0.283)	(0.0215)	(0.0311)	(0.0188)
[14 °C, 17 °C)	−0.801***	−1.476***	−0.0772***	−0.00828	−0.0518**
	(0.291)	(0.405)	(0.0256)	(0.0394)	(0.0226)
[17 °C, 21 °C)	−1.774***	−3.413***	−0.0522	0.110	0.0167
	(0.548)	(0.744)	(0.0502)	(0.131)	(0.0438)
Control	Y	Y	Y	Y	Y
Weather fixed effects	Y	Y	Y	Y	Y
Year fixed effects	Y	Y	Y	Y	Y
N	35,704	35,704	22,904	22,904	22,904
Researchers					
[−9 °C, −6 °C)	0.329	1.523	−0.0183	−0.0888	−0.0327
	(1.052)	(1.530)	(0.104)	(0.164)	(0.0897)
[−6 °C, −3 °C)	1.184	2.492	0.280**	0.593	0.0637
	(1.318)	(1.693)	(0.140)	(0.500)	(0.0989)
[−3 °C, 0 °C)	−0.107	0.776	0.162**	0.197*	0.0752
	(0.779)	(1.195)	(0.0755)	(0.111)	(0.0694)
[0 °C, 3 °C)	0.382	0.994	−0.0702	−0.0133	−0.128***
	(0.553)	(0.797)	(0.0476)	(0.0686)	(0.0405)
[3 °C, 6 °C)	−0.753	0.139	0.0842**	−0.00200	0.0157
	(0.522)	(0.763)	(0.0428)	(0.0693)	(0.0379)
[6 °C, 9 °C) Reference group	–	–	–	–	–
[9 °C, 12 °C)	−0.489	−0.929	0.00912	0.0883	−0.0277
	(0.509)	(0.746)	(0.0411)	(0.0616)	(0.0360)
[12 °C, 15 °C)	−1.337**	−1.795**	0.0437	0.151**	0.00388
	(0.543)	(0.759)	(0.0427)	(0.0731)	(0.0375)
[15 °C, 21 °C)	−1.469	−3.222**	0.0513	0.0603	0.0953
	(0.910)	(1.332)	(0.0745)	(0.0997)	(0.0674)
Control	Y	Y	Y	Y	Y
Weather fixed effects	Y	Y	Y	Y	Y
Year fixed effects	Y	Y	Y	Y	Y
N	5,105	5,105	4,778	4,778	4,778

Note: *, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively. Robust standard errors are in parentheses.

dicators showing a nonsignificant exposure–response relationship, notably with enterprise employees' blood pressure. However, the impact of extremely high temperatures remained unchanged, particularly with respect to the three blood lipid indicators used by researchers. This may be attributed to the removal of low-temperature samples, which

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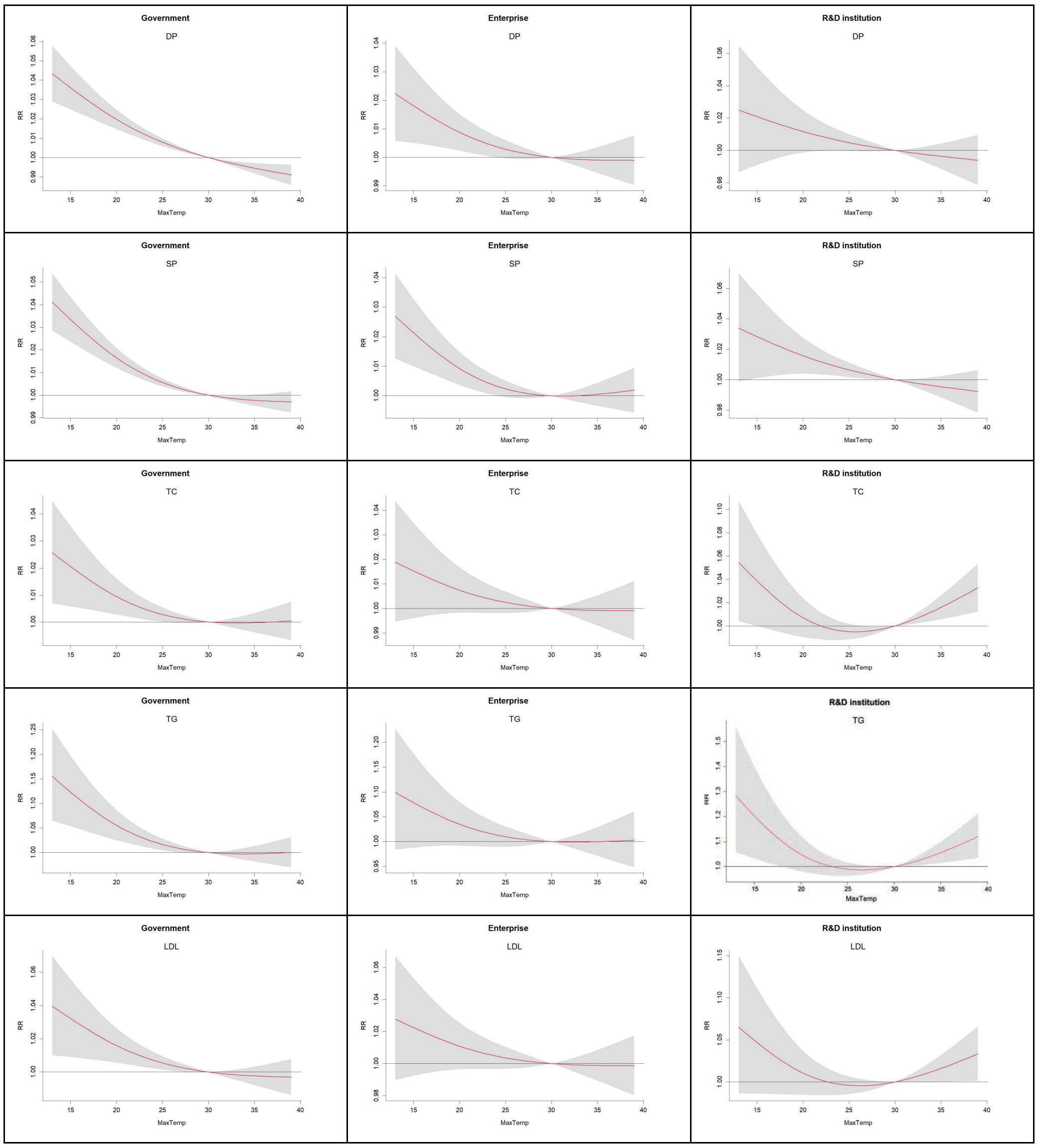

Fig. 1. The association between summer daily maximum temperatures and human biomarkers.

weakens their influence relative to the median level. Similarly, adjusting the winter samples resulted in a 1 °C decrease in the baseline median temperature, weakening the impact of extremely low temperatures while increasing the significance of extremely high temperatures.

4.3 Daily average temperature

We established that individuals exhibit stress responses to the daily maximum temperature in summer and the daily minimum temperature in winter. It is reasonable to hypothesize that extreme daily average temperatures can also elicit stress responses, leading to abnormal changes in health indicators. Hence, we investigated whether similar health risks are associated with daily average temperature.

Fig. S5 and Fig. S6 show the response of various physical indicators to the daily average temperature during the summer and winter periods. The response patterns of these indicators closely align with those shown in Fig. 1 and Fig. 2, where the daily maximum and minimum temperatures were used as exposure metrics. However, the 95% confidence intervals in Fig. S5 and Fig. S6 are slightly wider than that of the daily maximum and minimum temperatures. This suggests that the estimates of the exposure–response relationships for each physical indicator are more precise and reliable when the daily maximum and minimum temperatures are utilized as exposure metrics. Consequently, individuals are more responsive to the daily maximum and minimum temperatures in summer and winter, thus making them superior predictors of health risks than the daily average temperature is.

4.4 Changing the temperature measurement

Prior studies have shown that people are most impacted by high summer temperatures and are more responsive to low winter temperatures. However, some research suggests that cold weather has a greater effect in southern regions, whereas hot weather has a greater impact in northern regions[29,45,46]. This prompts an examination of the health effects of minimum daily temperatures in summer and maximum daily

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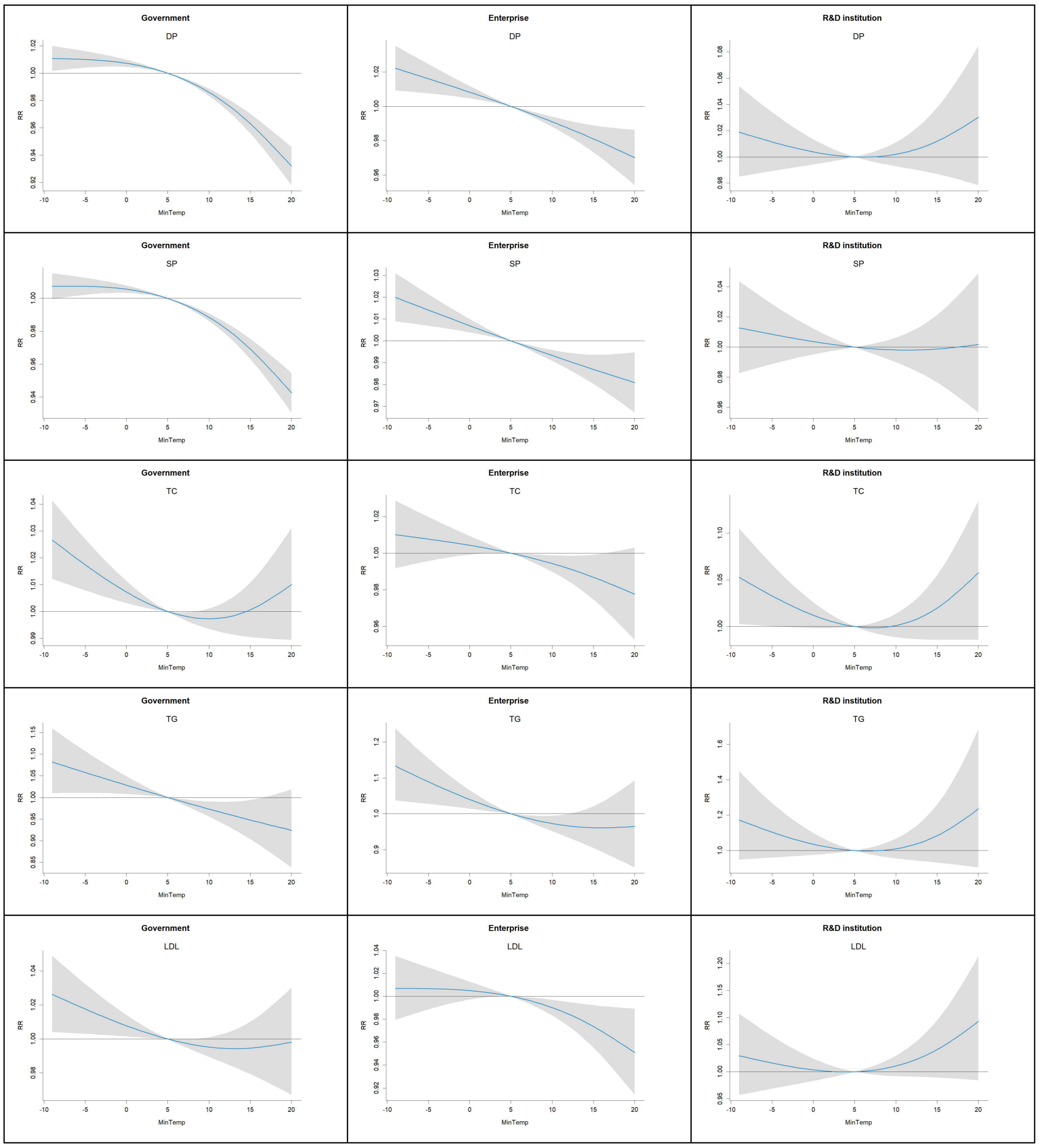

Fig. 2. The association between winter daily minimum temperatures and human biomarkers.

temperatures in winter[22]. The results in Fig. S7 and Fig. S8 reveal trends similar to those in Fig. 1 and Fig. 2 for the summer minimum temperatures and winter maximum temperatures. However, the 95% confidence intervals are wider, and the significance levels for certain factors are lower, further confirming the impact of summer maximum temperatures and winter minimum temperatures on health. Additionally, when combined with the earlier analysis of mean daily temperatures, summer maximum temperatures and winter minimum temperatures are the best predictors of health outcomes.

5 Further analysis

5.1 Long-term lagged effect

The DLNM model aids in investigating the delayed impact of extreme temperatures on health. We assessed the influence of weather conditions for up to 21 days[47] prior to the current health indicators, as depicted in Fig. S9 and Fig. S10. The results of the model with a 21-day lag were comparable to those without a lag, revealing the existence of prolonged lagged effects of extreme temperatures on health.

5.2 Impact of temperature fluctuations

We estimated parameters for daytime temperature fluctuations to examine their impact on health in terms of direction and magnitude. In Figs. S11–S13, circular markers represent cooling relative to the previous day, whereas square markers indicate warming. The dotted line represents the reference line for an estimated response (ER) value of 0. The ER value on the y-axis reflects the fit of the observed data or the values predicted via the GLM. The red and blue areas correspond to summer and winter, respectively. Our analysis revealed that government staff are more sensitive to temperature changes, particularly with significant effects on blood pressure. Notably, among the indicators significantly influenced by temperature fluctuations, the estimated value for cooling is generally positive, whereas the estimated value for warming is

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below the 0 scale line. These findings suggest that small-scale temperature fluctuations pose greater health risks than do larger-scale temperature fluctuations.

5.3 Response to seasonal transitions

In our analysis of seasonal transitions between summer and winter, we excluded the months of April and October. These months serve as transitional phases, with April transitioning from winter to summer and October acting as a buffer phase from summer to winter. An analysis of the temperature ranges revealed that April has higher temperatures for winter and lower temperatures for summer, whereas October is characterized by lower temperatures for summer and higher temperatures for winter. Overall, our findings indicate that health risks associated with extreme or high temperatures in winter and low temperatures in summer decrease as temperatures rise.

Consequently, during the transitional periods of April and October, there is a significant negative correlation between health risks and both maximum and minimum temperatures. For example, in April, the maximum temperatures fall within the low-temperature range of summer, whereas the minimum temperatures align with the high-temperature range of winter. As the maximum and minimum temperatures increase, health risks decrease. We observe a similar pattern in October. The results presented in Table S3 demonstrate predominantly negative significant temperature estimates, with most nonsignificant coefficients also being negative and a few positive estimates approaching zero. This confirms that health risks decrease with increasing temperature in April, whereas they increase with decreasing temperature in October. On the basis of our earlier descriptive results, we can conclude that the temperature trend in April generally shows an upward trajectory, whereas that in October gradually decreases. This suggests that people exhibit better adaptability during the transition from winter to summer but face greater health risks when they transition from summer to winter.

To account for temperature differences between April and October and their impacts on health risks, Fig. S14 illustrates the distribution differences in maximum and minimum temperatures for both months, with density shown on the y-axis. Notably, the distributions of maximum and minimum temperatures in both months are similar, indicating no significant disparities in temperature.

We evaluated the model's goodness-of-fit by examining the significance of the coefficient estimates. When daily maximum temperature was significant but daily minimum temperature was not significant, we considered daily maximum temperature to be a superior predictor. In cases of equal significance, we assessed additional indicators such as the Akaike information criterion (AIC), Bayesian information criterion (BIC), deviance residuals, and Pearson residuals, where smaller values indicate better fit. Across all the analyses, our findings consistently demonstrated that daily maximum temperature outperformed daily minimum temperature as a predictor in April, whereas the opposite was observed in October. These results further validate the effectiveness of using maximum temperatures for health risk prediction during summer (April–September) and minimum temperatures during winter (October–March), supporting the robustness of our seasonal divisions.

Government staff exhibit heightened sensitivity to seasonal transitions, particularly in April. Their health improves during the gradual transition from winter to summer, but they face increased risks during the shift from fall to winter in October, which is marked by declining temperatures. In contrast, researchers display minimal responsiveness to seasonal changes. Transitional temperature fluctuations significantly impact blood pressure, with notable effects on blood lipids observed specifically in April.

6 Discussion

Understanding how people link climate change to personal health and safety threats can improve communication strategies and promote adaptive health-protective behaviors. Blood pressure and lipids can predict chronic disease risk and assess human capital losses during extreme climate events. Our study revealed that extremely low temperatures increase blood pressure levels in adults, regardless of season. Government staff, corporate employees, and researchers respond differently to extreme temperature exposure.

High daily temperatures in summer are often associated with heatwaves, making them a reliable predictor of disease occurrence. Sociodemographic factors influence individuals' perceptions of heat-related risks, resulting in varying levels of perceived risk and preventive behaviors[48]. During heatwaves, living alone increases the risk of heat-related illnesses and death[49], whereas living with others increases awareness of dangers[48]. In comparison with government staff and corporate employees, researchers often require a working environment characterized by quietude and minimal disruptions, with relatively secluded social interactions rendering them more prone to overlooking weather fluctuations. Moreover, government staff and corporate employees often share office spaces, whereas researchers typically have relatively independent workspaces. An imbalance between high work pressure and effort rewards increases the risk of cardiovascular disease mortality[50]. Owing to the impact of extremely high temperatures, researchers are at an even greater risk of developing cardiovascular diseases.

The minimum daily temperature in winter reflects the severity of the cold wave. The lowest daily temperatures typically occur during the early morning and nighttime hours. Corporate employees often have longer commute times, with commutes beginning earlier, and they are more likely to engage in evening activities such as gatherings after work. This greatly increases their frequency and duration of exposure to extreme temperatures, making them most vulnerable to the impact of extremely low temperatures in winter, while mild winters are most beneficial to them. Furthermore, an increase in commuting time is associated with elevated stress levels, decreased subjective well-being, lower life satisfaction, and fatigue[51,52]. Additionally, prolonged commutes and greater distances traveled entail health hazards such as diminished physical activity, impaired sleep quality, hypertension, and negative affective states[53–56]. Long-distance commuting further diminishes the time allocated for engaging in health-promoting activities[57]. A survey involving white-collar work-

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ers suggested that commuting for more than 90 minutes each is associated with a greater likelihood of experiencing symptoms of chronic stress and obesity, which may subsequently contribute to cardiovascular disease and heart-related complications[58].

Government regulations for energy use result in significant indoor–outdoor temperature differences, with the indoor temperature having a greater impact on blood pressure and lipids[59]. Therefore, when extremely low temperatures in summer do not reach the outdoor temperature threshold requiring the use of cooling devices such as air conditioning, government staff face greater health risks, particularly in terms of blood pressure and lipid profiles. The dress codes associated with activities such as meetings and official functions also render government staff more vulnerable to seasonal transitions, especially during the transition from summer to winter. They exhibit the greatest response to temperature fluctuations among the three groups.

Temperature fluctuations significantly affect blood pressure and lipids, but different body indicators are heterogeneous among groups. Researchers in stable environments are the least sensitive to temperature changes. Preventive behaviors improve adaptability to large temperature changes, but small ones may be overlooked and pose greater health risks.

7 Conclusions

The maximum temperatures in summer (minimum temperatures in winter) best predict health risks. People are more susceptible to maximum temperatures in summer and minimum temperatures in winter.

Blood pressure is consistently related to temperature among government staff, corporate employees, and researchers. Extreme low temperatures in summer and winter increase blood pressure levels, whereas extremely high temperatures worsen lipid profiles for researchers. Corporate employees are most vulnerable in winter, benefiting from mild winters. These effects persist even after a lag of 21 days.

Small temperature fluctuations impact health more than large changes do. Blood pressure is significantly influenced by temperature fluctuations and is also affected by temperature during seasonal transitions, with a trend toward improved blood lipid levels observed only during the transition from winter to summer in April. Government staff have the strongest reaction to temperature fluctuations and are most sensitive to seasonal changes, whereas researchers are less sensitive to seasonal transitions. People have better adaptability during the transition from winter to summer but face greater health risks during the transition from summer to winter.

Supporting information

The supporting information for this article can be found online at https://doi.org/10.52396/JUSTC-2024-0019.

Acknowledgements

This work was supported by the National Natural Science Foundation of China (72072169) and the Fundamental Research Funds for the Central Universities (YD2040002015).

Conflict of interest

The authors declare that they have no conflict of interest.

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