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Impact of extreme temperatures on emergency hospital admissions by age and socio-economic deprivation in England

Dheeya Rizmie [a,*], Laure de Preux [a], Marisa Miraldo [a], Rifat Atun [b]

[a] *Centre for Health Economics & Policy Innovation, Department of Economics & Public Policy, Imperial College Business School, UK*
[b] *Harvard T.H. Chan School of Public Health, Harvard Medical School, Harvard University, USA*

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ABSTRACT

Climate change poses an unprecedented challenge to population health and health systems' resilience, with increasing fluctuations in extreme temperatures through pressures on hospital capacity. While earlier studies have estimated morbidity attributable to hot or cold weather across cities, we provide the first large-scale, population-wide assessment of extreme temperatures on inequalities in excess emergency hospital admissions in England. We used the universe of emergency hospital admissions between 2001 and 2012 combined with meteorological data to exploit daily variation in temperature experienced by hospitals (N = 29,371,084). We used a distributed lag model with multiple fixed-effects, controlling for seasonal factors, to examine hospitalisation effects across temperature-sensitive diseases, and further heterogeneous impacts across age and deprivation. We identified larger hospitalisation impacts associated with extreme cold temperatures than with extreme hot temperatures. The less extreme temperatures produce admission patterns like their extreme counterparts, but at lower magnitudes. Results also showed an increase in admissions with extreme temperatures that were more prominent among older and socioeconomically-deprived populations - particularly across admissions for metabolic diseases and injuries.

1. Introduction

Climate change is recognised as the biggest global threat of the 21st century (Watts et al., 2015). Between 2000 and 2016, there was a global increase of 125 million vulnerable people over the age of 65 years exposed to heatwaves (Watts et al., 2017). While not all conditions are heat- or cold-sensitive, temperature shocks have been found to impact mortality and morbidity across certain diseases (e.g. Schwartz et al., 2004; Sugg et al., 2016).

The human body has a thermoregulatory system that monitors thermal stress and maintains thermal comfort (Heal and Park, 2016). One adapts to extreme temperatures by inducing vasodilation, or vasoconstriction, to facilitate, or minimise, heat loss. For example, under sustained heat, thermoregulatory mechanisms are pushed into thermal stress; increasing blood viscosity and cholesterol levels (Kovats and Hajat, 2008). Various thermal stimuli can invoke different shocks on the immune system, which remains largely understood (Repasky et al., 2013). Therefore, temperature-related hospitalisations likely extend beyond mortality and morbidity alone, and include not only direct heat, or cold, stress, but also exacerbations of pre-existing diseases of respiratory and cardiovascular systems. These physiological mechanisms mean that circulatory, respiratory, metabolic, and neoplastic-diseases, for example, are clinically vulnerable to temperature shocks (White, 2017; Karlsson and Ziebarth, 2018; Basu and Samet, 2002; Li et al., 2015). Given the high prevalence of these conditions at population level (Watts et al., 2017), increased acute events associated with these conditions will meaningfully impact care needs at population level.

As a result, amongst a multitude of potential social impacts, extreme weather shocks can challenge health systems' resilience and ability to anticipate external threats, which are crucial to ensure service delivery and responsiveness. Extreme weather events produce excessive fluctuations in the demand for hospital care. While hospital patient flows typically follow seasonal patterns, extreme temperature events can create unexpected variations in unscheduled patient admissions. Heatwaves are projected to increase in frequency and intensity by 5- to 10-fold over the next 40 years (Goodess, 2013). As we expect more

Abbreviations: NHS, National Health Service; SES, Socioeconomic Status; HES, Hospital Episode Statistics; MIDAS, Met Office Integrated Data Archive System; IMD, Index of Multiple Deprivation; LSOA, Lower Layer Super Output Area; ICD, International Statistical Classification of Diseases.

* Corresponding author.
E-mail address: dheeya.rizmie14@imperial.ac.uk (D. Rizmie).

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frequent weather events surging healthcare demand, it becomes of increasing importance to measure capacity pressures brought about these events and how they vary across the population.

A hospital's capacity to respond to increasing numbers of emergency admissions has been a contentious topic. Over the past few decades, hospitals in the National Health Service (NHS) in England have been under pressure to reduce capacity to improve efficiency (National Audit Office, 2014). With bed occupancy rates above 90% under standard care (The King's Fund, 2020), any unplanned deviation in the demand for treatment poses a concern to the NHS due to the financial and operational pressures they place on hospitals with constrained resources. These pressures have consequent effects on planned care, particularly during extreme weather shocks. For example, many hospitals found it difficult to cope with levels of demand for services in the winter of 2012–13 resulting in cancellations of elective care (National Audit Office, 2013). Therefore, it is important to assess how patient flows vary with external shocks, such as those posed by climate change.

The threat of climate change sparks recent literature to show sensitivity of numerous outcomes (e.g. psychological, economic, health) to weather (Dell et al., 2012). Studies in economics (Deschênes and Moretti, 2009; White, 2017; Karlsson and Ziebarth, 2018) and epidemiology (Basu et al., 2012; Ye et al., 2012) have empirically assessed the impact of extreme temperatures on mortality. While studies have explored morbidity impacts on specific diseases (e.g. Schwartz et al., 2004; Sugg et al., 2016), in specific geographical areas (e.g. Sugg et al., 2016; Basu et al., 2012), or on only one end of the temperature spectrum (e.g. Vaidyanathan et al., 2019; Sugg et al., 2016; Wang et al., 2016), the effects of extreme temperatures on healthcare utilisation, the differential impact on different socioeconomic and age groups, and the equity consequences have largely been overlooked. Temperature-related changes in morbidity are likely to translate into shocks in the demand for healthcare across all levels of health services (i.e. primary care, elective admissions, etc). Hence, analyses of such outcomes are also important, as not only do they provide an insight into the overall effects of extreme temperatures on health, but allow for an understanding of how health systems have to respond to potential shocks.

Therefore, we estimated heterogeneous relationships between extreme temperatures and emergency hospital admissions of selected diseases in England over the period 2001–12. Specifically, we exploited random daily and geographical variation in temperature across NHS Trusts (henceforth *hospitals*) to document how emergency hospital admissions respond to extreme temperatures on the day of the event, as well as the following 30-day period.

It is plausible that the effects of extreme temperatures are experienced differently across population subgroups, with the corresponding risk being disproportionately borne by the most vulnerable. Earlier studies found that the elderly are more prone to weather-related mortality (Basu and Samet, 2002; Karlsson and Ziebarth, 2018). Urbanisation and subsequent changes in living standards have produced different exposures and disease risk among different socioeconomic and demographic groups (Paciência and Moreira, 2017). Such populations also experience differential susceptibility to non-communicable diseases, such as cardiovascular disorders. Therefore, given an ageing population and widening socioeconomic inequalities (Steel et al., 2018; The Lancet, 2017), it is crucial to model the effects of extreme temperature on demand for weather-sensitive hospital services by different age and socioeconomic groups.

Consequently, we further assessed the heterogeneity of temperature effects on admissions by age and socioeconomic deprivation across six different diseases most vulnerable to weather-induced thermoregulatory changes in the body.

This study makes two contributions to the existing literature. Most studies explore temperature impacts on mortality, often at an aggregate level (e.g. Deschênes and Moretti, 2009; Deschênes and Greenstone, 2011). Whilst mortality captures the most severe health-impacts related to temperature shocks, it remains a crude estimate in understanding and preparing for associated surges in hospital utilisation. As a result, the effects of temperature on nonfatal health outcomes, such as morbidity or hospital admissions, have been excluded from most climate impact assessments (Watts et al., 2017). Whilst research into a temperature-morbidity relationship has been evolving, it remains primarily focused around specific weather events or specific cities over time (e.g. Basu and Samet, 2002; Hajat et al., 2007), and remains restricted in generalisibility.

Two notable exceptions are the contributions of Karlsson and Ziebarth (2018), studying the impacts of temperature on mortality and morbidity in Germany, and White (2017), studying the impacts of temperature on morbidity in California. Both papers use hospitalisations to explore these impacts across disease categories and age groups over a significant period of time. However, the geographical heterogeneity across countries' population characteristics, meteorological profiles, and health-seeking behaviours emphasises the importance of quantifying these effects in each country. Therefore, we add to this literature in that we develop reliable reduced-form estimates for the effects of temperature on emergency hospital admissions for six high-volume disease categories that are nationally representative to England at the provider level. Notably, focusing on the NHS also enables a better identification of the effects of temperature on hospitalisations controlling for potential confounders, on the supply- and demand-side, that may impact healthcare utilisation. In the NHS healthcare is free at the point of use and patients don't choose where to receive emergency care — therefore, we can abstract from demand-side affordability considerations that may impact care utilisation. Furthermore, all hospitals in the NHS are centrally managed and funded, operate under the same financial incentives, and physicians are salaried with their payment neither dependent on the care provided nor on the volumes of patients seen. Accordingly, there are limited, if any, supply-side incentives that could influence hospital activity as there would be in other healthcare systems. Thus, using data for the NHS in England enables mitigating important endogegeneity issues that may arise in the identification of the impact of temperature events on hospital admissions.

Our second contribution relates to a broader literature that measures equity and inequality impacts of climate change on hospitalisations (Carleton et al., 2020; Hsiang et al., 2019). It has been speculated that the risk posed by temperature extremes is not of the same magnitude across age and individual socioeconomic status (SES) (Barr et al., 2017). Their relationships with morbidity have been largely underexplored. Karlsson and Ziebarth (2018) suggest that there is a progressive increase in risk of disease following a hot day from individuals aged over 50 years, while White (2017) provides evidence that those under 5 years are the most vulnerable to cold and hot temperatures. Together, their studies suggest that there could be underlying heterogeneity of temperature effects that are unique to each population across age. Furthermore, SES is often a contributor to health inequities. Addressing this gap in our understanding of temperature effects, for age and SES, is crucial in allowing interventions to be designed effectively — particularly when targeting the most vulnerable. Therefore, we investigate the temperature-hospitalisations relationship separately for nine age groups and quintiles of SES deprivation at the patient level.

We found that a day of extreme heat conferred the largest effect on admissions related to metabolic diseases, increasing emergency admissions per hospital by 25.8% on the day of the event, relative to a 10–15°C day, which was the largest effect across the six diseases considered. The largest effect on admissions from a day of extreme cold was observed for injuries with an increase of approximately 20.9% per hospital on the day of the event, relative to a 10–15°C day. The contemporaneous and average cumulative effects confirmed that demand for healthcare was affected by both hot and cold weather. Effects were stronger and larger for the elderly and more deprived populations.

2. Data

We used the universe of emergency inpatient hospital admissions (N = 29,371,084) from the Hospital Episode Statistics (HES) provided by NHS Digital (NHS Digital, n.d.). Each observation relates to a hospital episode and includes details on admission type (e.g. admission date, illness classification), patient characteristics (e.g. age, gender, and deprivation), and hospital characteristics (e.g. hospital type, postcode). As HES is a discharge dataset, we built a balanced panel by adding dates with zero admissions when these were observed for hospitals on a specific day.

Meteorological data were obtained from the Met Office Integrated Data Archive System (MIDAS) (Met Office, 2012). The dataset contains daily weather measurements, such as daily air temperatures and rainfall, recorded by 579 stations, providing 8,145,763 observations over our study period. We assigned temperature exposure at hospital level as, under the NHS Choice Framework, individuals do not have legal rights to hospital choice if urgent treatment is required (NHS, 2016). Therefore, the temperature experienced in the geographical area of where the hospital is located is representative of that experienced by each patient and is unlikely to gravitate within the surrounding location of the hospital.

We began with data on hospital episodes to the NHS, measured at the patient level. We collapsed these observations at hospital level by each subgroup analysed to obtain the daily admissions per group. We merged daily admissions with daily temperature and rain using inverse squared distance weighted averages to each hospital postcode from 1st April 2001 to 31st March 2012. This study covers 11 fiscal years which include seven of the ten hottest years on record (UK Met Office, 2019).

For each patient admission, we further observed patient age and residential deprivation level. Patient age at admission was measured in age bands (<5, 5–14, 15–24, 25–34, 35–44, 45–54, 55–64, 65–74, and >74). This grouping was used to understand the temperature effect for each age-group and for further analysis of the heterogeneous effects by age-disease and age-deprivation. A patient's deprivation level was designated using the Index of Multiple Deprivation (IMD) score of the patient's residential postcode at the time of admission. The IMD is commonly used as a proxy of individual deprivation and is a weighted measure constructed of seven subdomains of deprivation reported across England. The IMD is defined for lower layer super output areas (LSOAs), defined as areas with a population of about 1500 people. Population classes' thresholds were determined using the IMD distributions obtained from Communities and Local Government National Archives for census year 2011 (The National Archives, n.d.). As a result, each IMD variable is categorical taking on values from one to five, which correspond to the quintile of deprivation the patient falls into. Quintile one is the least deprived group, while quintile five represents the most deprived. Using the quintiles for each subdomain, we were able to investigate the temperature effect for the extreme ends of deprivation. See Appendix A for further information on the IMD.

Our outcome variable was the number of hospital emergency hospital admissions per day, per hospital, and per main diagnosis. We used emergency admissions as they were more likely to represent actual 'health shocks' and to observe the most severe effects of extreme temperatures, aside from death. We removed admissions that were transferred from one hospital to another (less than 0.03% of observations). As our objective was not to identify possible or new conditions sensitive to temperatures, but instead estimate the impact of temperature shocks on hospital services, we restricted our analysis to diseases for which there is established evidence of being directly affected by temperature. Our primary analysis focused on six diseases, selected as they are considered to be health conditions most sensitive to temperature (White, 2017; Karlsson and Ziebarth, 2018; Basu and Samet, 2002). Using all admissions as our outcome variable would impose noise in the estimates, given that several conditions are not weather-sensitive. We leveraged this understanding to select disease categories that are clinically relevant to changes in temperature (White, 2017; Karlsson and Ziebarth, 2018; Basu and Samet, 2002). We used disease codes as classified by the International Statistical Classification of Diseases (ICD-10) codes *A00-B99* (Infectious Diseases), *E00-E89* (Metabolic Diseases), *C00-D48* (Neoplastic Diseases), *J00-J99* (Respiratory Diseases), *I00–I99* (Circulatory Diseases), and *S00-T14* (Injuries). These conditions are also high-volume conditions and, therefore, representative of changes in patients' flows caused by external shocks that are likely to be meaningful for hospital capacity management. Over our period of analysis, the six ICD codes constituted 48.22% of all emergency admissions annually.

The primary variables of interest were nine five-degree (Celsius, °C) daily temperature bins, constructed using maximum and minimum temperatures, ranging from under −5°C (lowest bin, referred to as an *extreme cold day*) to over 30 °C (highest bin, referred to as an *extreme heat day*). See Appendix B for further details on variable construction. In section 3, we use these definitions to quantify the cumulative effects of extreme hot and cold days. The annual number of *extreme hot and cold* days is skewed and exhibits substantial variation with many hospitals experiencing many *extreme cold* days per year. Fig. 1 illustrates how our identifying variation roots from the majority of hospitals and not just a small subset clustered in "cold" counties. Thus, findings are not driven solely by a subsample of hospitals experiencing extreme cold (Deschênes and Greenstone, 2011; Dell et al., 2012). Extreme heat days and extreme cold days represent 0.12% and 0.52% of our hospital-day sample, respectively. As daily temperature is defined at the hospital level, we preserved spatial variation in temperature to allow for the identification of its effects. The 10–15°C bin is used as the reference category, as average daily temperature falls in this bin, consequently, all estimates are interpreted as the number of excess admissions (henceforth described as *excess admissions*) on a day in the given temperature range relative to a day in the 10–15 °C range. The coefficient on this variable semi-parametrically describes the temperature-admissions relationship, net of seasonal influences and other confounders. We tested this indicator variable in Appendix S. Fig. 2 plots the distributions of (i) the maximum daily and (ii) minimum daily hospital-level temperatures. The figure shows that maximum and minimum temperatures follow a bimodal distribution. The substantial overlap in their distribution supports the construction of a combined variable to accurately capture the extremes, which are not represented by the use of only the maximum, minimum, or mean temperatures.

The mean age of patients admitted was 58.4 years, with 43% of admissions occurring in those aged over 74 years old. More admissions occurred among males (52%) than females (n = 14,098,121) (48%). The average overall number of admissions, with one of the six diagnoses above, was 44.43 (SD 27.1) per day per NHS hospital. See Table 1 and Appendix C Tables 2–3 for further summary statistics.

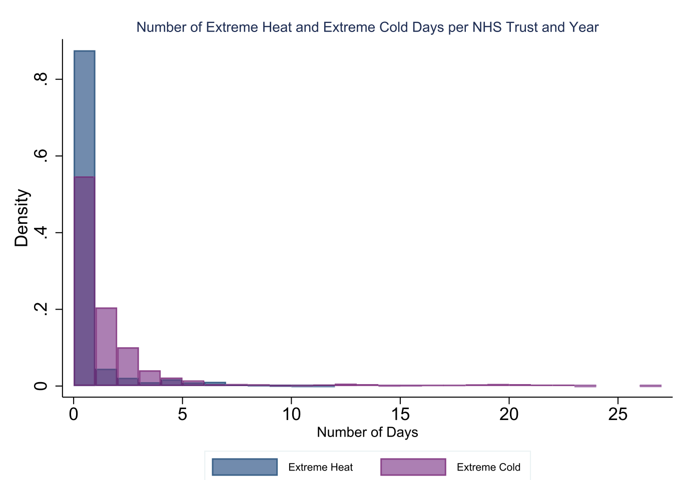

Fig. 1. Number of extreme heat and extreme cold days.

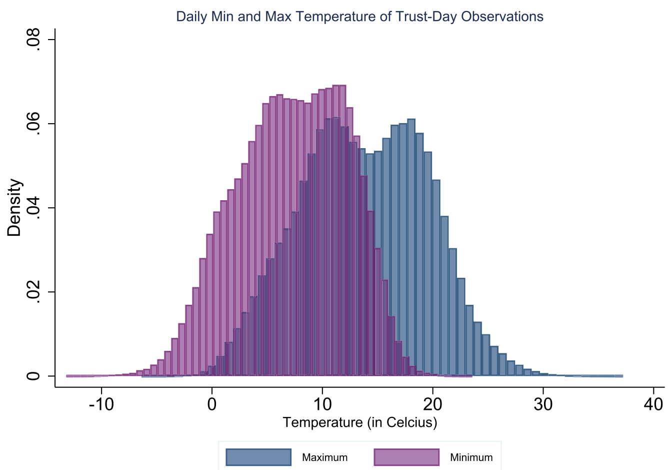

Fig. 2. Minimum and maximum temperatures (in °C).

3. Identification and empirical specification

To identify the effect of temperature, we exploited exogenous variation in daily temperatures across hospitals and years and built on the panel approach of Deschênes and Greenstone (2011). Our focus on England allows for an improved identification of temperature effects on hospital utilisation as the nature of the English health system mitigates concerns of heterogeneous management policies, financially-linked hospital activity, and hesitant health-seeking behaviour associated with affordability of care. Given that weather variation is exogenous to hospital admissions, this strategy allowed us to use hospitals in dates without weather-related events as a counterfactual for hospitals that do have events that day, after accounting for fixed differences between the hospitals and common time effects. The key assumption is that the exact timing of a temperature event on a given day is as good as random. We argue this is plausible, given the idiosyncrasies and random variation of weather (Karlsson and Ziebarth, 2018; White, 2017). Naturally, many hospitals had multiple events over the period of the analyses.

Using panel data, we employed a distributed lag Poisson regression model with multiple fixed effects to estimate the impact of temperature on daily emergency admissions, and for the 30 days following the last day with a temperature falling into an extreme temperature bin. The choice of a lag of 30 days was informed by temperature-mortality literature and findings suggest that the effects do not persist beyond this period (Karlsson and Ziebarth, 2018; White, 2017).

The goal was to estimate the effect of temperature on day d on admissions, and for 30 days that follow:

$$log(Y_{jid}) = \alpha + \sum_{h\in(\leq-5,..,\geq30)} \beta_h Temperature^{h}_{jd} + \sum_{l=1}^{30} \pi_l Temperature^{\geq30}_{jl} + \sum_{c=1}^{30} \eta_c Temperature^{\leq-5}_{jl} + S_d + \sigma_{Hospital} + \tau_{Hospital-FiscalYear} + \zeta_{jd} Rain_{jd} + \varepsilon_{jid} \quad (1)$$

where Y_{jid} was the number of emergency admissions for hospital, j with diagnosis code i per day, d.

$Temperature^{h}_{jd}$ were a series of regressors that equal 1 if the daily temperature at hospital j falls into a predefined temperature bin and zero otherwise. These were our primary variables of interest. Consequently, the exponents of these coefficients β_h semi-parametrically described the temperature-admissions relationship as incidence risk ratios (IRR), net of seasonal influences and hospitals' characteristics. For an estimated IRR of 1.092 on the ≥30°C temperature bin on hospitalisations related to respiratory diseases, the interpretation is: a day above 30°C is associated with an increase in incidence risk of 1.092, or an increase of approximately 9.2% admissions per hospital on the day of the event, relative to a 10–15°C day. We considered this as the *contemporaneous effect* of temperature.

Furthermore, to account for potential confounders, we controlled for a set of hospital, seasonality, and hospital-year fixed effects. Seasonality was crucial for our analysis as admissions, health, and weather vary seasonally. S_d was a vector of seasonal effects controlling for cyclical variation (including day of week, month, fiscal year, school holiday and bank holiday fixed effects). These parameters also controlled for confounders of a seasonal nature, such as influenza and changes in hospital staffing. This approach was attractive because it does not impose any assumptions on how seasonal effects impact admissions, does not constrain the model to a specific functional form, and reduces the risk of specification errors. As seasonality was measured at a relatively fine scale, the flexibility inherited from such granular fixed effects also accounted for health changes that are driven by behavioural changes. For example, a day during summer holidays may be different from a typical day during term time in a behavioural sense (which could be related to health, e.g. injuries).

Hospital fixed effects ($\sigma_{Hospital}$) controlled for potential non-time varying differences in hospitals that can confound the main effect. Each hospital fixed effect was also interacted with fiscal year indicators ($\tau_{Hospital-FiscalYear}$) to capture unobservable hospital specific time-varying secular differences in hospitals, such as administrative hospital changes, changes in catchment population, socioeconomic deprivation, and varying hospital sizes. They also controlled for inter-annual and micro-climatic weather events (like El Niño) that can vary by hospital (and its surrounding area) and could potentially confound the main effect we

Table 1
Study Descriptive Statistics. Panel A summarises the number of admissions across all NHS hospitals. The daily weather variables shown in Panel B are measured across all monitoring stations across all NHS hospitals.

	Mean	SD	Min	Max	N
A. Hospital Characteristics					
Number of Admissions					
Infectious Diseases	2.91	2.83	0.00	38.00	659,156
Neoplasms	4.08	3.93	0.00	68.00	659,156
Metabolic Diseases	1.97	2.26	0.00	52.00	659,156
Circulatory Diseases	13.44	9.63	0.00	160.00	659,156
Respiratory Diseases	12.94	9.94	0.00	146.00	659,156
Injuries and Fractures	9.21	6.58	0.00	79.00	659,203
B. Environmental Characteristics					
Daily Rainfall (in mm)	2.18	3.83	0.00	75.51	695,667
Daily Temperature Difference (Max-Min, in °C)	6.51	2.52	0.05	21.81	695,667
Daily Maximum Temperature (in °C)	13.80	5.77	−6.39	37.23	695,667
Daily Mean Temperature (in °C)	10.54	5.25	−8.57	29.95	695,667
Daily Minimum Temperature (in °C)	7.28	5.00	−13.21	23.57	695,667

estimated.

Similarly, the unobserved time-varying effects are collectively captured as coefficients on their dummies (i.e. month, day of week, holiday and fiscal year). These capture the strong seasonal pattern of admissions and any time trends. These fixed effects also capture the expected admissions attributable to the seasonality of influenza, which correlates with month and academic dates. Thus, the inclusion of month fixed effects should absorb the seasonal pattern of influenza and its confounding relationship.

Overall, all these fixed effects ensure a conservative estimate of the effect of extreme temperatures.

$Temperature_{jl}^{\geq 30}$ and $Temperature_{jl}^{\leq -5}$ are indicator variables for up to 30 days following an extreme heat or extreme cold day at the hospital level. Therefore, the extreme heat lag effect is estimated for 30 days following an extreme heat day. Similarly, the extreme cold lag effect is estimated for 30 days following an extreme cold day. The distributed lag model decomposes the 30-day lag effect into daily effects following an extreme heat day or an extreme cold day. These variables are included to account for any delayed effects of extreme temperature.

$Rain_{jd}$ represents the precipitation (in mm) on day d at hospital j, and is included as a proxy to the effects of humidity as humidity is documented to influence admissions (Higuma et al., 2021). Finally, ε_{jid} represents the standard idiosyncratic disturbance term.

Equation (1) denotes the reduced-form relationship between temperature and emergency admissions. This includes documenting the total net effect of temperature on admissions by flexibly modelling temperature by including a series of indicator variables for temperature. The effects are calculated as separate and stratified regressions for each of our six disease categories using patient level characteristics to identify nine age groups, quintiles of IMD, and quintiles of IMD subdomains.

The cumulative effect following extreme temperature events is calculated by summing all coefficients, using the *lincom* command in Stata, on the lag indicator variable with the coefficient for an extreme hot or cold event from the distributed lag model. As these are a linear combination of coefficients, the calculation of the standard errors for these estimates does not require additional assumptions (Stock and Watson, 2011).

In all specifications, we used clustered and robust standard errors to account for heteroskedasticity and allow for arbitrary within-group correlations at the hospital level (Bertrand et al., 2004; Colin Cameron and Miller, 2015). We clustered over individual hospitals as they represent the unit of analysis.

All regressions were run using Stata MP 15.

3.1. Quantifying capacity occupied

To contextualise the impacts of temperature on hospital capacity, we used estimates from Equation (1) to identify the proportion of total beds occupied on days of extreme temperature. We calculated the number of extra admissions per hospital on a day of extreme heat or extreme cold for each disease (relative to the baseline number of admissions observed per hospital on a day of 10–15°C). After aggregating these additional admissions across all diseases, we then divided this by the total number of beds for each hospital. This allowed us to estimate the proportion of overall beds occupied by admissions associated with extreme temperature per hospital.

3.2. Robustness checks

Several robustness checks were conducted and are presented in the appendix.

First, while we believe the included fixed effects are key to control for potential confounders, it could be argued their combination might capture part of the good variation that allows identifying the impact of temperature on hospitalisations. It could also be argued that there are region-specific unobservable factors that influence the temperature-admissions relationship beyond those that are captured through hospital fixed effects. Therefore, we repeat our regression analysis with different levels of fixed effects: (1) week (*Week*), (2) week interacted with fiscal year indicators ($Week - FiscalYear$), (3) region (*Region*), and (4) region interacted with month indicators ($Region - Month$) (see Appendix P Table 25 and Appendix T Table 29).

Second, although a panel fixed effects methodology allows for the inclusion of a range of fixed effects to flexibly control for unobservable factors, it should be noted that the analysis relies on variation in weather within a single country. Therefore, an important consideration to make is that, within a given time period, weather could be correlated across all cross-sectional units (i.e. hospitals). In this instance, if weather is imperfectly measured, correlation in weather across hospitals will induce correlation in the error term across hospitals within a given time period. Thus, as an additional robustness check, we employed a two-way clustering strategy and cluster on both the hospital and week level (see Appendix Q Table 26).

Our stratified approach allows our fixed effects to be heterogeneous and flexible to each disease group of interest. For example, seasonality varies across diseases — with respiratory diseases (e.g. influenza) showing peaks over winter that are not consistent across other disease groups (e.g. metabolic diseases). However, we recognised that stratified regressions make the results vulnerable to concerns of multiple hypothesis testing and type I error. Therefore, we calculated false discovery rate (FDR) sharpened q-values (Anderson, 2008) to adjust our p-values accordingly (see Appendix R Table 27).

Fourth, temperature studies typically use one measure of temperature (e.g. maximum daily temperature, mean daily temperature *or* minimum daily temperature (Karlsson and Ziebarth, 2018; White, 2017; Deschênes and Greenstone, 2011). Our study constructed temperature bins using both maximum daily temperature and minimum daily temperature, as we believe this allows us to accurately capture the effects at the very extremes of the temperature spectrum. As a sensitivity test, we performed the above specification with three sets of temperature bins constructed using maximum, mean, and minimum daily temperatures separately (see Appendix S Table 28).

Finally, one could argue that deprivation captures unobserved heterogeneity, such as age, if not controlled for in the same specification. In such an instance, the stratified analyses conducted separately for age and IMD quintiles would be capturing the same heterogeneity. Thus, we also ran alternative specifications in which we stratified by both age and IMD quintiles (see Appendix U Tables 30–35).

4. Results

Fig. 3 (see Appendix E) reports the effect of the different temperature bands on the change in daily admissions for the six different causes of admissions modelled in our analysis. All types of admissions were sensitive to extreme temperatures but the patterns vary by disease group. Respiratory diseases and injuries were sensitive to both hot and cold temperature changes, displaying an asymmetric U-shaped curve. This indicates a generally increasing admission risk for temperatures higher and lower than the baseline temperature, 10–15°C. Temperature-related effects on respiratory disease and injuries were of a larger magnitude than other diseases studied, with effects also experienced for temperature bins preceding their extreme counterparts (i.e. at temperatures between 25-30°C and -5-0°C).

The effect of extreme heat, in comparison to 10–15°C, was positive and statistically significant for admissions across all disease categories, except from circulatory diseases and neoplasms. This increase in admissions was smaller for respiratory diseases (9.2%) and injuries (6.0%). Metabolic diseases had the largest effect magnitude, suggesting that, at temperatures above 30°C, there was an increase of 25.8% in admissions, per day per hospital, relative to a day between 10°C and 15°C. This was followed by an increase of 21.1% admissions for infectious diseases (p-

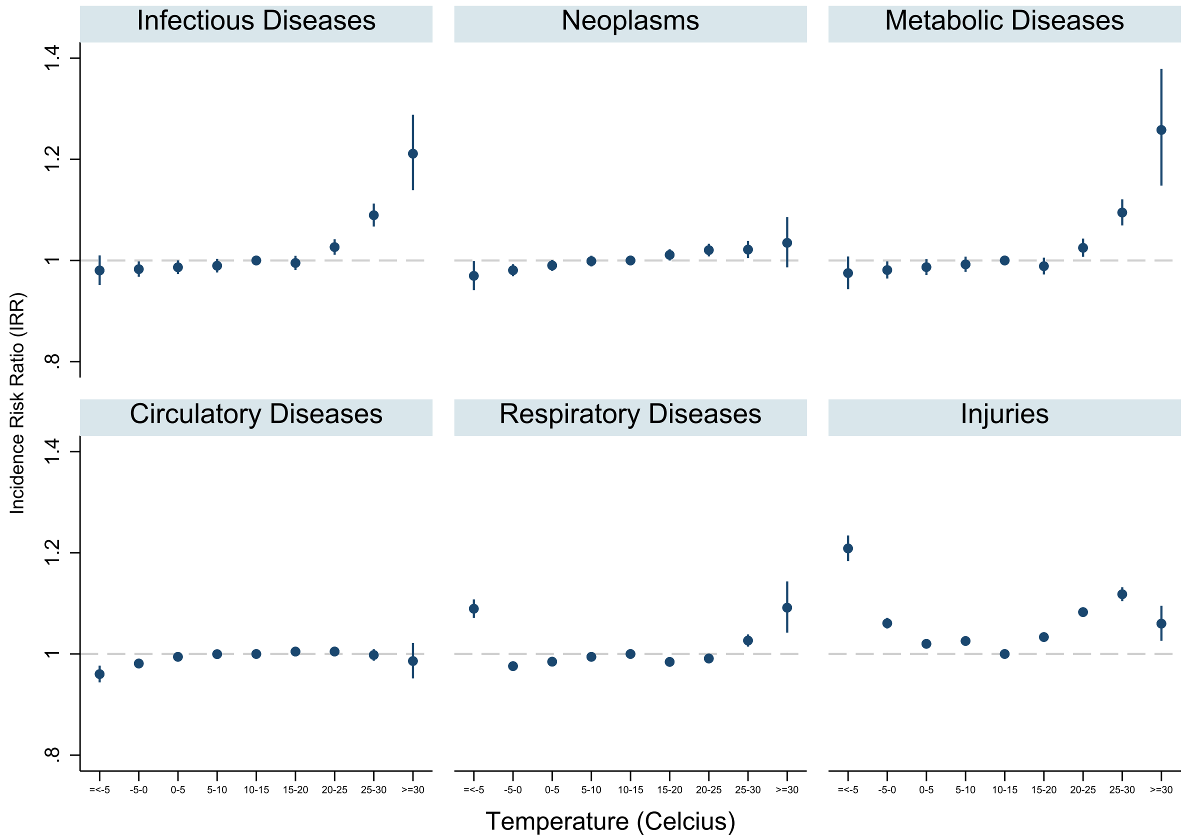

Fig. 3. Incidence Risk Ratios (IRR) of the contemporaneous effect of temperature by disease.

value<0.001).

The effect of extreme cold, in comparison to 10–15°C, saw increases in admissions only for respiratory diseases (8.9%) and injuries (20.9%). This relationship appeared to be no statistically significant for infectious diseases, and metabolic diseases. However, circulatory diseases and neoplasms experienced a slight fall (4.0% and 3.0% respectively) in admissions when exposed to extreme cold to a statistically significant level. The strongest effects were seen for injuries, where temperatures below −5°C conferred a 20.9% increase in admissions, per day per hospital, relative to a day between 10°C and 15 °C.

Surprisingly, our findings suggested that admissions for circulatory diseases had a non-significant relationship with hot temperatures. Circulatory diseases appeared to be sensitive to weather changes resulting in colder temperatures, although resulting in a decrease in admissions from the reference temperature group. Given that previous literature suggests that there is a temperature effect on cardiovascular morbidity (e.g. Karlsson and Ziebarth, 2018), this category was investigated and decomposed to reveal no positive relationship with temperature (see Appendix D).

The lag effects of extreme temperatures were heterogeneous across diseases (see Appendix F and Appendix G), with effects being more prominent following extreme cold events and a harvesting effect only observed for respiratory diseases. Infectious diseases ($p < 0.001$), metabolic diseases ($p < 0.001$), and respiratory diseases ($p < 0.001$) had statistically significant cumulative lag effects following extreme heat (Appendix F). Contrastingly, the cumulative lag effects following extreme cold (Appendix F) were significant for all disease groups.

Overall, our results show that, over the eleven fiscal years, there were 1,009,617 excess admissions on days of extreme temperatures – 911,708 for extreme cold days and 97,909 for extreme heat days. On average, a day of extreme heat, these excess admissions constituted approximately 6% of hospital capacity. Conversely, excess admissions on a day of extreme cold constituted approximately 3% of hospital capacity. This varied geographically across hospitals, with instances of extreme temperature accounting for nearly 10.3% of hospital capacity (Appendix H). When combined with expected baseline activities, hospitals required, on average, 90% of their capacity on days of extreme temperature events.

When considering an average cost of a hospital admission of £1176 (Curtis and Burns, 2017), the estimated total excess admissions cost the NHS approximately £208.3 million over 11 years. Although this translated to an annual average excess cost of approximately £17.3 million, the frequency of extreme temperature events was not homogeneous over our study period — the cold temperatures observed in the winter of 2010 led to £88.1 million costs in excess to the NHS. Appendix I decomposes these estimates by disease and fiscal year.

Results remain qualitatively the same following robustness checks and sensitivity tests (see Appendices P–U).

4.1. Age heterogeneity by disease

All diseases displayed an age-gradient in response to temperature (Fig. 4; see Appendix J for regression tables across all age groups). The slopes for older age groups were steeper than those for the younger age groups, with ages <5, 65–74, and >74 being the most strongly affected by extreme temperature. Across these age groups, infectious diseases, metabolic diseases and injuries appeared sensitive to hot temperatures. However, only respiratory diseases and injuries retained an asymmetric U-shaped curve, and also displayed deviations in admissions following extreme cold events. Across all ages and diseases, the largest effects were observed for injuries amongst those between 55 and 64 years (IRR = 1.66; $p < 0.001$).

For infectious diseases, the most vulnerable ages were those below 5 and above 74. This age effect was only visible across the warmer end of the spectrum of temperatures, where the change in admissions per hospital increases as temperature increases. For metabolic diseases, an

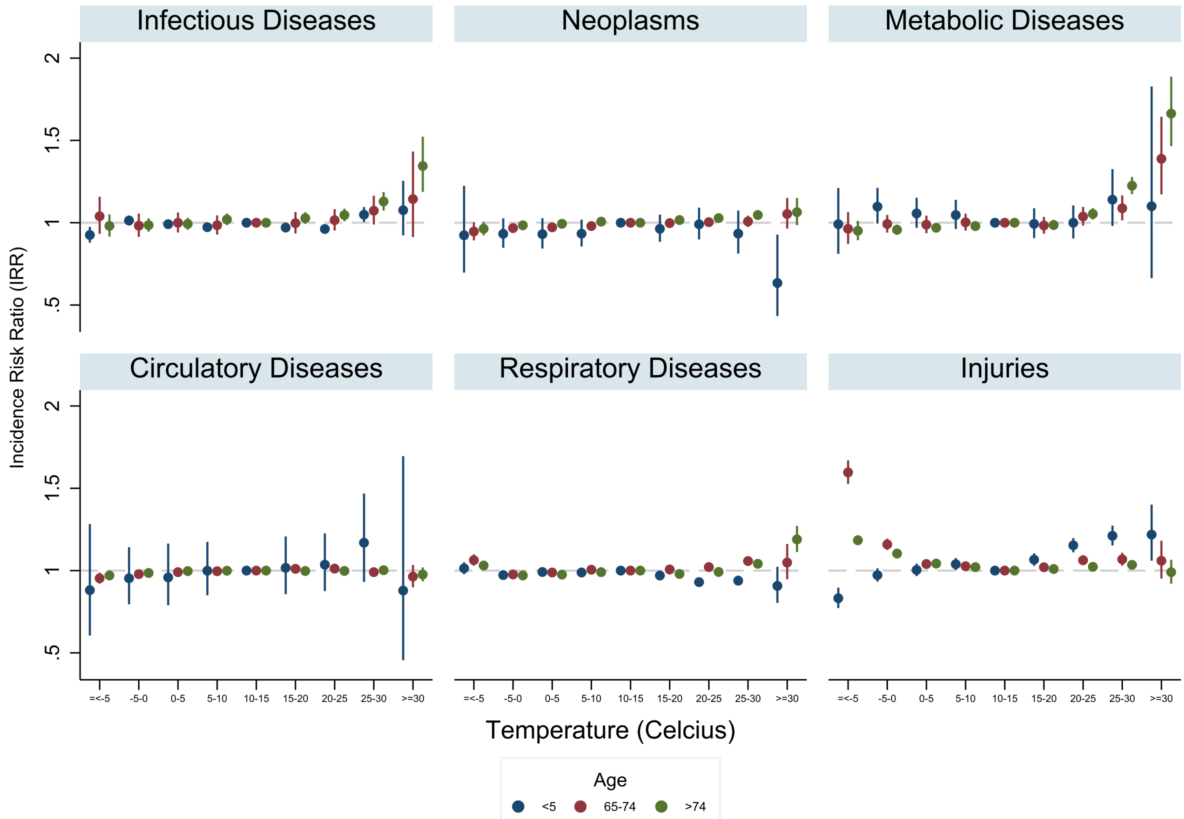

Fig. 4. Incidence Risk Ratios (IRR) of the contemporaneous effect of temperature by disease and age.

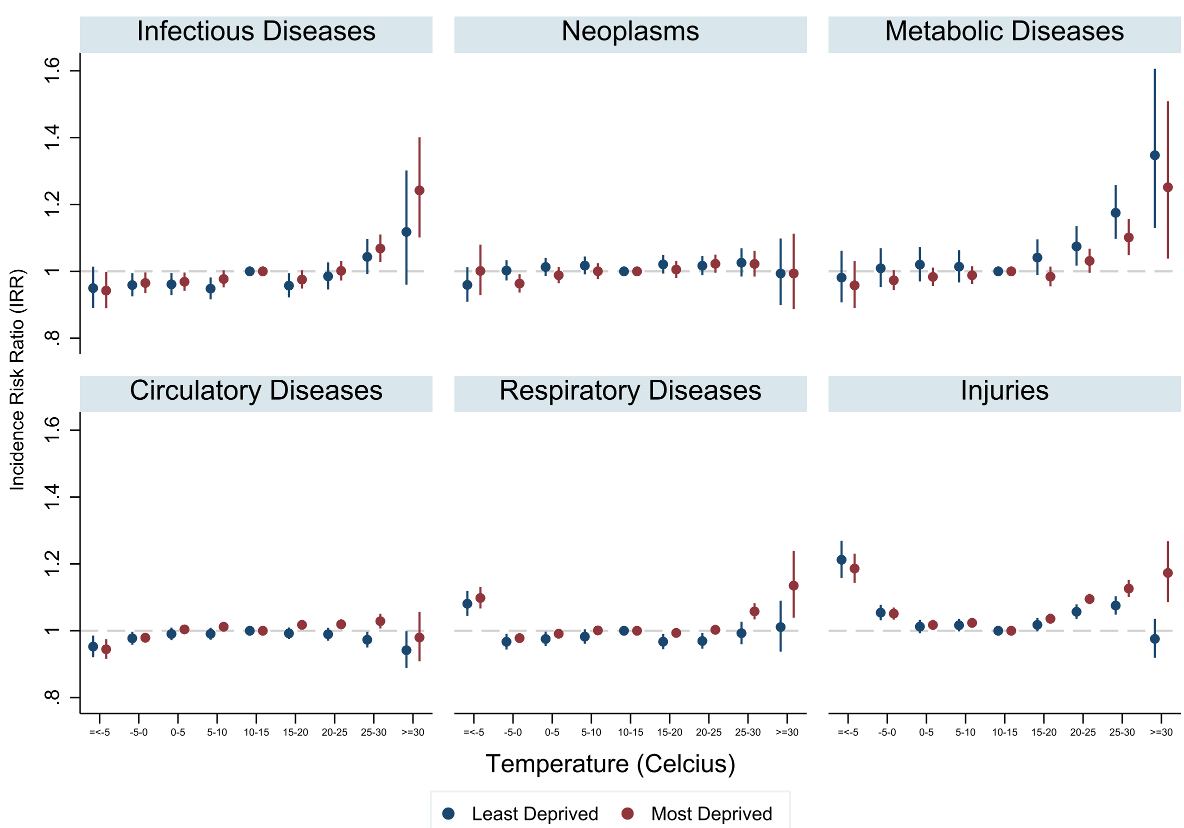

Fig. 5. Incidence Risk Ratios (IRR) of the contemporaneous effect of temperature by disease and deprivation.

increase in admissions was observed in those between 65 and 74, and above 74, from temperatures 25°C and above. The largest increases were 38.8% and 66.3%, respectively, on days above 30°C, relative to a day of 10–15°C. The contemporaneous effect across circulatory diseases suggested a small decrease in admissions on days below −5°C from ages 55 and above.

Admissions related to the respiratory system observed an age-gradient. During extreme heat, adults aged above 74 were admitted into hospitals more for this disease group. During colder temperatures, a larger share of the population appeared to be affected with all age groups displaying a significant relationship with cold temperatures. However, the largest change in admissions was observed for those between 25 and 34 years (IRR = 1.379, $p < 0.001$). The contemporaneous effect of hot weather was greater than cold weather on respiratory diseases for those aged above 74.

The temperature-age relationship for injuries deviated slightly from patterns observed in other diseases. Injuries were affected by both hot and cold weather. Hotter temperatures, from 20°C onwards (i.e. warm temperatures), conferred increased admissions across all age groups. However, there was a dip in this increase for temperatures above 30°C. The stronger effects over warm temperatures were observed for those between the ages of 5–44, who are likely to be more active and undertake risky-behaviours. The largest effects were observed for those below 5, on days above 30°C, with 21.9% increase in admissions ($p < 0.01$). Over cold temperatures, the relationship observed was retained with changes in admissions observed across all age groups to different degrees. The largest effect was observed for those between 55 and 64 years, with a 66% on days of extreme cold ($p < 0.001$).

The lag effects were also heterogeneous across age for each disease (Appendix K Table 15 and Appendix L). The youngest ages (<5 years) were the most susceptible to infectious diseases following extreme heat. While the elderly, above 74 years, experienced the largest effects for metabolic diseases following extreme heat and also for circulatory diseases following extreme cold. The strongest effects were still observed for respiratory diseases following extreme cold events.

4.2. Deprivation heterogeneity by disease

Fig. 5 illustrates the effects of temperature and deprivation across each of the six disease categories studied (see Appendix M Tables 17–23 for analysis by deprivation subdomains). All diseases, with the exception of neoplasms, displayed a deprivation-gradient in response to temperature. The slopes and magnitudes for the most deprived quintile were steeper than those for the least deprived quintile. These effects are further decomposed by age groups in Appendix U.

Admissions related to injuries observed the strongest deprivation-gradient. Injuries were affected by both hot and cold weather days. Over extreme heat and cold, the most deprived groups were more negatively affected than the least deprived groups. The latter group displayed no statistical significance. Similar to the relationship identified in the previous section, this temperature-deprivation relationship deviated slightly from patterns observed in other diseases with a slight dip over the hottest temperature bin. Hot temperatures, from 20°C onwards (i.e. warm temperatures), conferred increased admissions across both deprivation groups for all IMD domains. Over cold temperatures, both the most and least deprived quintiles were affected with no statistical difference between them. A similar relationship is observed for respiratory diseases.

The cumulative effects were also heterogeneous across deprivation for each disease (Appendix N and Appendix O). While the least deprived group displayed no cumulative lag effect, the most deprived group were the most susceptible to respiratory diseases ($p < 0.001$) following extreme heat. This disparity was also observed following an extreme cold event, whereby there were statistically significant increases in admissions for the most deprived group for metabolic diseases ($p < 0.001$), and respiratory diseases ($p < 0.001$). Contrastingly, the largest effects were observed for the most deprived group for respiratory diseases ($p < 0.001$).

5. Discussion

This is the first study to examine temperature changes on age-specific and deprivation-specific admissions and inequality impacts of extreme weather changes. We examine this effect between 2001 and 2012 on emergency admissions across the entire population of England. Our study has shown wide inequalities in admission patterns, where disease-specific admissions are higher in populations of the elderly, young children, and in those who live in more deprived areas.

Our findings show that hospitals experience an increase in admissions with both extreme hot and cold temperatures. The less extreme temperatures produce admission patterns like their extreme counterparts, but at lower magnitudes. While assessing temperature impacts for managerial purposes would require looking at all admissions, it remains meaningful to understand its impacts on high-volume weather-sensitive disease categories to glean insights to how patient flows may change in departments already functioning at, or close to, full capacity. We show that these excess admissions, associated with extreme temperature shocks, constitute a significant share of hospital activity. With total excess admissions being nearly 20,000 per year, the NHS would have required, following standard care guidelines (Royal College of Nursing, n.d.; Royal College of Physicians, n.d.), at least 4,000 nurses and 2,600 doctors. Relative to each hospital's size, such shocks can occupy 10% of total beds, in addition to daily baseline activity, pushing the average hospital to the brim of its capacity. Thus, these admissions can potentially strain an average hospital substantially.

Our estimates suggest that, on average, an additional cost to the NHS of at least £20.8 million was incurred annually to treat excess admissions associated with extreme temperatures. Nonetheless, it is the size of Public Health England's entire budget for environmental hazards and emergency preparedness of £18.2 million in 2017–18 (Public Health England, 2017), suggesting there should be more investment in preventative interventions that mitigate weather effects. Given that £108 million only represents the direct costs associated with certain diseases and emergency admissions, the cost burden to the health system and society is likely to be much larger.

Our findings identified a U-shaped relationship between temperature and admissions, similar to that observed in the literature that assesses the relationship between temperature and mortality (Deschênes and Greenstone, 2011; Karlsson and Ziebarth, 2018). Our findings are consistent with those identified by a study in Germany (Karlsson and Ziebarth, 2018), whereby strong positive effects were seen at both hot and cold extremes with the latter at a larger magnitude, but differ from others who observe negative admissions during colder temperatures in California (White, 2017).

We contributed to the literature by showing that the effects of temperature on hospitalisations are highly compounded by the three determinants studied - namely disease, age, and deprivation. Most changes in hospitalisations associated with temperature effects are higher in the elderly and groups with high deprivation levels. Although hot weather had a stronger effect, the effects of cold temperatures were generally experienced in the days that follow it. These estimates are conservative as they represent the effects associated with extreme temperatures only. As effects were also observed at less extreme temperatures, the true burden on admissions is likely to have been higher.

Extreme temperatures impact the elderly due to changes in the thermoregulatory system with ageing (Flynn et al., 2005). We observed a clear age-gradient for admissions on hot and cold days, and the days that follow extreme cold and hot weather. While those above 74 years appeared to have the strongest relationship with extreme temperatures, we also saw increases in admissions, albeit at lower magnitudes, at younger ages.

Hot temperatures, but not colder temperatures, led to increased admissions for children aged less than 5 years. This might be because parents are more likely to engage in protective behaviours to limit cold exposure and its adverse effects, whereas heat waves may be harder to protect against. This finding is similar to the results of earlier work (Karlsson and Ziebarth, 2018). However, it was reported that the cumulative effects of cold amongst children under 5 are 27.7% above the mean daily visit rate in California (White, 2017). Explanations for the discrepancies in effect sizes could also be related to spatial heterogeneity according to geography and a different climate baseline.

We also observed a clear deprivation gradient in terms of SES. Admissions in the most deprived quintiles were responsible for a larger share of the increase in admissions than their least deprived counterparts. The strongest effects were observed for respiratory diseases. The most deprived group likely includes individuals with higher levels of existing morbidities, which increases their vulnerability to extreme temperatures. Social deprivation is also likely associated with worse housing, limited opportunities to counter extreme temperatures measures and a greater likelihood of employment in physically-intensive or outdoor jobs (Bennett et al., 2014). These issues are further exacerbated by the health inequities already imposed by fuel poverty on the socially and economically vulnerable populations of the country and their limited ability to afford living in a warmer household (Marmot Review Team, 2011).

There are several caveats to our analyses. First, we do not observe individual-level temperature exposure. Individual exposure to temperature was assumed to be that of the hospital they were admitted at. An individual's actual exposure may have been different due to geographical, environmental or behavioural factors. This is unlikely to be large, as there is little spatial variation in temperature, and our focus on admissions suggests that patients were near the hospital where they have been admitted to. Second, we cannot exclude potential confounding impacts of environmental factors, such as pollution. Weather directly affects health, but it could also be correlated with or affect pollution, which in turn could affect health (Buckley et al., 2014). Controlling for pollution requires more evidence on their short- and long-term interactions with temperature, and their inclusion would not capture the total effect of temperature (Buckley et al., 2014). In the real-world, pollution will likely persist in the environment and the impacts of extreme temperature will not be felt in isolation. Third, our data covers an 11-year window that can potentially affect the generalisability of our findings to future years. This is particularly true if there are differences across time in: i) temperature distribution; ii) the duration and frequency of extreme temperature events and; iii) the implementation of mitigation and adaptation strategies. However, the temperature distribution in recent years is similar to the one in our data. The hottest temperature, recently recorded in 2019, at 38.7 °C, is of similar magnitude to the second hottest temperature recorded in 2003 (38.5 °C). Therefore, we expect our findings to hold in the same order of magnitude in recent years. Further, the increased frequency and duration of these weather events implies that our results are an underestimation of the true effects in more recent years. Furthermore, it is likely that due to increased behavioural mitigation and adaptation actions, such air conditioning in recent years, individuals are less exposed to extreme temperatures (Neidell, 2009). While these could imply a smaller change in the admissions, the Committee on Climate Change has identified "*a substantial gap between current plans and future requirements and an even greater shortfall in action*" (House of Commons Environmental Audit Committee, 2018), suggesting that the same patterns on admissions might still be valid. More broadly, our analyses focuses on six high prevalence weather-sensitive conditions, and, therefore, does not enable the assessment of overall temperature impacts on healthcare provision. While from a hospital capacity management purpose it remains meaningful to understand the impact of temperature on these high-volume diseases, hospitals can respond by organising services in ways that may (indirectly) impact care provision in other disease areas. Assessing these broader impacts is of relevance for policies at national levels, including those that relate to care capacity, resource allocation, and prioritisation strategies.

Despite these caveats, our study is the first to clearly demonstrate equity implications of extreme temperatures in health with a significantly greater adverse impact of extreme temperatures on older and more deprived population groups, leading to higher admissions. With the increasing variability of extreme weather patterns that is expected to increase with climate change, the existing health inequalities will likely be further exacerbated. Given the importance of vulnerability and capacity assessments in adapting national health systems to climate change (WHO, 2013), our research emphasises the need to conduct thorough studies of how temperature impacts hospital capacity deferentially through the different departments. Our findings suggest the imperative need for targeted policies and actions to mitigate the adverse effects of increasingly more common extreme temperatures on at-risk populations and health equity.

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Contribution statement

The study was conceived, and the research question was developed by MM, LP, RA, and DR. The methodological approach was developed by MM, LP and DR, with input from RA. DR did the data cleaning, linking and statistical analysis, supported by MM and LP. DR wrote the manuscript with input from LP, MM, and RA. All authors have seen and approved the final version of the manuscript for publication.

Declaration of competing interest

We declare that we have no conflicts of interest.

Data availability

The authors do not have permission to share data.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.socscimed.2022.115193.

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