MAX PLANCK INSTITUTE
FOR DEMOGRAPHIC RESEARCH

Konrad-Zuse-Strasse 1 · D-18057 Rostock · Germany · Tel +49 (0) 3 81 20 81 - 0 · Fax +49 (0) 3 81 20 81 - 202 · www.demogr.mpg.de

MPIDR Working Paper WP 2022-028 I Novmber 2022
https://doi.org/10.4054/MPIDR-WP-2022-028

Racial disparities in deaths related to extreme temperatures in the United States between 1993 and 2005

Risto Conte Keivabu I contekeivabu@demogr.mpg.de
Ugofilippo Basellini I basellini@demogr.mpg.de
Emilio Zagheni I office-zagheni@demogr.mpg.de

Racial disparities in deaths related to extreme temperatures in the United States between 1993 and 2005

Risto Conte Keivabu[1], Ugofilippo Basellini[1], and Emilio Zagheni[1]

[1]*Max Planck Institute for Demographic Research (MPIDR), Rostock, Germany*

November 3, 2022

Abstract

Extreme temperatures are associated with higher overall mortality at the population level, but some individuals are more vulnerable than others. Here, we investigate how extreme temperatures affect mortality and how race stratifies this relationship in the United States. We use highly granular administrative and census data on monthly mortality in over 3,000 counties from 1993 to 2005, and link them to precise meteorological information. We find that extreme temperatures increase mortality risk, and that the extent of this increase varies between racial groups. For example, an extra hot day increases the monthly mortality rate of Blacks and Others by 6.3 and 11.3 per 1,000, respectively, but by just 2.4 per 1,000 among Whites. Conversely, of these groups, Blacks are the least vulnerable on cold days. Moreover, we simulate the number of additional deaths that would have occurred in the study period if temperatures had increased to those projected for the middle of the 21st century. Our findings highlight disparities in mortality risks under these projected higher temperatures. In particular, we show that excess mortality due to higher temperatures is six times higher among Blacks than it is among Whites. Thus, climate change could exacerbate existing racial inequalities in deaths related to extreme temperatures.

Climate change is predicted to increase the occurrence of extreme temperatures, which pose health and mortality risks throughout the United States (U.S.) and the entire world, especially for the most vulnerable populations. A growing body of literature has documented the impact of extreme temperatures on mortality[1–6]. A key question is how different demographic groups are affected by extreme temperatures,[7] whether future climate change could affect specific subgroups disproportionately. [8].

Extreme temperatures pose critical public health risks, especially for the elderly, who have a frail cardiovascular system[9,10]. A recent global study found that cold has long lagged effects (of up to 21 days) on mortality, and accounts for the largest share of temperature-related deaths[11]. For North America specifically, it has been shown that approximately 7% of premature deaths are related to temperature, of which 6.3% are cold-related and 0.7% are heat-related[11]. The larger share of temperature-related deaths associated with cold is explained by the higher number of deaths observed at moderately cold temperatures, which are rather common in many countries[12]. However, findings indicating that exposure to moderately cold temperatures causes mortality should be interpreted with caution, as the choice of thresholds for cool temperatures, and possible confounding factors (such as higher prevalence of infectious diseases determined by longer time spent indoors), could bias these results[13]. Conversely, deaths due to exposure to heat occur on days when the temperatures are high, leading to short-term spikes in mortality[12]. Notably, some racial groups face a greater risk of heat-related mortality than others.Thus, targeted policies could help to offset the expected increase in mortality due to climate change[8].

In the U.S., race-based inequalities are ubiquitous across life domains, and environmental inequalities have significant consequences. . There is historical evidence of seasonal fluctuations in mortality by race in the 18th[14] and 19th centuries[15]. Recent studies on racial disparities in the U.S. have found a higher mortality risk due to heat exposure among the Black population in North Carolina, South Carolina, and Georgia from 2007 to 2011[16]; in four U.S. cities[17]; and during the 1995 heatwave in Chicago[18]. However, one analysis found no racial differences in temperature-related morbidity in 9 counties in California from 1999 to 2005,[19] while another found some evidence of a lower risk of heat-related mortality among Hispanics and Asians[20,21].

The mechanisms that explain racial disparities in temperature-related mortality are rooted in differences in exposure, vulnerability and access to medical and social support[22,23]. Disparities in exposure are related to poorer housing conditions and access to air conditioning[17]. In addition, minority groups are more likely than the majority population to live in environmentally disadvantaged neighbourhoods, such as in the hottest areas of cities[24]. There are also disparities in vulnerability as some racial groups are more likely to have pre-existing health conditions that can be aggravated by extreme temperatures. For example, the Black population in the U.S. are more likely to suffer from cardiovascular diseases that increase their vulnerability to heat[25]. Moreover, Blacks may have less access to medical information or treatment, and often lack adequate social support[26]. Thus, concerns have been raised that future climate change could exacerbate existing racial disparities in temperature-related mortality.

Recently, the so-called 'Mortality Cost of Carbon' metric has been proposed to quantify the number of lives lost in the future due to anthropogenic climate change[27]. On the one hand, an increase in average temperatures could lead to a decrease in the number of cold-related deaths in some geographical areas that are predicted to have high economic development[28]. On the other hand, global warming could result in a further increase in mortality in poorer and warmer countries[28]. Studies conducted in the European context have projected that climate change will lead to an increase in heat-related premature deaths[29] and a decrease in life expectancy[30]. Similar effects are expected to occur in the U.S. and in other world regions[31]. Additionally, a study on 208 U.S. cities, based on a scenario in which temperatures increase by about 6°C called for greater efforts to mitigate the negative health effects of the projected increase in heat-related vulnerability[32]. At the same time, certain sub-populations, such as Blacks, may, on average, face an even higher risk of heat-related mortality. As Blacks are expected to bear a higher Mortality Cost of Carbon, policies aimed at protecting them and other vulnerable groups are needed[8].

In this paper, we go beyond the state of the art by investigating racial disparities in extreme temperature-related mortality at a detailed geographical level. Focusing on the contiguous U.S. between 1993 and 2005, we analyze the link between extreme temperatures and mortality within a solid statistical framework. To do so, we combine the Berkeley Unified Numident Mortality Database (BUNMD)[33], a detailed individual-level dataset on mortality among older individuals in about 3,000 counties, with precise meteorological information. Our research advances the previous literature, in three main ways. First, we analyze the stratified effect of extreme temperatures on mortality by race for the entirety of the contiguous U.S., capturing the association in a broad spectrum of climatic and socio-economic contexts. Second, we provide results on racial disparities related to cold temperatures; an issue on which previous studies have failed to generate conclusive evidence. Third, we provide for the first time an assessment of expected excess deaths by racial group, based on projected future temperatures.

Results

Racial inequalities in temperature-related mortality in the U.S.

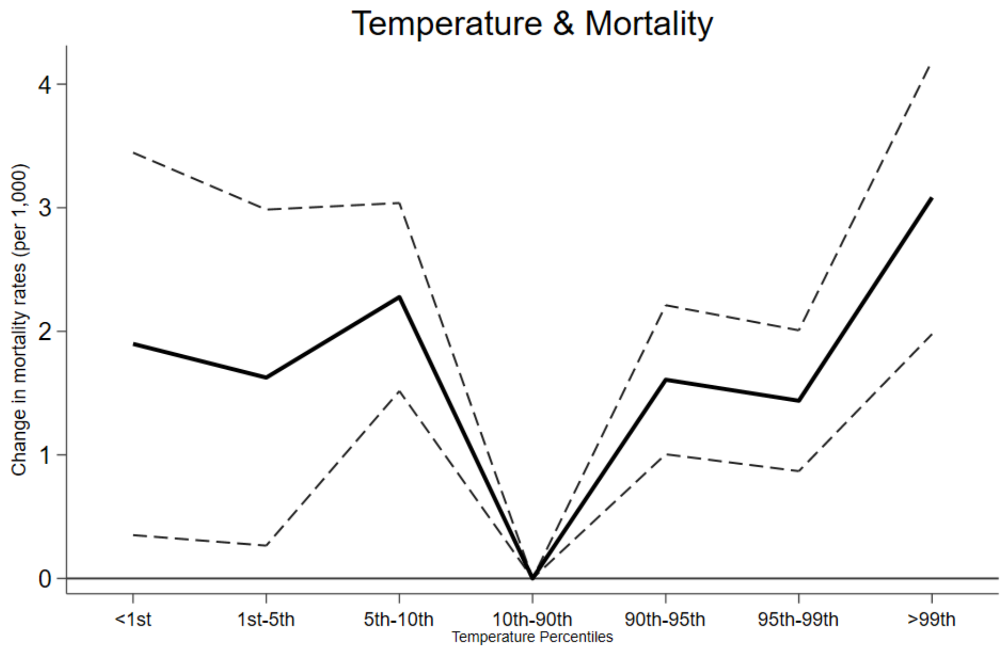
In our analysis, we employ Poisson regression to study the relationship between the monthly mortality rate and the temperatures at the county level, controlling for different covariates and fixed effects (see 'Estimation method' for additional details). Table A1 in the Supplementary Materials (hereafter SM) presents the descriptive statistics for all the variables employed in our study. Figure 1 shows the estimated coefficients of the temperature covariate, describing how temperatures affect mortality in the general population of the United States. We observed positive coefficients for temperature percentiles outside the comfort zone (10^{th}–90^{th} percentiles, taken as the reference category), which corresponds to an increase in mortality rates for all temperatures outside of the comfort zone. The estimated temperature-mortality curve displays a U shape, with greater increases in mortality at more extreme (cold and hot) temperatures. These findings are in line with those of previous studies[1,34]. An additional day in the coldest percentile ($< 1^{st}$) increased the monthly mortality rate by 1.9 per 1,000, while the figure is 3.1 per 1,000 for the hottest percentile ($> 99^{th}$). All estimated coefficients are statistically significant at the 95% level. The estimated coefficients for the other covariates in the model were also significant and had the expected sizes: mortality increased by age, it was higher for males than for females, and it was highest for Blacks, followed by Whites and than Others racial groups (for our definition of racial groups, see 'Methods'). The full results from the model are provided in Table A2 of the SM.

Importantly, we found that when the number of days with extreme temperatures in a single month increased the mortality rate rose. For example, five hot days occurring in a single month would lead to the mortality rate increasing by $3.1 \times 5 = 15.5$ per 1,000. However, caution is needed in interpreting these estimates as threshold effects could be present that resulted in an even steeper increase or decrease in mortality with additional days of extreme temperatures. For example, previous research has found that higher heat-related mortality in the early summer months could be followed by a harvesting effect[35]. Thus, successive hot days in a month may have a decreasing effect size.

The results shown in Figure 1 might hide heterogeneous racial effects: some specific groups might be at higher or lower risk of temperature-related mortality. To investigate such racial disparities, we added an interaction between the temperature variables and race. Figure 2 presents the results of this interaction model. Like in the general model, we observe that cold and hot temperatures have an increasing effect on mortality. However, the magnitude of this increase was race-specific. On the coldest days ($< 1^{st}$ percentile), mortality increased by 2.1 and 3.6 per 1,000 for Whites and Others, respectively; but decreased by -0.7 per 1,000 for Blacks (with the estimate being not statistically significant at the 95% level). An additional day in the hottest percentile ($> 99^{th}$) increases the mortality rate by 2.4, 6.3 and 11.3 per 1,000 for Whites, Blacks and Others, respectively. As was already mentioned, when the number of days with extreme temperatures in a single month increased, the mortality rate also tended to rise. The results from the model are also provided in Table A3 of the SM.

Some sociodemographic characteristics could compound racial disparities in temperature-related deaths. More precisely, gender and age categories could be associated with greater vulnerabilities that could differ between racial groups. Racial minorities may be particularly at risk as they are more likely than Whites to suffer from cardiovascular diseases and other chronic illnesses such as diabetes. In addition, older cohorts are more likely than younger cohorts to have lower educational attainment. To test for such compound racial disparities, we performed a three-way interaction between temperature exposures, age categories and racial groups (SM Table A4). The only significant effect detected by this analysis was that Blacks aged 85+ had a

Figure 1. Estimated coefficients with 95% confidence intervals of the temperature variable on mortality.

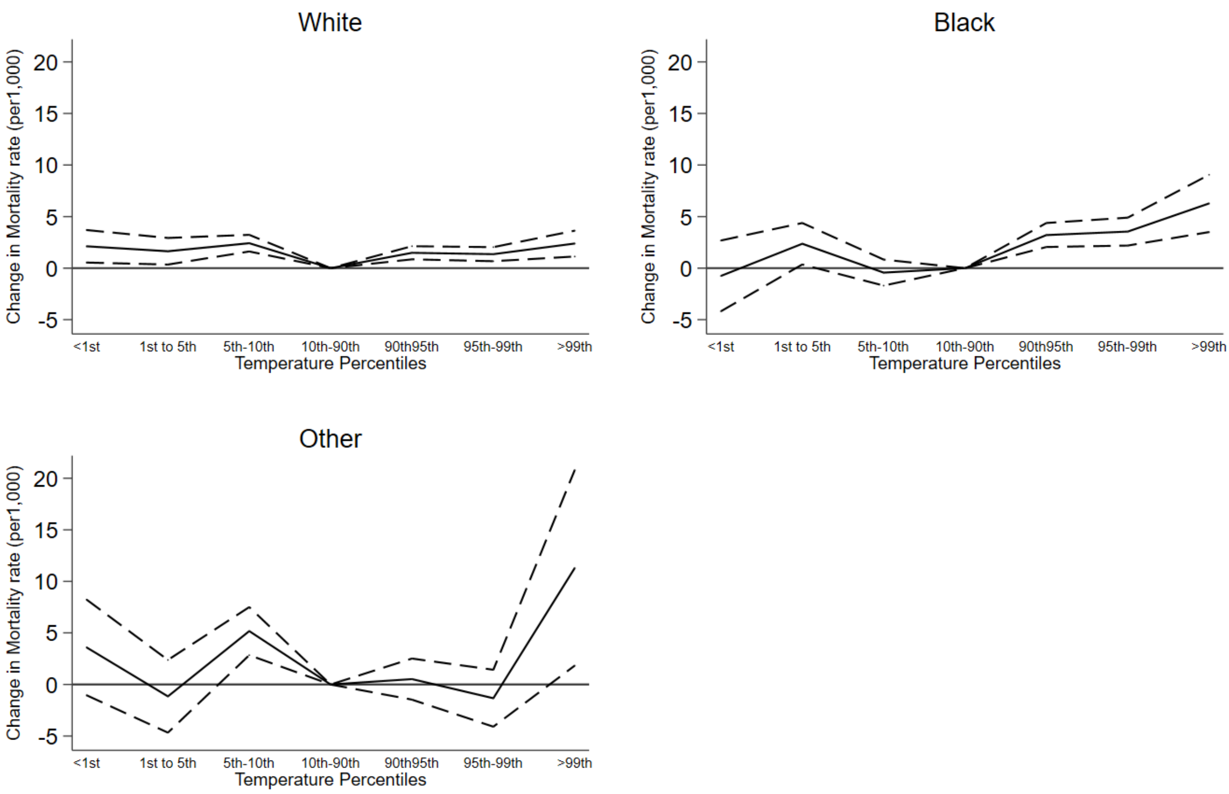


higher mortality risk than other groups on hot days. When we examined a potential three-way interaction between temperature, race and gender, we found no substantial pattern (SM Table A5).

Geographical differences in the impact of extreme temperatures on mortality are particularly relevant for understanding the racial disparities observed in Figure 2. On one hand, Blacks are mostly concentrated in the South and South East, which are two areas of the U.S. that are particularly susceptible to high temperatures. Moreover, Blacks often reside in the warmest areas of cities[24]. On the other hand, as individuals living in northern counties are less prepared to deal with unexpected heat spells[36], Blacks in these counties could face even higher health risks.

We investigated the geographic disparities in the relationship between extreme temperatures and mortality by performing a series of additional analysis. First, we ran an interaction between the temperature variables and the eight climatic regions. The results shown in Figure A3 in the SM indicate that hot days ($> 99^{\text{th}}$ percentile) had a larger impact in some of the colder regions. In particular, we observed that compared to the Central region, days with temperatures above the 99^{th} percentile had a greater impact in the Northwestern and West North Central regions, which experienced an intense heatwave in 2021[37]. Conversely, we found that exposure to cold days ($< 1^{\text{st}}$ percentile) had a more substantial impact in the South and East North Central regions. Thus, our results corroborate previous findings suggesting southern regions are the most adapted to warmer temperatures[1,36,38]. Nevertheless, racial disparities might differ depending on the climatic region and compound existing inequalities. Therefore, we explored geographical patterns in racial disparities with a three-way interaction between racial categories, climatic regions, and temperature exposures. The results (SM Table A6) show that relative to the Central region, the largest racial disparities for both minority groups in the impact of exposure to hot days ($> 99^{\text{th}}$ percentile) on mortality were in the East North Central region, but also that the mortality risk was lower in the Northwest for Blacks. Conversely, we did not observe any major differences between climatic regions in the impact of exposure to cold

Figure 2. Estimated coefficients with 95% confidence intervals of the temperature variable on mortality by racial groups.



days (< 1st percentile) on mortality among different racial groups, with the exception of the Northwest where Blacks show a lower risk. Our observation that racial inequalities were larger in the East North Central region appears to corroborate previous studies that examined the impact of the 1995 heatwave and found a higher burden for Blacks[18].

Climate change and excess mortality by race

We investigated the extent of future racial disparities in temperature-related mortality by simulating the number of race-specific excess deaths in our study period that would have occurred if the temperatures were as high as the levels predicted for the middle of the 21st century. This counterfactual analysis was performed by replacing the observed temperatures with those projected between 2051 and 2055, keeping fixed the estimated coefficients of the race interaction model. All other covariates were assumed to remain constant. Future temperature data were retrieved from the Multivariate Adaptive Constructed Analogs dataset based on the RCP4.5 emissions scenario[39,40] (see 'Meteorological Data').

Table 1 shows the number of excess deaths and excess mortality rate that would have occurred if temperatures were to change to levels predicted for the years 2051-2055. This counterfactual analysis uncovered important racial disparities in the effect of temperature changes on mortality. In particular, we found that the excess mortality rate due to higher temperatures was much higher for Blacks and for Others, while the excess mortality rate for Whites increased more moderately. These racial disparities grew when we considered the mid-century RCP8.5 emission scenario and the end of century scenarios (SM Tables A7-A9) and when we looked at excess deaths by race and age category (SM Table A10). Figure 3 shows the excess deaths plotted on the U.S. map for all racial groups, as well as disaggregated by race. In the maps, we can observe a larger increase in excess deaths in the South and Southeast regions of the United States, and a slight decline in the Northeast. Moreover, different patterns emerge when we look at race-specific maps. These maps show, for example, that mortality increased almost everywhere for Blacks, but decreased in some areas for Whites and for Others. The largest mortality increases were among Blacks, particularly in the southern counties, where Others were also particularly vulnerable. While our findings for the entire U.S. population align well with the projections by Carleton Carleton et al. [28], we made a further contribution to the literature on future temperature-related mortality in the United States by adding the racial perspective. Additionally, we leveraged the three-way interaction between temperatures, racial groups and climatic regions (Table A6 in the SM) to provide estimates of excess deaths based on the RCP4.5 projections by race and climatic regions. Table 2 shows that the Northwest, the Southeast and the South suffer the highest numbers of excess deaths. However, there could be substantial racial differences within regions. Table 3 deepens this analysis by looking at excess mortality by race and region. The results show that Blacks had the highest excess death rate in the South, Southeast and East North Central regions; whereas, Whites had the highest excess death rate in the Northwest.

Table 1. Excess deaths and mortality rates in 1993-2005 if the temperatures were as high as the mid-century levels projected in the RCP4.5 scenario.

	Observed deaths	Simulated deaths	Excess deaths	Total exposure	Excess rate (per 100,000)
White	19,633,036	19,682,144	49,107	374,910,266	13
Black	2,128,672	2,158,969	30,296	36,189,517	84
Other	797,371	810,464	13,093	32,797,250	40
Total	22,559,081	22,651,579	92,497	443,897,033	21

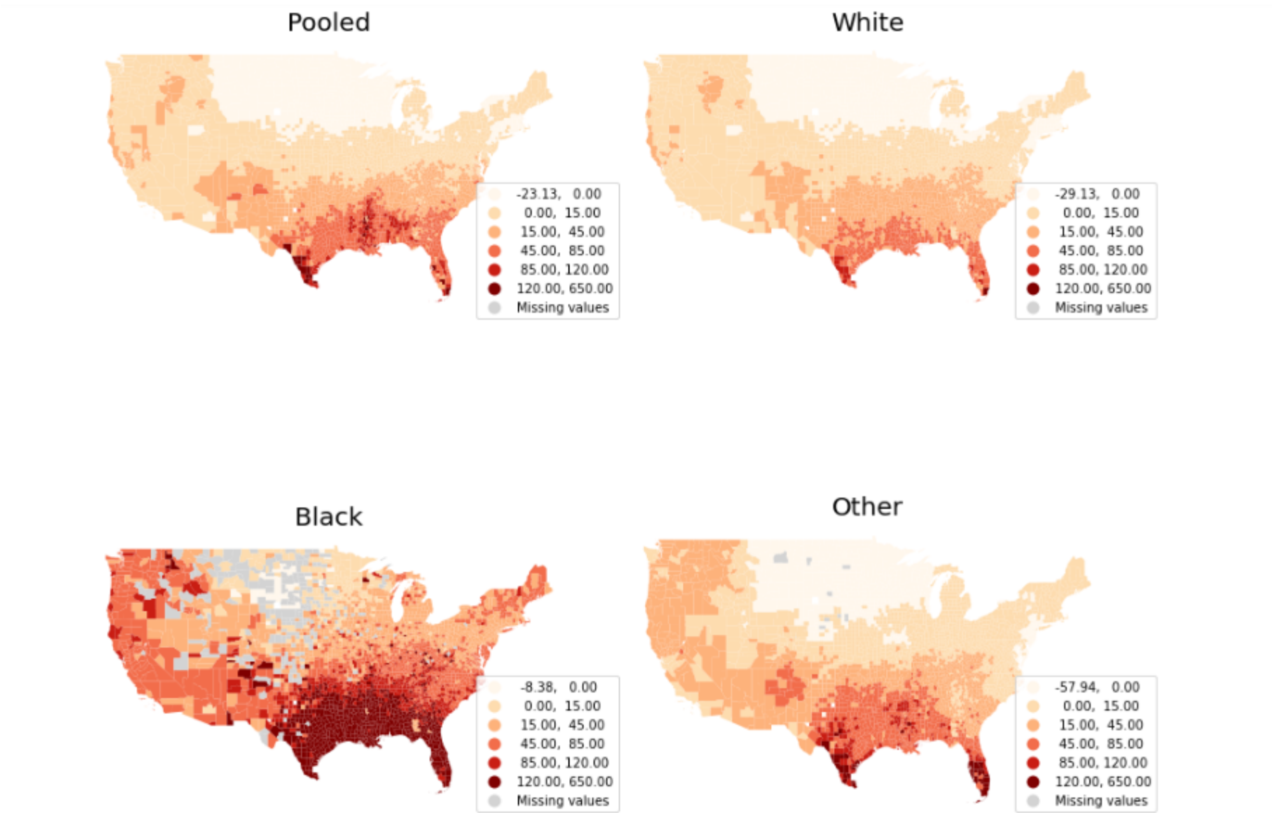
Notes: Estimates are obtained by predicting the number of the deaths based on Equation (2) using mid-century temperatures (2051-2055) based on the RCP4.5 emission scenario.

Table 2. Excess deaths and mortality rates in 1993-2005 by climatic region if the temperatures were as high as the mid-century levels projected in the RCP4.5 scenario.

Climate region	Obs. deaths	Sim. deaths	Ex. deaths	Tot. Exposure	Excess rate
Center	4,229,926	4,242,000	12,074	77,063,491	15
East North Central	1,891,892	1,891,367	-525	37,887,249	-1
Northeast	5,397,985	5,401,414	3,429	103,057,827	3
Northwest	809,709	821,054	11,344	16,940,384	67
South	2,822,465	2,833,668	11,202	52,669,445	21
Southeast	3,912,396	3,938,074	25,677	80,652,557	32
Southwest	817,373	820,568	3,195	18,951,795	17
West North Central	2,677,332	2,688,208	10,876	5,6674,282	19
Total	22,559,081	22,636,354	77,271	443,897,033	17

Notes: Estimates are obtained by predicting the number of deaths by extending Equation (2) to a three-way interaction (temperature-race-climatic regions) using the mid-century temperatures (2051-2055) projected in the RCP4.5 emission scenario.

Figure 3. Excess deaths (per 100,000) by counties based on the mid-century RCP4.5 scenario for the full sample and for different racial groups.



Note: Estimates are obtained by predicting the excess deaths (per 100,000) by counties based on temperatures projected for 2051 to 2055 in the RCP4.5 scenario.

Table 3. Excess deaths and mortality rate in 1993-2005 by race and climatic region if temperature were as high as the mid-century levels projected in the RCP4.5 scenario.

Race	Climatic region	Obs. deaths	Sim. deaths	Ex. deaths	Tot. Exposure	Excess rate
White	Central	3,801,807	3,809,184	7,377	69,134,654	10
Black	Central	387,598	392,253	4,655	6,253,957	74
Other	Central	40,520	40,562	42	1,674,879	2
White	East North Central	1,762,313	1,760,030	-2,283	35,358,065	-6
Black	East North Central	111,082	112,757	1,675	1,882,099	89
Other	East North Central	18,497	18,580	82	647,084	13
White	Northeast	4,809,850	4,808,946	-904	89,054,074	-1
Black	Northeast	444,741	449,027	4,286	8,253,992	52
Other	Northeast	143,394	143,441	47	5,749,760	1
White	Northwest	742,737	753,331	10,594	15,284,043	69
Black	Northwest	43,074	43,536	463	807,227	57
Other	Northwest	23,898	24,186	287	849,114	34
White	South	2,322,188	2,324,645	2,458	41,245,657	6
Black	South	375,599	381,970	6,371	5,776,551	110
Other	South	124,678	127,052	2,373	5,647,238	42
White	Southeast	3,212,733	3,210,461	-2,272	66,166,605	-3
Black	Southeast	607,798	617,288	9,490	10,349,823	92
Other	Southeast	91,865	110,323	18,458	4,136,129	446
White	Southwest	749,981	753,912	3,931	16,074,882	24
Black	Southwest	15,567	15,555	-11	303,617	-4
Other	Southwest	51,825	51,100	-725	2,573,295	-28
White	West North Central	2,231,427	2,238,147	6,720	42,592,285	16
Black	West North Central	143,213	144,960	1746	2,562,250	68
Other	West North Central	302,690	305,100	2,410	11,519,747	21
Total		22,559,081	22,636,354	77,271	443,897,033	17

Notes: Estimates are obtained by predicting the number of deaths by extending Equation (2) to a three-way interaction (temperature-race-climatic regions) using the mid-century temperatures (2051-2055) projected in the RCP4.5 emission scenario.

Conclusion

In this article, we have analyzed the impact of extreme temperatures on mortality, and the related disparities by race, using data on the contiguous United States from 1993 to 2005. We provided further evidence of the impact of extreme temperatures on mortality, while highlighting the greater vulnerability to heat of minority groups, and especially Blacks. Importantly, for the first time, we provided evidence of the stratified effect of temperature by race using a comprehensive sample of more than 3,000 counties. Thus, we added to the previous literature, which focused on only a partial sample of the U.S. territory. Additionally, we provided estimates of excess deaths based on several RCP scenarios, and mapped the counties where temperature-related deaths are expected to increase the most.

In line with the existing evidence, we observed that exposure to extreme cold and hot temperatures led to an increase in mortality risk.[1,6]. Our findings on the impact of temperature on mortality by race indicated that the effects differed for heat and cold. We found that relative to the effects on Whites, moderate temperatures were deadlier for Others, but not for Blacks. Conversely, we found that heat was consistently deadlier for Blacks and for Others. It is possible that the higher risk of mortality due to cold observed for people of color in northern cities in the 18th and 19th century was peculiar to the historical context, which was heavily influenced by slavery and discrimination against people of color[15]. The abolition of slavery, economic growth and the broader availability of cheaper heating may explain why cold-related mortality is no longer higher among Blacks in contemporary U.S. society[41]. However, we also found evidence of the persistence in heat-related deaths affecting Blacks in particular which corroborates the results of existing studies[16–18] and highlights the existence of important racial inequalities in vulnerability to high temperatures. Accordingly, when we analyzed excess deaths by racial group based on RCP4.5 temperature projections for the middle of the 21st century, we observed a larger increase in excess deaths for Blacks and Others, and a smaller increase for Whites. When we analyzed excess deaths by race and age category we observed Blacks aged 85 or older were the most at risk. Additionally, we found that Blacks in the East North Central area faced the highest risk of excess mortality. However, we also observed that the projected increase in temperatures is expected to lead to a greater increase in excess deaths among Blacks in the South and Southeast. Importantly, when we tested the effects of larger increases in temperature using the RCP8.5 end-of-century scenario, we observed a widening of the racial gap and an increased risk for the Black population.

This study has three main limitations. The first limitation is related to the data on mortality. We employed the BUNMD dataset, as it provided us with precise information on the main characteristics of interests. Unfortunately, the information covered only the years 1993 to 2005, which limited the scope of our analysis. Additionally, the dataset has several missing observations due to the lack of comprehensive information on the full sample of individuals. Nevertheless, we addressed the existence of missing values by adjusting the BUNMD dataset based on the HMD database (see the "Mortality and Population Data" subsection). Second, we were unable to directly test the mechanisms that explain racial disparities. Thus, we attempted to explain the observed disparities based on previous theoretical and empirical studies. Similarly, due to the high correlation between socioeconomic status (SES) and race, we were not able to rule out the possibility that the observed disparities were partly determined by a racial gradient in educational attainment. While a smaller database with information on several SES measures (including educational attainment) is available, we lacked population estimates at the county level for the period of our analysis. Consequently, we were not able to test whether the findings by race would have differed from those by SES. Third, our calculation of excess deaths should be interpreted with caution, as we assumed that all factors other than temperature remained constant over time. On the one hand, we may have overestimated the increase in heat-related deaths, as we did not consider economic development, higher educational attainment, and adaptation to high temperatures. On the other hand, population aging is expected to enlarge the pool of older individuals who are at higher risk of death when exposed to heat. Future studies could address some of the drawbacks of the current study. First, data on mortality in the past 15 years would allow researchers to compare the estimates we found with the impact of temperatures in more recent years, in which extreme heat events have been rather common. Second, testing mechanisms could provide further evidence on the policies that might be most effective in reducing disparities. For example, evidence that preexisting medical conditions or neighborhood segregation are the main causes of the observed disparities could indicate which public health interventions are required. Third, further analysis of the impact of climate change on race disparities in mortality in the future could incorporate population projections and differential adaptations.

We conclude by noting that the dangers posed by climate change are likely to exacerbate the existing racial disparities in the United States. Compared to White Americans, Blacks contribute less to the total carbon emissions derived from the consumption of goods[42] and use of household energy[43]; however, studies suggest that they will bear a higher Mortality Cost of Carbon[27]. Thus, policies should particularly target Black communities living in heat islands, which are expected to be the most affected by future climate change[8]. In sum, as the effects of climate change continue to unfold, the existing disparities in exposure and vulnerability to extreme temperatures, and in the access to resources could become even wider in the future, exacerbating existing environmental inequalities. This would have dire consequences for the racial gap in life expectancy, and would pose substantial challenges for the Black population in particular.

Methods

Mortality and Population Data

In this study we use three main datasets to construct mortality rates: the Berkeley Unified Numident Mortality Database, the Human Mortality Database and Population Estimates from the National Center for Health Statistics (NCHS) Bridged-Race Population Estimates.

The Berkeley Unified Numident Mortality Database (BUNMD) is a unique dataset covering approximately 50 million individuals who were listed in the 1940 Census and who died from 1988 to 2005[33]. The BUNMD is the harmonized version of information collected by the Social Security Administration on the individuals in the dataset with a social security number. It is stored by the National Archives and Records Administration (NARA)[33]. The dataset is unique as it provides individual-level data with key characteristics on the deceased individuals. For our purposes, we retained the age at death, sex, the racial group as well as the ZIP code of residence, which allowed us to accurately identify the sociodemographic characteristics and geographical location at the time of death for each individual. For race, we used three categories based on the classification used prior to 1980: White, Black or Others. The BUNMD dataset also contains the classification used after 1980 with five categories: White, Black, Asian American or Pacific Islander, Hispanic and North American Indian or Alaskan native[33]. However, due to the small sample size resulting from using the latter categorization, we used the three categories in our analysis. For each sex and race group, we aggregated death counts at the county level by connecting the zip codes to county identifiers using information from the Housing & Urban Development Office (HUD), allocating zip codes to a county if more than 50% of the residential addresses were part of that county.

In our dataset, we only included individuals aged above 65 for two main reasons. First, the elderly are the most vulnerable to extreme temperatures[9,10,44]. Secondly, the BUNMD covers a substantial proportion (above 95%) of all elderly deaths (aged 65+) occurred in the

United States during this time period[33], while coverage at younger ages is more limited. More precisely, it has been estimated to cover around 50 to 75% of individuals under age 65[33]. Consequently, we focused on three main age groups comprised of individuals who died at ages 65–74, 75–84, and 85+, respectively. To further reduce bias due to missing values, we limited the analysis to the years 1993 to 2005. Still, 95% coverage for individuals aged 65+ was not achieved after we dropped missing values for certain individual characteristics. For example, the race categorization was missing for approximately 30% of the sample[33]. Figure A1 in the Supplementary Materials compares our sample of death counts with the observed data in the U.S. (derived from the Human Mortality Database[45]). It shows that the coverage was greater from 1993 to 2005. We thus derived our main dependent variable composed of monthly death counts by sex, age, race and county. Finally, in order to further reduce the discrepancy of the BUNMD with respect to the observed deaths in the United States, we adjusted death counts so that they match the observed ones in the Human Mortality Database[45] for each year, sex and age-group. We display the results of the adjustment in Figure A2 in the Supplementary Materials.

We then linked our dependent variable to the corresponding population estimates provided by the U.S. National Center for Health Statistics[46], which are available by age, sex, race and county and that we used to construct population exposures. This allowed us to compute, for each subgroup in our analysis, monthly mortality rates as the ratio between death counts and corresponding monthly exposures. The latter was computed by dividing annual population estimates by 12 (the number of months) and by using linear interpolation between consecutive years, hence obtaining an estimate of the monthly exposure to the risk of death for all months considered in the analysis.

Meteorological Data

We combined our mortality estimates with precise meteorological data provided by gridMet[47]. The gridMet dataset provides daily information on several climatic variables such as maximum temperature, minimum temperature, precipitation, specific humidity, wind velocity and short-wave radiation at a 4x4km resolution. The high quality of the data has been validated using information from local weather stations[47]. We computed the average minimum and maximum temperature of the grid cells falling within each county boundaries and used it to compute: i) the daily average temperature proxied as the mean between minimum and maximum temperatures, and ii) the monthly temperature bins counting the number of days in 7 categories capturing the percentiles of the county temperature distribution, respectively: days below and equal to the 1st percentile; from the 1st to the 5th percentile; from the 5th to the 10th percentile ; from the 10th to the 90th (comfort zone); from the 90th to the 95th percentile; from the 95th to the 99th percentile; above the 99th percentile. We considered this approach preferable to computing groups from raw temperatures as it allowed us to capture the county-specific local climatic condition, which have been shown to vary[36] and to better capture the relationship between temperature and mortality[48]. However, we performed further analysis using alternative temperature bins (see Tables A13-A15 in the Supplementary materials). Additionally, we include meteorological information provided by gridMet on monthly average solar radiation, precipitation, wind speed and specific humidity for each county.

For the projected temperatures, we used a dataset that provided gridded downscaled estimates of future meteorological observations at a 4km resolution constructed based on the historical gridMet data and the Coupled Model Intercomparison Project 5 (CMIP5) Global Climate Models (GCM)[49]. We used this dataset to construct the average count of days in the temperature bins described above based on the RCP4.5 and RCP8.5 mid(2051-2055) and end(2086-2100) of century scenarios.

Air pollution and socioeconomic indicators

In addition to the meteorological variables, we added other covariates at the county level to control for biases emerging from omitted variables that might correlate with temperature and mortality. First, we retrieved information on the monthly average level of the air pollutant particulate matter 2.5 (PM2.5) at the county level from the Atmospheric Composition Analysis Group dataset[50]. Moreover, we collected three socioeconomic indicators at the county level provided by the Federal Reserve Bank of St. Louis[51]. The indicators we retrieved are the monthly unemployment rate, the yearly percentage of Supplemental Nutrition Assistance Programme (SNAP) beneficiaries and the median household income. For the latter two indicators we interpolated values across years to create the monthly values.

Estimation method

Let $c = 1, \ldots, 3083$ denote the U.S. counties, $r =$ W,B,O denote race, $s =$ F,M denote sex, and $a = 1, 2, 3$ denote age groups (65–74, 75–84, 85+). To ease notation, let j denote a given combination of county, race, sex and age group. Furthermore, let $t = 1, \ldots, 156$ denote the time observations in the dataset, corresponding to twelve monthly observations from year 1993 to 2005. We assume that deaths Y_{jt} in group j at time t are realizations of a Poisson distribution with expected value equal to the product of exposures E_{jt} and force of mortality μ_{jt}[52].

In our analysis, we model Poisson death counts in the standard Generalized Linear Model (GLM) framework using a log-link function and exposures as an offset. In particular, the expected value of the Poisson distribution $\mathbb{E}(Y_{jt})$ can be described as:

$$\ln\left[\mathbb{E}(Y_{jt})\right] = \ln(E_{jt}) + \sum_k \theta_k \mathrm{TEMP}^k_{jt} + \boldsymbol{X}_{jt}\boldsymbol{\beta}_{jt} + \alpha_t + \gamma_{jt}\,, \tag{1}$$

where $\ln(E_{jt})$ is the offset term, TEMP^k_{ct} denotes the number of days in the k-th of the 7 temperature bins to which individuals in county c were exposed at time t. Days in the comfort zone are not introduced in the model, so that this group becomes the baseline to which other bins are compared to. The coefficients θ_k is then interpreted as the effect on mortality of exchanging one day in the comfort zone for a day in the k-th bin.

We add a 1×11 matrix of both time-unvarying and time varying covariates $\boldsymbol{X}_{jt}$ with associated coefficients $\boldsymbol{\beta}_{jt}$. The three time-unvarying covariates include three demographic variables: sex, age group and race. The eight time-varying covariates include five environmental variables at the county level: the monthly average level of the air pollutant particulate matter 2.5 (PM2.5), average solar radiation, precipitation, wind speed and specific humidity; and three socioeconomic indicators: unemployment rate, SNAP beneficiaries and median household income. The inclusion of meteorological covariates, air pollution and socioeconomic indicators is common in the literature[1,53] and allows to adjust for possible biases. For example, previous studies have highlighted air pollution to reduce the estimates of cold-related mortality in an urban context[54] or to modify heat-related mortality[55]. The demographic covariates are specified as categorical variables corresponding to the groups r, s and a. Furthermore, we include month-by-year and county-by-month fixed effects to capture specific yearly and seasonal variations in mortality in each county that could affect the outcome variable (as in, for example, Barreca et al.[1]) Specifically, α_t captures the month-by-year fixed effects for each time t in the dataset, and γ_{jt} is the county-by-month fixed effect, corresponding to the county in group j and the month $m = 1, \ldots, 12$ corresponding to time t. Finally, we cluster standard errors at the county level assuming them to correlate within units over time[56,57]. We tested alternative model specifications adding common or state-specific time trends to the analysis. We decided not to include these as results did not substantially change, while computation time highly increased.

We also tested clustering standard errors at the state level as performed in previous research[57], and results did not differ. Moreover, we run a placebo test with temperatures in the 5 months after and did not find any significant or sizable results (SM Table A16).

Finally, in order to investigate racial disparities in temperature related mortality, we considered a modification of Eq. (1), where we include a model matrix $\boldsymbol{Z}_{jt}$ that corresponds to the interaction between the temperature variable TEMP^k_{jt} and the race variable R_j. Specifically, the model can be expressed as:

$$\ln\left[\mathbb{E}\left(Y_{jt}\right)\right] = \ln\left(E_{jt}\right) + \boldsymbol{Z}_{jt}\boldsymbol{\theta}_{jt} + \boldsymbol{X}_{jt}\boldsymbol{\beta}_{jt} + \alpha_t + \gamma_{jt}\,, \tag{2}$$

where the other covariates (excluding temperature and race) are the same as in Eq. (1) and contained in the model matrix $\boldsymbol{X}_{jt}$.

Data availability

- Data on meteorological information is accessible here: https://www.climatologylab.org/gridmet.html
- Data on air pollution is accessible here: https://sites.wustl.edu/acag/datasets/historical-pm2-5-across-north-america/
- Data used to correct death and population counts is accessible here: https://www.mortality.org/
- Data to connect zip codes to counties is provided here: https://www.huduser.gov/portal/datasets/usps_crosswalk.html#codebook
- Data on projected temperature is accessible here: https://www.climatologylab.org/maca.html
- Data on the individual deaths are accessible here: https://censoc.berkeley.edu/
- Data on population counts are accessible here: https://www.cdc.gov/nchs/nvss/bridged_race.htm
- Data on socioeconomic control variables are accessible here: https://fred.stlouisfed.org/

Code availability

The code necessary for data management and analysis to reproduce the main results is provided at: https://osf.io/k5dcx/?view_only=26a3caee0a4e4ffdb43bfd109f7a4e68

References

[1] Alan Barreca, Karen Clay, Olivier Deschenes, Michael Greenstone, and Joseph S. Shapiro. Adapting to Climate Change: The Remarkable Decline in the US Temperature-Mortality Relationship over the Twentieth Century. *Journal of Political Economy*, 124(1):105–159, February 2016. ISSN 0022-3808, 1537-534X. doi: 10.1086/684582. URL https://www.journals.uchicago.edu/doi/10.1086/684582.

[2] Isabel Hovdahl. Deadly Variation: The Effect of Temperature Variability on Mortality. Working Papers No 01/2020, Centre for Applied Macro- and Petroleum economics (CAMP), BI Norwegian Business School, February 2020. URL https://ideas.repec.org/p/bny/wpaper/0084.html.

[3] Antonella Zanobetti and Joel Schwartz. Temperature and mortality in nine us cities. *Epidemiology*, 19(4), 2008. URL https://journals.lww.com/epidem/Fulltext/2008/07000/Temperature_and_Mortality_in_Nine_US_Cities.11.aspx.

[4] Francesco Nordio, Antonella Zanobetti, Elena Colicino, Itai Kloog, and Joel Schwartz. Changing patterns of the temperature–mortality association by time and location in the us, and implications for climate change. *Environment international*, 81:80–86, 2015.

[5] Kate R Weinberger, Daniel Harris, Keith R Spangler, Antonella Zanobetti, and Gregory A Wellenius. Estimating the number of excess deaths attributable to heat in 297 united states counties. *Environmental Epidemiology (Philadelphia, Pa.)*, 4(3), 2020.

[6] Alan I. Barreca. Climate change, humidity, and mortality in the United States. *Journal of environmental economics and management*, 63(1):19–34, 2012. ISSN 0095-0696. doi: 10.1016/j.jeem.2011.07.004. URL https://www.ncbi.nlm.nih.gov/pmc/articles/PMC4199665/.

[7] Ji-Young Son, Jia Coco Liu, and Michelle L Bell. Temperature-related mortality: a systematic review and investigation of effect modifiers. *Environmental Research Letters*, 14 (7):073004, jul 2019. doi: 10.1088/1748-9326/ab1cdb. URL https://doi.org/10.1088/1748-9326/ab1cdb.

[8] Jason Vargo, Brian Stone, Dana Habeeb, Peng Liu, and Armistead Russell. The social and spatial distribution of temperature-related health impacts from urban heat island reduction policies. *Environmental Science & Policy*, 66:366–374, December 2016. ISSN 14629011. doi: 10.1016/j.envsci.2016.08.012. URL https://linkinghub.elsevier.com/retrieve/pii/S1462901116305627.

[9] Hicham Achebak, Daniel Devolder, and Joan Ballester. Trends in temperature-related age-specific and sex-specific mortality from cardiovascular diseases in Spain: a national time-series analysis. *The Lancet Planetary Health*, 3(7):e297–e306, July 2019. ISSN 25425196. doi: 10.1016/S2542-5196(19)30090-7. URL https://linkinghub.elsevier.com/retrieve/pii/S2542519619300907.

[10] Daniel Oudin Åström, Forsberg Bertil, and Rocklöv Joacim. Heat wave impact on morbidity and mortality in the elderly population: A review of recent studies. *Maturitas*, 69(2):99–105, June 2011. ISSN 03785122. doi: 10.1016/j.maturitas.2011.03.008. URL https://linkinghub.elsevier.com/retrieve/pii/S0378512211000806.

[11] Qi Zhao, Yuming Guo, Tingting Ye, Antonio Gasparrini, Shilu Tong, Ala Overcenco, Aleš Urban, Alexandra Schneider, Alireza Entezari, Ana Maria Vicedo-Cabrera, Antonella Zanobetti, Antonis Analitis, Ariana Zeka, Aurelio Tobias, Baltazar Nunes, Barrak Alahmad, Ben Armstrong, Bertil Forsberg, Shih-Chun Pan, Carmen Íñiguez, Caroline Ameling, César De la Cruz Valencia, Christofer Åström, Danny Houthuijs, Do Van Dung, Dominic Royé, Ene Indermitte, Eric Lavigne, Fatemeh Mayvaneh, Fiorella Acquaotta, Francesca de'Donato, Francesco Di Ruscio, Francesco Sera, Gabriel Carrasco-Escobar, Haidong Kan, Hans Orru, Ho Kim, Iulian-Horia Holobaca, Jan Kyselý, Joana Madureira, Joel Schwartz, Jouni J. K. Jaakkola, Klea Katsouyanni, Magali Hurtado Diaz, Martina S. Ragettli, Masahiro Hashizume, Mathilde Pascal, Micheline de Sousa Zanotti Stagliorio Coélho, Nicolás Valdés Ortega, Niilo Ryti, Noah Scovronick, Paola Michelozzi, Patricia Matus Correa, Patrick Goodman, Paulo Hilario Nascimento Saldiva, Rosana Abrutzky, Samuel Osorio, Shilpa Rao, Simona Fratianni, Tran Ngoc Dang, Valentina Colistro, Veronika Huber, Whanhee Lee, Xerxes Seposo, Yasushi Honda, Yue Leon Guo, Michelle L. Bell, and Shanshan Li. Global, regional, and national burden of mortality

associated with non-optimal ambient temperatures from 2000 to 2019: a three-stage modelling study. *The Lancet Planetary Health*, 5(7):e415–e425, July 2021. ISSN 2542-5196. doi: 10.1016/S2542-5196(21)00081-4. URL https://www.thelancet.com/journals/lanplh/article/PIIS2542-5196(21)00081-4/fulltext. Publisher: Elsevier.

[12] Antonio Gasparrini, Yuming Guo, Masahiro Hashizume, Eric Lavigne, Antonella Zanobetti, Joel Schwartz, Aurelio Tobias, Shilu Tong, Joacim Rocklöv, Bertil Forsberg, Michela Leone, Manuela De Sario, Michelle L Bell, Yue-Liang Leon Guo, Chang-fu Wu, Haidong Kan, Seung-Muk Yi, Micheline de Sousa Zanotti Stagliorio Coelho, Paulo Hilario Nascimento Saldiva, Yasushi Honda, Ho Kim, and Ben Armstrong. Mortality risk attributable to high and low ambient temperature: a multicountry observational study. *The Lancet*, 386 (9991):369–375, 2015. ISSN 0140-6736. doi: 10.1016/S0140-6736(14)62114-0. URL http://www.sciencedirect.com/science/article/pii/S0140673614621140.

[13] Katherine Arbuthnott, Shakoor Hajat, Clare Heaviside, and Sotiris Vardoulakis. What is cold-related mortality? a multi-disciplinary perspective to inform climate change impact assessments. *Environment International*, 121:119–129, 2018. ISSN 0160-4120. doi: 10.1016/j.envint.2018.08.053. URL https://www.sciencedirect.com/science/article/pii/S0160412018308997.

[14] Susan E. Klepp. Seasoning and society: Racial differences in mortality in eighteenth-century philadelphia. *The William and Mary Quarterly*, 51(3):473–506, 1994. ISSN 0043-5597. doi: 10.2307/2947439. URL https://www.jstor.org/stable/2947439. Publisher: Omohundro Institute of Early American History and Culture.

[15] Christian Warren. Northern chills, southern fevers: Race-specific mortality in american cities, 1730-1900. *The Journal of Southern History*, 63(1):23–56, 1997. ISSN 0022-4642. doi: 10.2307/2211942. URL https://www.jstor.org/stable/2211942. Publisher: Southern Historical Association.

[16] Mihye Lee, Liuhua Shi, Antonella Zanobetti, and Joel D. Schwartz. Study on the Association Between Ambient Temperature and Mortality Using Spatially Resolved Exposure Data. *Environmental research*, 151:610–617, November 2016. ISSN 0013-9351. doi: 10.1016/j.envres.2016.08.029. URL https://www.ncbi.nlm.nih.gov/pmc/articles/PMC5071163/.

[17] Marie S. O'Neill, Antonella Zanobetti, and Joel Schwartz. Disparities by race in heat-related mortality in four US cities: The role of air conditioning prevalence. *Journal of Urban Health*, 82(2):191–197, June 2005. ISSN 1468-2869. doi: 10.1093/jurban/jti043. URL https://doi.org/10.1093/jurban/jti043.

[18] Reinhard Kaiser, Alain Le Tertre, Joel Schwartz, Carol A. Gotway, W. Randolph Daley, and Carol H. Rubin. The effect of the 1995 heat wave in chicago on all-cause and cause-specific mortality. *American Journal of Public Health*, 97:S158–S162, 2007. ISSN 0090-0036. doi: 10.2105/AJPH.2006.100081. URL https://ajph.aphapublications.org/doi/10.2105/AJPH.2006.100081. Publisher: American Public Health Association.

[19] Rochelle S. Green, Rupa Basu, Brian Malig, Rachel Broadwin, Janice J. Kim, and Bart Ostro. The effect of temperature on hospital admissions in nine California counties. *International Journal of Public Health*, 55(2):113–121, April 2010. ISSN 1420-911X. doi: 10.1007/s00038-009-0076-0. URL https://doi.org/10.1007/s00038-009-0076-0.

[20] Alana Hansen, Linda Bi, Arthur Saniotis, and Monika Nitschke. Vulnerability to extreme heat and climate change: is ethnicity a factor? *Global Health Action*, 6 (1):21364, December 2013. ISSN 1654-9716. doi: 10.3402/gha.v6i0.21364. URL

https://doi.org/10.3402/gha.v6i0.21364. Publisher: Taylor & Francis _eprint: https://doi.org/10.3402/gha.v6i0.21364.

[21] R. Noe, J. Jin, and A. Wolkin. Exposure to natural cold and heat: hypothermia and hyperthermia Medicare claims, United States, 2004-2005. *American journal of public health*, 2012. doi: 10.2105/AJPH.2011.300557.

[22] Massimo Stafoggia, Francesco Forastiere, Daniele Agostini, Annibale Biggeri, Luigi Bisanti, Ennio Cadum, Nicola Caranci, Francesca de'Donato, Sara De Lisio, Moreno De Maria, Paola Michelozzi, Rossella Miglio, Paolo Pandolfi, Sally Picciotto, Magda Rognoni, Antonio Russo, Corrado Scarnato, and Carlo A. Perucci. Vulnerability to Heat-Related Mortality: A Multicity, Population-Based, Case-Crossover Analysis. *Epidemiology*, 17(3):315–323, May 2006. ISSN 1044-3983. doi: 10.1097/01.ede.0000208477.36665.34. URL https://journals.lww.com/epidem/Fulltext/2006/05000/Vulnerability_to_Heat_Related_Mortality__A.18.aspx.

[23] Shakoor Hajat and Tom Kosatky. Heat-related mortality: a review and exploration of heterogeneity. *Journal of Epidemiology & Community Health*, 64(9):753–760, September 2010. ISSN 0143-005X, 1470-2738. doi: 10.1136/jech.2009.087999. URL https://jech.bmj.com/content/64/9/753. Publisher: BMJ Publishing Group Ltd Section: Essay.

[24] Angel Hsu, Glenn Sheriff, Tirthankar Chakraborty, and Diego Manya. Disproportionate exposure to urban heat island intensity across major US cities. *Nature Communications*, 12(1):2721, May 2021. ISSN 2041-1723. doi: 10.1038/s41467-021-22799-5. URL https://www.nature.com/articles/s41467-021-22799-5. Bandiera_abtest: a Cc_license_type: cc_by Cg_type: Nature Research Journals Number: 1 Primary_atype: Research Publisher: Nature Publishing Group Subject_term: Climate-change impacts;Environmental health;Environmental impact;Environmental social sciences Subject_term_id: climate-change-impacts;environmental-health;environmental-impact;environmental-social-sciences.

[25] Anita K. Kurian and Kathryn M. Cardarelli. Racial and ethnic differences in cardiovascular disease risk factors: a systematic review. *Ethnicity & Disease*, 17(1):143–152, 2007. ISSN 1049-510X.

[26] David R. Williams and Toni D. Rucker. Understanding and Addressing Racial Disparities in Health Care. *Health Care Financing Review*, 21(4):75–90, 2000. ISSN 0195-8631. URL https://www.ncbi.nlm.nih.gov/pmc/articles/PMC4194634/.

[27] R. Daniel Bressler. The mortality cost of carbon. *Nature Communications*, 12(1):4467, July 2021. ISSN 2041-1723. doi: 10.1038/s41467-021-24487-w. URL https://www.nature.com/articles/s41467-021-24487-w. Bandiera_abtest: a Cc_license_type: cc_by Cg_type: Nature Research Journals Number: 1 Primary_atype: Research Publisher: Nature Publishing Group Subject_term: Climate-change policy;Environmental economics Subject_term_id: climate-change-policy;environmental-economics.

[28] Tamma Carleton, Amir Jina, Michael Delgado, Michael Greenstone, Trevor Houser, Solomon Hsiang, Andrew Hultgren, Robert E Kopp, Kelly E McCusker, Ishan Nath, James Rising, Ashwin Rode, Hee Kwon Seo, Arvid Viaene, Jiacan Yuan, and Alice Tianbo Zhang. Valuing the global mortality consequences of climate change accounting for adaptation costs and benefits*. page qjac020. ISSN 0033-5533. doi: 10.1093/qje/qjac020. URL https://doi.org/10.1093/qje/qjac020.

[29] Giovanni Forzieri, Alessandro Cescatti, Filipe Batista e Silva, and Luc Feyen. Increasing risk over time of weather-related hazards to the European population: a data-driven prognostic study. *The Lancet Planetary Health*, 1(5):e200–e208, August 2017. ISSN

2542-5196. doi: 10.1016/S2542-5196(17)30082-7. URL https://www.thelancet.com/journals/lanplh/article/PIIS2542-5196(17)30082-7/fulltext. Publisher: Elsevier.

[30] Mathew E. Hauer and Alexis R. Santos-Lozada. Inaction on Climate Change Projected to Reduce European Life Expectancy. *Population Research and Policy Review*, 40(3): 629–638, June 2021. ISSN 1573-7829. doi: 10.1007/s11113-020-09584-w. URL https://doi.org/10.1007/s11113-020-09584-w.

[31] Yuming Guo, Antonio Gasparrini, Shanshan Li, Francesco Sera, Ana Maria Vicedo-Cabrera, Micheline de Sousa Zanotti Stagliorio Coelho, Paulo Hilario Nascimento Saldiva, Eric Lavigne, Benjawan Tawatsupa, Kornwipa Punnasiri, Ala Overcenco, Patricia Matus Correa, Nicolas Valdes Ortega, Haidong Kan, Samuel Osorio, Jouni J. K. Jaakkola, Niilo R. I. Ryti, Patrick G. Goodman, Ariana Zeka, Paola Michelozzi, Matteo Scortichini, Masahiro Hashizume, Yasushi Honda, Xerxes Seposo, Ho Kim, Aurelio Tobias, Carmen Íñiguez, Bertil Forsberg, Daniel Oudin Åström, Yue Leon Guo, Bing-Yu Chen, Antonella Zanobetti, Joel Schwartz, Tran Ngoc Dang, Dung Do Van, Michelle L. Bell, Ben Armstrong, Kristie L. Ebi, and Shilu Tong. Quantifying excess deaths related to heatwaves under climate change scenarios: A multicountry time series modelling study. *PLOS Medicine*, 15(7):e1002629, July 2018. ISSN 1549-1676. doi: 10.1371/journal.pmed.1002629. URL https://dx.plos.org/10.1371/journal.pmed.1002629.

[32] Claire R. Lay, Marcus C. Sarofim, Alina Vodonos Zilberg, Dave M. Mills, Russell W. Jones, Joel Schwartz, and Patrick L. Kinney. City-level vulnerability to temperature-related mortality in the USA and future projections: a geographically clustered meta-regression. *The Lancet Planetary Health*, 5(6):e338–e346, June 2021. ISSN 2542-5196. doi: 10.1016/S2542-5196(21)00058-9. URL https://www.thelancet.com/journals/lanplh/article/PIIS2542-5196(21)00058-9/fulltext. Publisher: Elsevier.

[33] Casey Breen and Joshua R. Goldstein. Berkeley Unified Numident Mortality Database: Public administrative records for individual-level mortality research. *Demographic Research*, 47:111–142, jul 2022. doi: 10.4054/demres.2022.47.5.

[34] Noah Scovronick, Francesco Sera, Fiorella Acquaotta, Diego Garzena, Simona Fratianni, Caradee Y. Wright, and Antonio Gasparrini. The association between ambient temperature and mortality in south africa: A time-series analysis. 161:229–235. ISSN 0013-9351. doi: 10.1016/j.envres.2017.11.001. URL https://www.sciencedirect.com/science/article/pii/S0013935117307193.

[35] Antonio Gasparrini, Yuming Guo, Masahiro Hashizume, Eric Lavigne, Aurelio Tobias, Antonella Zanobetti, Joel D. Schwartz, Michela Leone, Paola Michelozzi, Haidong Kan, Shilu Tong, Yasushi Honda, Ho Kim, and Ben G. Armstrong. Changes in susceptibility to heat during the summer: A multicountry analysis. *American Journal of Epidemiology*, 183(11):1027–1036, 2016. ISSN 0002-9262. doi: 10.1093/aje/kwv260. URL https://doi.org/10.1093/aje/kwv260.

[36] M. Medina-Ramón and J. Schwartz. Temperature, temperature extremes, and mortality: a study of acclimatisation and effect modification in 50 US cities. *Occupational and Environmental Medicine*, 64(12):827–833, 2007. ISSN 1351-0711, 1470-7926. doi: 10.1136/oem.2007.033175. URL https://oem.bmj.com/content/64/12/827. Publisher: BMJ Publishing Group Ltd Section: Original article.

[37] Vikki Thompson, Alan T. Kennedy-Asser, Emily Vosper, Y. T. Eunice Lo, Chris Huntingford, Oliver Andrews, Matthew Collins, Gabrielle C. Hegerl, and Dann Mitchell. The 2021 western north america heat wave among the most extreme events ever recorded globally. 8

(18):eabm6860. doi: 10.1126/sciadv.abm6860. URL https://www.science.org/doi/10.1126/sciadv.abm6860. Publisher: American Association for the Advancement of Science.

[38] Risto Conte Keivabu. Extreme temperature and mortality by educational attainment in spain, 2012–2018. *European Journal of Population*, 2022. ISSN 1572-9885. doi: 10.1007/s10680-022-09641-4. URL https://doi.org/10.1007/s10680-022-09641-4.

[39] R.J. Taylor K.E., Stouffer and G.A. Meehl. An overview of cmip5 and the experiment design. *MS-D-11-00094.1*, 2012.

[40] J.T. Abatzoglou and Brown T.J. A comparison of statistical downscaling methods suited for wildfire applications. *International Journal of Climatology*, 2012. doi: 10.1002/joc.2312.

[41] Janjala Chirakijja, Seema Jayachandran, and Pinchuan Ong. Inexpensive heating reduces winter mortality. SSRN Scholarly Paper ID 3359481, Social Science Research Network, 2019. URL https://papers.ssrn.com/abstract=3359481.

[42] Christopher W. Tessum, Joshua S. Apte, Andrew L. Goodkind, Nicholas Z. Muller, Kimberley A. Mullins, David A. Paolella, Stephen Polasky, Nathaniel P. Springer, Sumil K. Thakrar, Julian D. Marshall, and Jason D. Hill. Inequity in consumption of goods and services adds to racial–ethnic disparities in air pollution exposure. *Proceedings of the National Academy of Sciences*, 116(13):6001–6006, 2019. ISSN 0027-8424, 1091-6490. doi: 10.1073/pnas.1818859116. URL https://www.pnas.org/content/116/13/6001. Publisher: National Academy of Sciences Section: Physical Sciences.

[43] Benjamin Goldstein, Tony G. Reames, and Joshua P. Newell. Racial inequity in household energy efficiency and carbon emissions in the united states: An emissions paradox. *Energy Research & Social Science*, 84:102365, 2022. ISSN 2214-6296. doi: 10.1016/j.erss.2021.102365. URL https://www.sciencedirect.com/science/article/pii/S2214629621004552.

[44] William P. Cheshire. Thermoregulatory disorders and illness related to heat and cold stress. *Autonomic Neuroscience: Basic and Clinical*, 196:91–104, April 2016. ISSN 1566-0702. doi: 10.1016/j.autneu.2016.01.001. URL https://www.autonomicneuroscience.com/article/S1566-0702(16)30001-7/abstract. Publisher: Elsevier.

[45] HMD. Human Mortality Database. *University of California, Berkeley (USA), and Max Planck Institute for Demographic Research (Germany).*, 2021. URL www.humanmortality.de.

[46] National Center for Health Statistics. Bridged-race population estimates - data files and documentation, 2021. URL https://www.cdc.gov/nchs/nvss/bridged_race/data_documentation.htm.

[47] John T. Abatzoglou. Development of gridded surface meteorological data for ecological applications and modelling. *International Journal of Climatology*, 33(1):121–131, 2013. doi: https://doi.org/10.1002/joc.3413. URL https://rmets.onlinelibrary.wiley.com/doi/abs/10.1002/joc.3413.

[48] Giuliano Masiero, Fabrizio Mazzonna, and Michael Santarossa. The effect of absolute versus relative temperature on health and the role of social care. *Health Economics*, n/a, 2022. ISSN 1099-1050. doi: 10.1002/hec.4507. URL https://onlinelibrary.wiley.com/doi/abs/10.1002/hec.4507. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1002/hec.4507.

[49] John T. Abatzoglou and Timothy J. Brown. A comparison of statistical downscaling methods suited for wildfire applications. 32(5):772–780. ISSN 1097-0088. doi: 10.1002/joc.2312. URL https://onlinelibrary.wiley.com/doi/abs/10.1002/joc.2312. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1002/joc.2312.

[50] Melanie S. Hammer, Aaron van Donkelaar, Chi Li, Alexei Lyapustin, Andrew M. Sayer, N. Christina Hsu, Robert C. Levy, Michael J. Garay, Olga V. Kalashnikova, Ralph A. Kahn, Michael Brauer, Joshua S. Apte, Daven K. Henze, Li Zhang, Qiang Zhang, Bonne Ford, Jeffrey R. Pierce, and Randall V. Martin. Global Estimates and Long-Term Trends of Fine Particulate Matter Concentrations (1998–2018). *Environmental Science & Technology*, 54 (13):7879–7890, July 2020. ISSN 0013-936X. doi: 10.1021/acs.est.0c01764. URL https://doi.org/10.1021/acs.est.0c01764. Publisher: American Chemical Society.

[51] FRED. Federal Reserve Bank of St. Louis and US. Office of Management and Budget, GeoFRED. 2022. URL https://geofred.stlouisfed.org/.

[52] David R Brillinger. A biometrics invited paper with discussion: The natural variability of vital rates and associated statistics. *Biometrics*, 42(4):693–734, 1986.

[53] Antonella Zanobetti, Marie S. O'Neill, Carina J. Gronlund, and Joel D Schwartz. Susceptibility to Mortality in Weather Extremes: Effect Modification by Personal and Small Area Characteristics In a Multi-City Case-Only Analysis. *Epidemiology (Cambridge, Mass.)*, 24 (6):809–819, November 2013. ISSN 1044-3983. doi: 10.1097/01.ede.0000434432.06765.91. URL https://www.ncbi.nlm.nih.gov/pmc/articles/PMC4304207/.

[54] Svetlana Stanišić Stojić, Nemanja Stanišić, and Andreja Stojić. Temperature-related mortality estimates after accounting for the cumulative effects of air pollution in an urban area. *Environmental Health*, 15(1):73, 2016. ISSN 1476-069X. doi: 10.1186/s12940-016-0164-6. URL https://doi.org/10.1186/s12940-016-0164-6.

[55] Xin Hu, Wenxing Han, Yuxin Wang, Kristin Aunan, Xiaochuan Pan, Jing Huang, and Guoxing Li. Does air pollution modify temperature-related mortality? a systematic review and meta-analysis. *Environmental Research*, 210:112898, 2022. ISSN 0013-9351. doi: 10.1016/j.envres.2022.112898. URL https://www.sciencedirect.com/science/article/pii/S0013935122002250.

[56] A. Colin Cameron, Jonah B. Gelbach, and Douglas L. Miller. Robust Inference With Multiway Clustering. *Journal of Business & Economic Statistics*, 29(2):238–249, 2011. ISSN 0735-0015. URL https://www.jstor.org/stable/25800796. Publisher: American Statistical Association.

[57] Solomon Hsiang. Climate econometrics. *Annual Review of Resource Economics*, 8(1):43–75, 2016. ISSN 1941-1340, 1941-1359. doi: 10.1146/annurev-resource-100815-095343. URL http://www.annualreviews.org/doi/10.1146/annurev-resource-100815-095343.

1 Supplementary Materials for: Racial disparities in temperature-related deaths in the United States between 1993 and 2005

Contents

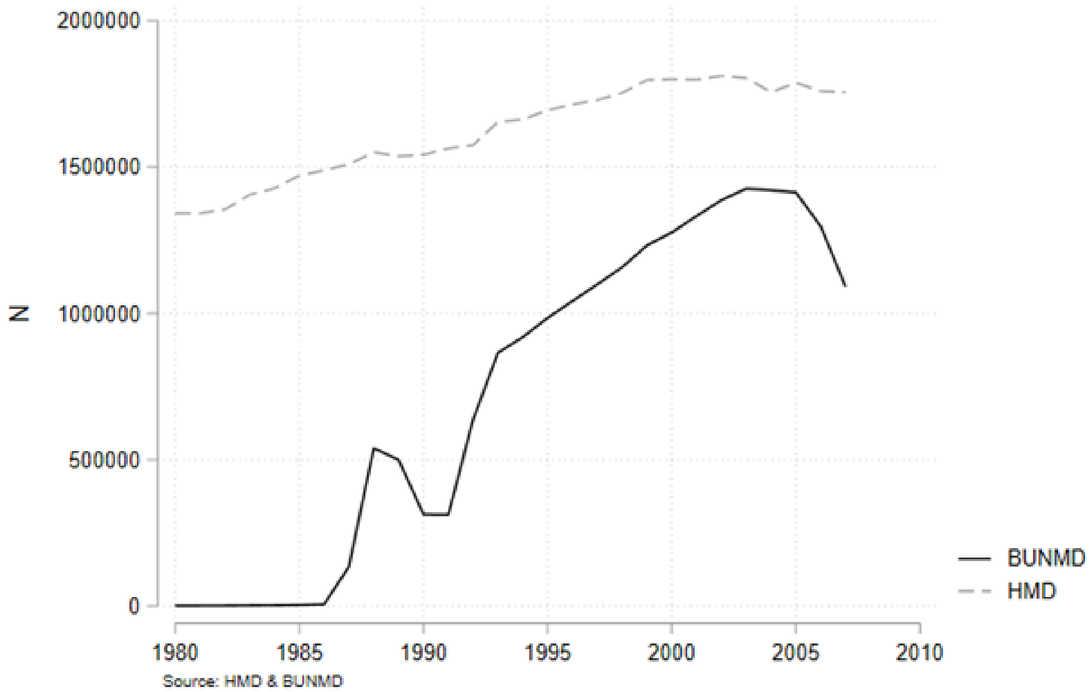
1.a Mortality Data, descriptives and main analysis

Figure A1 shows the total number of deaths occurred in the U.S. (as reported by the Human Mortality Database) along with the deaths contained in the BUNMD. In order to remove the bias in the data, we adjust the BUMND mortality rate by age and sex using the Human Mortality Database (HMD). Figure A2 shows the original BUNMD death rates by sex and age-group for the years analysed, as well as the adjusted rates to match those derived from the HMD. From the figure, it clearly emerges that the original BUMND death series underestimates mortality, especially for the older age groups and the first years of analysis. It should be noted that the BUNMD provides weights to match deaths to the HMD, but these do not include missing values resulting from other variables such as the location of death. Consequently, we did not use the BUNMD weights and performed the adjustment to make our sample match the HMD. Our correction is not free from limitations. Similar caveats are shared by the weights available in the BUNMD[3]. The sub-populations included in the HMD allow us to have a good estimate of mortality by age categories and sex, but we do not have data by race categories or county of death determining the risk of biases emerging from the different likelihood of being excluded from the sample. For example, the missing values for race are of around 30% in the BUNMD[3], but we did not observe any substantial variation in the proportions of each race group when accounting for the additional missing observations. Nevertheless, our correction procedure permit us to work with death counts and exposures that are more representative of the observed mortality developments in the populations considered, allowing to compute more accurate estimates of excess mortality.

Table A1 shows the descriptive statistics for the main variables used in our analysis.

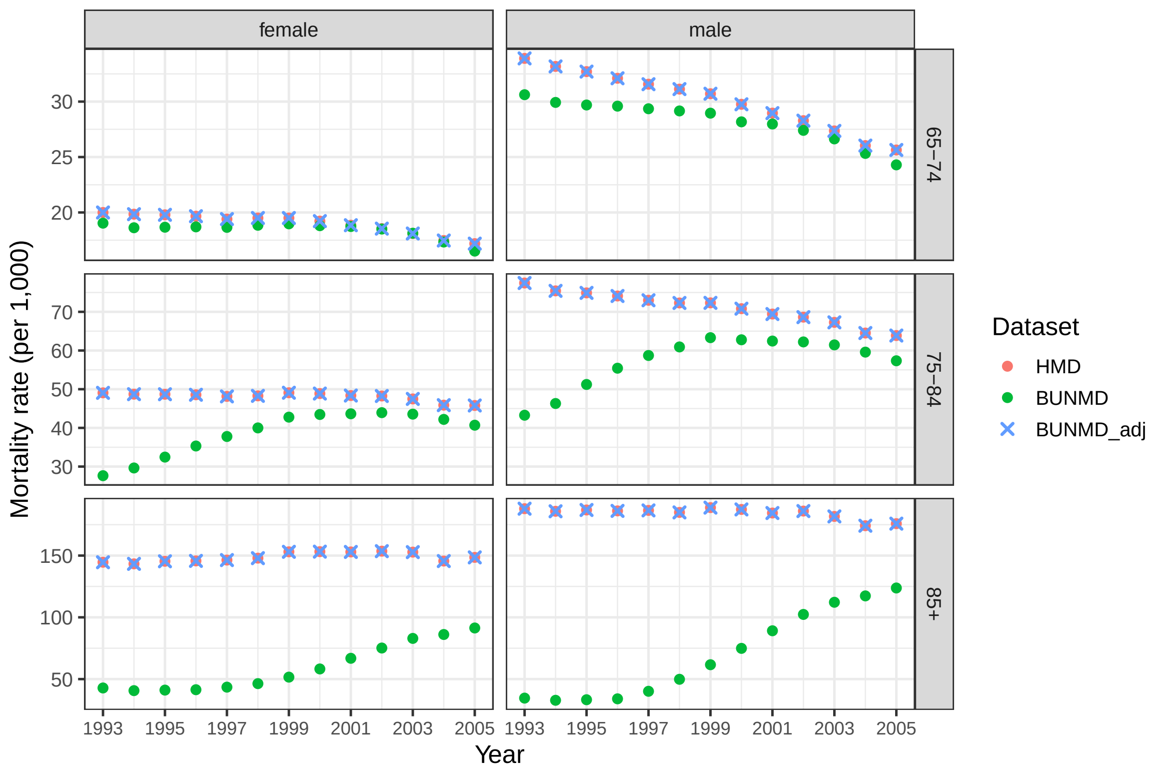
Tables A2 and A3 report results from the main analysis.

Figure A1. BUNMD after accounting for missings



Note: The figure exposes the total sample of death counts for individuals aged above 65 from 1980 to 2007 in the BUNMD dataset after accounting for missing values and compared to the estimates from the HMD.

Figure A2. BUNMD and HMD mortality rates (per 1,000) by sex and age-groups for the years 1993-2005, and BUNMD adjusted rates (BUNMD_adj) to match those of the HMD.



Notes: Authors own calculations based on data from [3] and [6].

Table A1. Descriptive Statistics

	Mean	SD	Min	Max
Mortality and population:				
Sum death adjusted	3.21	13.24	0.00	1,086.30
Tot population adjusted	63.18	266.36	0.01	14246.93
Temperature bins:				
< 1st percentile	0.25	0.93	0.00	15.00
1st to 5th percentile	1.18	2.54	0.00	21.00
5th to 10th percentile	1.56	2.65	0.00	19.00
10th to 90th percentile	24.60	6.49	0.00	31.00
90th to 95th percentile	1.47	2.78	0.00	23.00
95th to 99th percentile	1.14	2.77	0.00	29.00
> 99th percentile	0.25	1.08	0.00	20.00
Control Variables:				
PM2.5	10.68	4.52	0.18	54.99
Solar radiation	186.28	71.50	33.14	369.77
Wind	3.94	0.79	1.30	10.41
Precipitation	2.83	2.04	0.00	36.25
Specific Humidity	0.01	0.00	0.00	0.02
Unemployment rate	5.67	2.79	0.40	43.00
Median household income	34,952.86	9,526.19	10,510.00	100,077.58
SNAP beneficiaries	8,454.20	29,334.87	1.00	1,045,474.00
Observations:				
N. Counties	3,084			
N. County-years	7,026,032			

Note: We report summary statistics for the monthly values of the variables in our main analysis.

Table A2. Temperature and mortality

	(1)
Temperature bins:	
< 1st percentile	0.0019*
	(0.0008)
1st to 5th percentile	0.0016*
	(0.0007)
5th to 10th percentile	0.0023*
	(0.0004)
90th to 95th percentile	0.0016*
	(0.0003)
95th to 99th percentile	0.0015*
	(0.0003)
> 99th percentile	0.0031*
	(0.0006)
Control Variables:	
Male	0.3567*
	(0.0026)
75-84	0.8803*
	(0.0028)
85+	1.938*
	(0.0060)
Black	0.1372*
	(0.0094)
Other	-0.6991*
	(0.0407)
Precipitation	0.0002
	(0.0005)
Solar Radiation	-0.00004
	(0.00004)
Specific Humidity	-11.00***
	(1.389)
Wind	-0.0073***
	(0.0018)
Log PM25	0.0140***
	(0.0031)
Log Unemployment rate	-0.0189*
	(0.0080)
Log SNAP beneficiaries	0.0500***
	(0.0105)
Log Median household income	-0.0534
	(0.0457)
Counties	3,084
Observations	7,026,032

Note: Estimates are obtained by estimating Equation (1). Standard errors clustered at the county level and reported in parenthesis. Constant present but not reported. Moreover, we introduced month-year and county-month FE. * $p<0.05$

Table A3. Temperature and mortality by race

	(1)
< 1st percentile	0.0021**
	(0.0008)
< 1st percentile*Black	-0.0029
	(0.0016)
< 1st percentile*Other	0.0015
	(0.0025)
1st to 5th percentile	0.0016*
	(0.0007)
1st to 5th percentile*Black	0.0007
	(0.0007)
1st to 5th percentile*Other	-0.0028
	(0.0015)
5th to 10th percentile	0.0016*
	(0.0007)
5th to 10th percentile*Black	-0.0029*
	(0.0006)
5th to 10th percentile*Other	0.0028*
	(0.0012)
90th to 95th percentile	0.0015*
	(0.0003)
90th to 95th percentile*Black	0.0017*
	(0.0006)
90th to 95th percentile*Other	-0.0010
	(0.0010)
95th to 99th percentile	0.0014*
	(0.0004)
90th to 95th percentile*Black	0.0022*
	(0.0008)
90th to 95th percentile*Other	-0.0027
	(0.0016)
> 99th percentile	0.0024*
	(0.0006)
99th percentile*Black	0.0039*
	(0.0016)
99th percentile*Other	0.0089
	(0.0051)
Counties	3,084
Observations	7,026,032

Note: Estimates are obtained by estimating Equation (2). Whites are the baseline category. Standard errors clustered at the county level and reported in parenthesis. Constant present but not reported. The model includes all control variables but these are not reported. Moreover, we introduced month-year and county-month FE. * p<0.05

1.b Temperature, age, gender and climatic regions

In this section, we test how the effect of temperature is stratified by race and other relevant characteristics. An individual characteristic that determines a higher risk to extreme temperature is age. Adding a three way interaction with race we find a larger effect of heat on the eldest Blacks in Table A4. Previous studies have shown women to be more vulnerable to the exposure to heat[1], but there is also contrasting evidence[7]. We tested a three-way interaction with gender, race and temperature but did not find any substantive results (Table A5). Finally, we run analysis with an interaction with the climatic regions in Figure A3 observing the highest increase in mortality in North West relative to the center. In Table A6 we provide the three-way interaction with climatic regions, temperature and race that we described in the main text.

Table A4. Temperature and mortality by age categories and race

	(1)
Cold(< 1st):	
x 65-74	0.0021* (0.0010)
x 65-74 x Blacks	-0.0056** (0.0021)
x 65-74 x Other	-0.0009 (0.0044)
x 75-84	-0.0016. (0.0008)
x 75-84 x Blacks	0.0024 (0.0024)
x 75-84 x Others	-0.0007 (0.0052)
x 85+	0.0017 (0.0012)
x 85+ x Blacks	0.0055 (0.0039)
x 85+ x Others	0.0059 (0.0065)
Heat(> 99th):	
x 65-74	0.0019* (0.0007)
x 65-74 x Blacks	0.0017 (0.0021)
x 65-74 x Other	0.0066 (0.0053)
x 75-84	5.37e-5 (0.0008)
x 75-84 x Blacks	-0.0010 (0.0025)
x 75-84 x Others	-0.0018 (0.0041)
x 85+	0.0014 (0.0012)
x 85+ x Blacks	0.0073* (0.0033)
x 85+ x Other	0.0079 (0.0059)
Counties	3,084
Observations	7,026,032

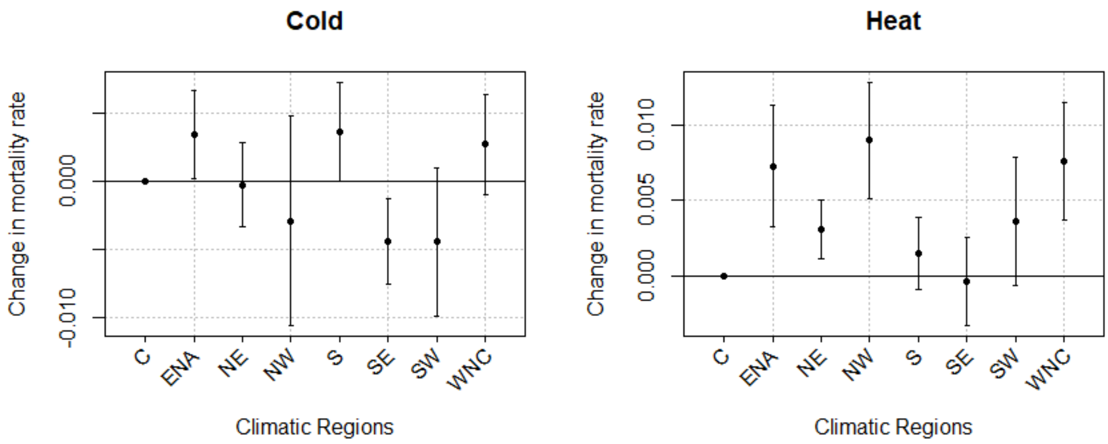
Note: Estimates are obtained by estimating Equation (2), but with an interaction with age categories and race. Standard errors clustered at the county level and reported in parenthesis. Whites are the reference category. For simplicity only the three-way interactions for temperatures < 1st and >99th percentile are reported. The age category 65 to 74 is at the baseline. Constant present but not reported. Moreover, we introduced month-year and county-month FE. * p<0.05

Table A5. Temperature and mortality by gender and race

	(1)
Cold(<1st percentile):	
x Male	-0.0016. (0.0008)
x Male x Black	0.0049. (0.0028)
x Male x Other	0.0006 (0.0050)
Heat(>99th percentile):	
x Male	0.0005 (0.0008)
x Male x Black	-0.0022 (0.0026)
x Male x Other	0.0086 (0.0050)
Counties	3,084
County-months	7,026,032

Note: Estimates are obtained by estimating Equation (2), but with an interaction with gender and race. Standard errors clustered at the county level and reported in parenthesis. For simplicity only the three-way interactions for temperatures < 1st and >99th percentile are reported. Constant present but not reported. We introduce all control variables but these are not reported. Moreover, we use month-year and county-month FE. The category female is the baseline level. * p<0.05

Figure A3. Effect of days <1st and >99th percentile on mortality by climatic regions



Note: The figure exposes estimates are obtained by estimating Equation (2), but with an interaction with climatic regions. Standard errors clustered at the county level. 95% Confidence intervals. The category Central is the baseline level.

Table A6. Temperature and mortality by race and climatic regions

	(1)
Cold(< 1st):	
East North Central x < 1st	-0.0028 (0.0020)
x Blacks x <1st	-0.0007 (0.0061)
x Others x < 1st	0.0154 (0.0191)
Northeast x < 1st	-0.0059* (0.0022)
x Blacks x < 1st	-0.0082 (0.0051)
x Others x < 1st	-0.0196 (0.0132)
Northwest x < 1st	-0.0083* (0.0037)
x Blacks x < 1st	-0.0156* (0.0070)
x Other x < 1st	0.0067 (0.0174)
South x < 1st	-0.0030 (0.0020)
x Blacks x < 1st	0.0042 (0.0051)
x Other x < 1st	-0.0050 (0.0141)
Southeast x <1st	-0.0115* (0.0019)
x Blacks x < 1st	0.0057 (0.0044)
x Other x < 1st	0.0014 (0.0130)
Southwest	-0.0091* (0.0034)
x Blacks x < 1st	0.0098 (0.0260)
x Other x < 1st	-0.0397* (0.0189)
West North Central x < 1st	-0.0062* (0.0022)
x Blacks x < 1st	0.0083 (0.0058)
x Other x < 1st x dr1	0.0104 (0.0127)
Heat(> 99th):	
East North Central x > 99th	0.0037 (0.0021)
x Blacks x >99th	0.0106* (0.0040)
x Other x >99th	0.0293* (0.0137)
Northeast x >99th	0.0002 (0.0014)
x Blacks x >99th	-0.0012 (0.0034)
x Other x >99th	-0.0086 (0.0086)
Northwest x >99th	0.0065* (0.0022)
x Blacks x >99th	-0.0054 (0.0070)
x Other x >99th	-0.0143 (0.0164)
South x >99th	-0.0020 (0.0016)
x Blacks x >99th	-0.0027 (0.0040)
x Other x >99th	-0.0045 (0.0086)
Southeast x >99th	-0.0042 (0.0022)
x Blacks x >99th	-0.0001 (0.0058)
x Other x >99th	0.0230 (0.0142)
Southwest x >99th	0.0023 (0.0026)
x Blacks x >99th	-0.0204* (0.0100)
x Other x >99th	-0.0242* (0.0089)
West North Central x >99th	0.0034 (0.0021)
x Blacks x >99th	0.0004 (0.0047)
x Other x >99th	0.0010 (0.0091)
Counties	3,084
Observations	7,026,032

Note: Estimates are obtained by estimating Equation (2) with an additional interaction with the climatic regions. Whites are the baseline race category. Moreover, central is the baseline climatic region and coefficients should be interpreted relative to it. For simplicity only the three-way interactions for temperatures < 1st and >99th percentile are reported. Standard errors clustered at the county level and reported in parenthesis. Constant present but not reported. The model includes all control variables but these are not reported. Moreover, we introduced month-year and county-month FE. * p<0.05

1.c Alternative RCP scenarios and excess deaths

Table A7. Excess deaths and mortality rate in 1993-2005 if temperature were to raise to mid century RCP4.5 projected levels. *Notes*: Estimates are obtained by predicting the number of deaths based on Equation (2) using data on end of century temperatures(2051-2055) based on the RCP8.5 emission scenario.

	Observed deaths	Simulated deaths	Excess deaths	Total exposure	Excess rate (per 100,000)
White	19,633,036	19,719,715	86,678	374,910,265	23
Black	2,128,672	2,173,325	44,652	36,189,516	123
Other	797,371	819,485	22,114	32,797,250	67
Total	22,559,081	22,712,527	153,446	443,897,033	35

Table A8. Excess deaths and mortality rate in 1993-2005 if temperature were to raise to end of century projected levels. *Notes*: Estimates are obtained by predicting the number of deaths based on Equation (2) using data on end of century temperatures(2086-2100) based on the RCP4.5 emission scenario.

	Observed deaths	Simulated deaths	Excess deaths	Total exposure	Excess rate (per 100,000)
White	19,633,036	19,688,679	55,642	374,910,265	14
Black	2,128,672	2,157,231	28,559	36,189,516	78
Other	797,371	809,578	12,207	32,797,250	37
Total	22,559,081	22,655,489	96,408	443,897,033	21

Table A9. Excess deaths and mortality rate in 1993-2005 if temperature were to raise to end century projected levels. *Notes*: Estimates are obtained by predicting the number of deaths based on Equation (2) using data on end of century temperatures(2086-2100) based on the RCP8.5 emission scenario.

	Observed deaths	Simulated deaths	Excess deaths	Total exposure	Excess rate (per 100,000)
White	19,633,036	19,809,730	176,693	374,910,265	47
Black	2,128,672	2,207,419	78,746	36,189,516	217
Other	797,371	842,450	45,079	32,797,250	137
Total	22,559,081	22,859,599	300,519	443,897,033	67

Table A10. Excess deaths and mortality rate in 1993-2005 if temperature were to raise to mid century projected levels based on RCP4.5 scenario by race and age categories.

Race	Age group	Obs. death	Simulated deaths	Excess deaths	Total Exposure	Excess rate
White	65-74	4,868,686	4,881,273	12,586	197,921,199	6
White	75-84	7,663,153	7,682,685	19,532	132,526,098	15
White	85+	7,101,197	7,118,185	16,988	44,462,967	38
Black	65-74	622,618	631,366	8,748	21,128,774	41
Black	75-84	792,204	803,372	11,167	11,383,775	98
Black	85+	713,850	724,230	10,380	3,676,966	282
Other	65-74	269,815	273,967	4,152	20,663,325	20
Other	75-84	299,811	304,749	4,938	9,574,592	52
Other	85+	227,745	231,747	4,002	2,559,332	156
Total		22,559,081	22,648,574	89,493	443,897,033	20

Notes: Estimates are obtained by predicting the number of deaths based on Equation(2) using mid century temperatures(2051-2055) based on the RCP4.5 emission scenario by age groups and race. The excess rate is multiplied by 100,000.

1.d Sensitivity analysis

In the literature different operationalizations of extreme temperatures have been used. For example, the highest and lowest percentiles have been alternatively used as the 10th and 90th[4]; 1st and 99th[8]; 5th and 95th[5]. We show results using 5th and 95th percentile bins as the extreme categories in Table A11. As expected, estimates show to be in the same direction but smaller to those found in the main analysis of Table A2 and Table A3. Additionally, several studies have captured exposure to temperature using fixed ranges for the whole national territory, instead of percentiles for the local temperature. For example, Barreca et al., (2016)[2] captured exposure to cold days with temperatures below 40°F(4.4°C), warm days with temperature between 80°F(26.6) to 89°F(31.6°C) and hot days with temperature above 90°F(32.2°C). We report results in Table A12. Our estimates for days above 90°F show an increase in the monthly mortality rate of 5 per 1,000 and are higher to the estimate of 3.4 per 1,000 found by Barreca et al., (2016)[2]. Similarly, for days betwen 80 to 89°F estimates show an increase in the monthly mortality rate of 3.4 per 1,000 that is larger to the 1.2 per 1,000 found by Barreca et al., (2016)[2]. Moreover, we found a smaller estimate for cold compared to the increase in monthly mortality of 3.4 per 1,000 of Barreca et al., (2016)[2] for days below 40°F. Possibly, the difference is determined by the addition of control variables such as race, specific humidity and air pollution that we included in our analysis, the broader number of temperature bins considered and the slighlty different time period.

Finally, we conducted a placebo test replicating results of Table A2 measuring the effect of temperatures in the 5 months after the actual death has been recorded. Results (Table A14 in Appendix) show opposite or not substantive effects corroborating our main results.

Table A11. Temperature and mortality with 5th and 95th percentile as extremes

	(1)
< 5th percentile	0.0017*
	(0.0006)
5th to 10th percentile	0.0023
	(0.0004)
90th to 95th percentile	0.0015*
	(0.0003)
> 95th percentile	0.0019*
	(0.0002)
Counties	3,084
Observations	7,026,032

Note: Estimates are obtained by estimating Equation 1. Standard errors clustered at the county level and reported in parenthesis. Constant present but not reported. We introduce all control variables but these are not reported. Moreover, we use month-year and county-month FE. * p<0.05

Table A12. Temperature and mortality with temperature ranges

	(1)
<30°F	0.0007
	(0.0004)
30 to 40°F	0.0005
	(0.0003)
70 to 80°F	0.0020*
	(0.0003)
80 to 89°F	0.0034*
	(0.0004)
>90°F	0.0050*
	(0.0008)
Counties	3,084
Observations	7,026,032

Note: Estimates are obtained by estimating Equation 1. Standard errors clustered at the county level and reported in parenthesis. Constant present but not reported. We introduce all control variables but these are not reported. Moreover, we use month-year and county-month FE. * $p<0.05$

Table A13. Temperature and mortality with alternative temperature bins

	(1)
<30°F	0.0005
	(0.0004)
<30°F*Black	0.0004
	(0.0004)
<30°F*Other	0.0060*
	(0.0016)
30 to 40°F	0.0006*
	(0.0003)
30 to 40°F*Black	-0.0013*
	(0.0006)
30 to 40°F*Other	-0.0012
	(0.0018)
70 to 80°F	0.0023*
	(0.0004)
70 to 80°F*Black	-0.0005
	(0.0004)
70 to 80°F*Other	-0.0057
	(0.0032)
80 to 89°F	0.0040*
	(0.0005)
80 to 89°F*Black	0.0008
	(0.0012)
80 to 89°F*Other	-0.0142*
	(0.0025)
>90°F	0.0037*
	(0.0009)
>90°F*Black	0.0077*
	(0.0038)
>90°F*Other	0.0087
	(0.0056)
Counties	3,084
Observations	7,026,032

Note: Estimates are obtained by estimating Equation 2, but with an interaction with race categories. Standard errors clustered at the county level and reported in parenthesis. Constant present but not reported. We introduce all control variables but these are not reported. White at the baseline level. Moreover, we use month-year and county-month FE. * $p<0.05$

Table A14. Temperature and mortality placebo

	(1) Placebo temperature
Placebo <1st percentile	0.0006
	(0.0006)
Placebo 1st to 5th percentile	-0.0005
	(0.0003)
Placebo 5th to 10th percentile	0.0008*
	(0.0004)
Placebo 90th to 95th percentile	0.0001
	(0.0003)
Placebo 95th to 99th percentile	0.0003
	(0.0003)
Placebo >99th percentile	0.0001
	(0.0006)
Counties	3,084
Observations	7,026,032

Note: Estimates are obtained by estimating Equation 1 with lead values of 5 months for exposure to temperature. Standard errors clustered at the county level and reported in parenthesis. Constant present but not reported. We introduce all control variables but these are not reported. Moreover, we use month-year and county-month FE. * $p<0.05$

References

[1] Achebak, H., Devolder, D., and Ballester, J. (2019). Trends in temperature-related age-specific and sex-specific mortality from cardiovascular diseases in Spain: a national time-series analysis. *The Lancet Planetary Health*, 3(7):e297–e306.

[2] Barreca, A., Clay, K., Deschenes, O., Greenstone, M., and Shapiro, J. S. (2016). Adapting to Climate Change: The Remarkable Decline in the US Temperature-Mortality Relationship over the Twentieth Century. *Journal of Political Economy*, 124(1):105–159.

[3] Breen, C. and Goldstein, J. R. (2022). Berkeley Unified Numident Mortality Database: Public administrative records for individual-level mortality research. *Demographic Research*, 47:111–142.

[4] Gasparrini, A., Guo, Y., Hashizume, M., Lavigne, E., Zanobetti, A., Schwartz, J., Tobias, A., Tong, S., Rocklöv, J., Forsberg, B., Leone, M., De Sario, M., Bell, M. L., Guo, Y.-L. L., Wu, C.-f., Kan, H., Yi, S.-M., de Sousa Zanotti Stagliorio Coelho, M., Saldiva, P. H. N., Honda, Y., Kim, H., and Armstrong, B. (2015). Mortality risk attributable to high and low ambient temperature: a multicountry observational study. *The Lancet*, 386(9991):369–375.

[5] Guo, Y., Gasparrini, A., Li, S., Sera, F., Vicedo-Cabrera, A. M., de Sousa Zanotti Stagliorio Coelho, M., Saldiva, P. H. N., Lavigne, E., Tawatsupa, B., Punnasiri, K., Overcenco, A., Correa, P. M., Ortega, N. V., Kan, H., Osorio, S., Jaakkola, J. J. K., Ryti, N. R. I., Goodman, P. G., Zeka, A., Michelozzi, P., Scortichini, M., Hashizume, M., Honda, Y., Seposo, X., Kim, H., Tobias, A., Íñiguez, C., Forsberg, B., Åström, D. O., Guo, Y. L., Chen, B.-Y., Zanobetti, A., Schwartz, J., Dang, T. N., Van, D. D., Bell, M. L., Armstrong, B., Ebi, K. L., and Tong, S. (2018). Quantifying excess deaths related to heatwaves under climate change scenarios: A multicountry time series modelling study. *PLOS Medicine*, 15(7):e1002629.

[6] HMD (2021). Human Mortality Database. *University of California, Berkeley (USA), and Max Planck Institute for Demographic Research (Germany).*

[7] Son, J.-Y., Liu, J. C., and Bell, M. L. (2019). Temperature-related mortality: a systematic review and investigation of effect modifiers. *Environmental Research Letters*, 14(7):073004.

[8] Zanobetti, A., O'Neill, M. S., Gronlund, C. J., and Schwartz, J. D. (2013). Susceptibility to Mortality in Weather Extremes: Effect Modification by Personal and Small Area Characteristics In a Multi-City Case-Only Analysis. *Epidemiology (Cambridge, Mass.)*, 24(6):809–819.