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Extreme Temperature, Morbidity and Behaviour: Evidence from A&E Attendances in England

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Abstract

Climate change is expected to lead to increases in the prevalence of extreme temperatures with potentially significant consequences for human health. This paper investigates the relationship between temperature and morbidity in a high-income country with a relatively mild climate and considers the role of behavioural responses to extreme temperatures. Using weekly data on accident and emergency (A&E) attendances for 429 hospitals across England over the period 2010-2015, we find that while higher temperatures are in general associated with significant increases in hospital attendances, there are distinct effects evident across the temperature distribution. In particular, while cold weather is associated with lower contemporaneous A&E attendances, this effect appears to be entirely attributable to displacement of A&E visits to subsequent weeks. In contrast, for hotter temperatures, we find evidence of substantial contemporaneous increases in weekly A&E attendances that are not offset by subsequent reductions. In a setup that includes hospital, week, year, region-by-week, and region-by-year fixed effects, we estimate that for weeks with maximum temperatures exceeding 28^{o}C, A&E attendances increase by 7.8% relative to weeks with maximum temperatures of 10-13^{o}C. Over the subsequent four-week period, the estimated net increase in A&E attendances remains large at 7.5%. Overall our results are consistent with differences in individual-level behavioural responses to extreme cold and hot temperatures in England, which have important consequences for health outcomes and health system capacity, particularly in the context of increasingly frequent and intense extreme heat days as a result of climate change.

Keywords: Extreme Temperature; Climate Change; Morbidity; Behaviour.

1. INTRODUCTION

Climate change is expected to lead to increases in the prevalence of extreme temperatures and destructive weather events, with potentially significant effects on human health (Costello et al., 2009). To date, while numerous studies have shown a link between extreme hot and cold temperatures and excess mortality (Deschenes, 2014; Campbell et al., 2018; Basu, 2009), the impact on morbidity has received much less attention and significant gaps remain in our understanding (White, 2017). For example, while studies such as White (2017), Karlsson and Ziebarth (2018), Agarwal et al. (2021), and Mullins and White (2019) have presented estimates of the effects of extreme temperatures on health outcomes, these effects have yet to be demonstrated in a country with a temperate climate and relatively mild extreme temperatures. This is important, as the greatest overall temperature increases from climate change are expected to occur in northern latitudes as a result of 'Arctic amplification' (Beusch et al., 2022).

As well as providing a more complete picture of the overall effects of climate on human health, analysing morbidity also presents an opportunity to develop a deeper understanding of the channels or mechanisms through which health is impacted by extreme temperatures. For example, adaptation behaviours are an important mechanism in mediating the biological relationship and, as a result, a critical challenge in assessing the human health threats posed by climate change is the degree to which "adaptation is possible" (Deschenes, 2014). However, it is not generally well understood why some populations adapt so effectively in some dimensions of climate, while entirely failing to adapt in other contexts, and this remains a critical research challenge (Carleton and Hsiang, 2016). In this context, this paper investigates the relationship between temperature and morbidity in a high-income country with a relatively mild climate and considers the likely role of behavioural responses to extreme temperatures. In particular, it focuses on potential short-term defensive/avoidance adaptive behaviours that may help mitigate the health impacts of extreme temperature events.

As noted, the relationship between temperature and human health has been considered extensively, including in the public health, epidemiology, and economics literatures. For the most part, the focus of the latter has been on the effects of exposure to extreme temperatures on mortality. For example, Deschenes and Greenstone (2011) found that days with mean temperatures above 90°F (32.2°C) and below 40°F (4.4°C) were associated with increases in mortality in the US. Barreca (2012) found comparable results, also in the US, after controlling for humidity, while Karlsson and Ziebarth (2018) found a similar relationship between temperature and mortality in Germany.

In contrast, the relationship between temperature and morbidity has received less attention, with some notable exceptions. For example, White (2017) examined the dynamic relationship between temperature and morbidity using emergency department (ED) visits in California, finding both extreme cold and hot days to be associated with net total increases in visits over a 31-day cumulative window. Similar 'U-shaped' relationships were found for hospital admissions in Germany by Karlsson and Ziebarth (2018) and in China by Agarwal et al. (2021), though the latter found extremely cold temperatures (less than -6°C) had no effect on admissions. Finally, Mullins and White (2019) considered the relationship between temperature and mental health, finding higher temperatures increase ED visits for mental illness, suicides, and self-reported days of poor mental health.

In terms of behavioural responses, the temperature-mortality literature has generally considered longer-term adaptations, with several studies focussing on the role of air conditioning. For example, Deschenes and Greenstone (2011) and Barreca (2012) showed increases in residential energy use linked to air conditioning as temperatures increase, while Barreca et al. (2016) found that much of the improvement in the temperature-mortality relationship in the US over the last century was attributable to the adoption of air conditioning. Other studies have highlighted the role of migration. For example, Deschenes and Moretti

(2009) argued that migration from cooler to warmer regions is responsible for some of the increases in life expectancy since the 1970s in the US, while Heutel et al. (2021) demonstrated variation in the ability of different regions to adapt to climate change, with the mortality effects of extreme heat being significantly higher in cold regions relative to warm regions. The factors driving this heterogeneity across climate regions is not clear.

In contrast to these longer-term adaptation responses, relatively few studies have considered short-term behavioural responses to extreme temperature. While such responses can influence the relationship between temperature and morbidity, they are not necessarily self-protecting in nature. Focusing on general behaviours, Graff-Zivin and Neidell (2014) investigated the relationship between temperature and time-use in the US, finding an increase in time devoted to indoor leisure at the expense of outdoor leisure in response to both extreme hot and cold weather. They also found decreased time devoted to labour among weather-exposed workers. White (2017) highlighted the potential role of behaviour in mediating the dynamic relationship between temperature and morbidity, noting behavioural responses are unlikely to be influenced only by individuals' expected health and that it is possible that behavioural responses may be utility enhancing yet damaging to health.

Within this context, this paper combines data on accident and emergency (A&E) attendances for 429 hospitals in England over the period 2010-2015 with weather data based on hospital locations to analyse the temperature-morbidity relationship. With daily maximum temperatures ranging from -3.5^{o}C to 32.8^{o}C, England represents an ideal context for studying the health effects of extreme temperatures in relatively cooler climates. To do so, we employ a distributed lag regression model that includes hospital, week, year, region-by-week, and region-by-year fixed effects and find that while higher temperatures are associated with significant increases in hospital attendances, there are distinct and noteworthy effects evident across the temperature distribution. In particular, while cold weather is associated with lower contemporaneous A&E

attendances, this effect appears to be entirely attributable to displacement of A&E visits to subsequent weeks. In contrast, for hotter temperatures, we find evidence of substantial contemporaneous increases in weekly A&E attendances that are not offset by subsequent reductions. Overall, our results are consistent with differences in behavioural responses of individuals to extreme cold and hot temperatures in England.

Our paper makes a number of specific contributions to the literature. First, using the near-universe of A&E attendance records for England over a 5-year time period, we provide new insights on the link between temperature, morbidity, and human behaviour in a high-income country with a temperate climate and relatively mild extreme temperatures. In particular, our analysis shows, for the first time, a significant effect of hot temperatures on human health in such a setting. In addition, we find net increases in A&E attendances at lower levels of temperature than in previous studies, perhaps reflecting a relative lack of adaptation to heat in our context. This finding has major implications for our current understanding of the health impact of climate change, illustrating the potentially significant negative health consequences of climate change for countries with cooler climates, many of which are located in regions currently projected to face significant temperature increases (Beusch et al., 2022).

Second, our results across the temperature distribution are consistent with differences in individual-level behavioural responses to extreme cold and hot temperatures in England. In particular, we show that while individuals may be engaging in self-protecting behaviours to mitigate the health consequences of cold temperatures, this does not appear to be the case for hot temperatures. This finding highlights the importance of local climate in determining behavioural responses to weather events.

Third, our results also highlight important differences in behavioural responses across regions. For example, while our results corroborate findings from White (2017) for contemporaneous effects of cold temperatures in California, we do not observe cumulative net increases over subsequent weeks in England. This suggests, for example, that England's population is well adapted to cold temperatures, in comparative terms, likely in part because of their generally cooler climate.

The rest of this paper is organised as follows: Section 2 describes the data, Section 3 outlines the empirical strategy, while Section 4 presents and describes the main results. Section 5 then discusses the possible behavioural mechanisms underpinning our findings and Section 6 concludes.

2. DATA

To analyse the temperature-morbidity relationship in England, we combine publicly available data on A&E attendances from National Health Service (NHS) England with regional population data from StatWales and weather data from the Centre for Environmental Data Analysis (CEDA). This section describes each of these data sources and the relevant variables in more detail.

2.1 A&E Attendances

We use *A&E Attendances and Emergency Admissions* data from NHS England that contains the near-universe of all A&E attendances for both public and private health providers in England, including NHS Trust, NHS Foundation Trust, and independent sector organisations (NHS, 2022). In particular, we analyse data on weekly A&E attendances at 429 unique A&E treatment facilities across England over the period from November 2010 to July 2015. The analysis focuses on A&E attendances, since these are likely to better capture the effects of heat-related health shocks. Other health outcomes, such as hospital admissions, are likely to also be affected by factors such as the number of available beds, which may be lower during periods of extreme temperatures due to excess demand for health services. In addition, A&E attendances also account for less severe and more easily treatable heat-related morbidity that do not require hospitalisation but are nonetheless important.

The primary outcome of interest in our analysis is the weekly A&E treatment facility attendance rate per 100,000 regional population, with the location of each treatment facility matched to one of nine strategic health regions in England. The regional population data is taken from StatWales and based on mid-year population estimates of local authorities by year, aggregated to the regional level (StatWales, 2022). A&E attendance rates, the primary outcome of interest in our analysis, are calculated by dividing the number of weekly A&E attendances at a treatment facility by its regional population. Table 1 presents descriptive statistics for A&E attendances for our balanced panel of 156 treatment facilities (for more details, see below). Overall, the mean weekly A&E treatment facility attendance rate was 34.9 per 100,000 regional population from a total of 76.7 million A&E attendances over the period. A breakdown in total attendances by region is also presented.

[Insert Table 1 about here]

One important caveat to note here relates to changes in the number of treatment facilities each week over the study period in our data (see Figure A1 in the Appendices), which is driven by two factors. First, only healthcare facilities with A&E attendances averaging more than 200 attendances per month are included in the NHS data, leading to variation in the number of treatment facilities per period. Second, there is also some attrition caused by organisational changes in the public health system in England during the period (including hospital mergers and hospital trust reorganisation) that led to the closure of some private healthcare facilities. To address and consider the likely impact of these issues for our analysis, we present estimates from models using balanced panels (i.e. including only hospitals with observations for all periods) as our main results, but also present results using an unbalanced panel as a robustness check. This implies we use data on 156 A&E treatment facilities in the balanced panel analysis and 429 in the unbalanced panel analysis.

2.2 Weather Data

To assess the impact of temperature on A&E attendances, we match the NHS provider-level A&E weekly attendance rates with weather data based on a treatment facility's location within a strategic health region and the end date of weekly A&E records. The weather data is taken from CEDA's *HadUK-Grid Climate Observations by Administrative Regions over the UK* dataset (Met Office et al., 2021). HadUK-Grid is a collection of gridded climate variables derived from the network of UK land surface observations and the data have been interpolated from meteorological station data onto a uniform grid, providing complete and consistent coverage across England at 1km resolution. The gridded data are produced for daily, monthly, seasonal, and annual timescales, and the primary purpose of these data are to facilitate monitoring of UK climate and research into climate change, impacts, and adaptation. The HadUK-Grid includes information on maximum temperature (degrees Celsius) and precipitation (millimetres), which are used in this paper, though it does not provide daily measures of humidity. A previous study by White (2017) found that the inclusion of humidity did not alter the results.

Table 2 presents definitions and descriptive statistics for the temperature variables used in our analysis i.e. ten separate *weekly* maximum temperature indicator bins. For example, the lowest temperature bin [1^{o}C, 4^{o}C) takes a value of 1 if the highest daily maximum temperature in a given week is greater than or equal to 1^{o}C but less than 4^{o}C. Subsequent bins increase in 3^{o}C intervals to the highest temperature indicator [28^{o}C,), which takes a value of 1 if the highest daily maximum temperature in a given week is greater than or equal to 28^{o}C. In other words, these variables are defined on the basis of the maximum of the seven daily maximum temperature observations for a given region-week. Overall Table 2 shows that the two highest temperature bins, [25ºC, 28ºC) and [28ºC,), account for approximately 7.6% of weekly maximum temperatures, while the two lowest bins, [1ºC, 4ºC) and [4ºC, 7ºC) , account for 4.1%. The modal bin is [10ºC, 13ºC), accounting for 20.4% of weekly maximum temperatures.

[Insert Table 2 about here]

Furthermore in relation to temperatures, and as a complement to the data in Table 2, Figure 1 presents the distribution of *daily* maximum temperatures at regional-level for England over the study period. It highlights that extreme temperatures are relatively rare in England at present, with a bimodal distribution centred around 10ºC and 17ºC.

[Insert Figure 1 about here]

Finally, in addition to the temperature data, we also include variables relating to weekly precipitation to act as controls in our models. In particular, we construct variables for four separate 10mm rainfall bins, defined as a count of the number of days in a given week with rainfall levels falling into various bins (summary statistics not presented but available from the authors on request).

3. EMPIRICAL APPROACH

Our empirical analysis aims to estimate the effect of temperature in a given week t on A&E attendance rates in the same week, as well as in subsequent weeks $t+1$, $t+2$, and $t+3$. To do so, we follow closely the approach of White (2017) and employ a distributed lag regression model whereby the weekly A&E attendance rate is regressed on the contemporaneous weekly temperature and three weekly temperature lags. Defining $A\&E\_Rate_{i,r,t}$ as the A&E attendance rate for treatment facility i located in region r in week t, the specification of our main model is given by:

$$A\&E\_Rate_{i,r,t} = \alpha + \sum_{j=1}^{9}\sum_{h=0}^{3}\beta_{j,t-h}Temp_{j,r,t-h} + \sum_{j=1}^{3}\sum_{h=0}^{3}\gamma_{j,t-h}Precip_{j,r,t-h} + \delta_{Wee} + \delta_{Year} + \delta_{Region-Wee} + \delta_{Region-Year} + \delta_{Treat\_Facility} + \epsilon_{i,r,t} \quad [1]$$

where the main explanatory variables of interest, $Temp_{j,r,t-h}$, are the weekly maximum temperature indicator bins defined in Table 2 and their lags. The omitted temperature category in our model is the 10-13°C bin[1], implying the estimated coefficients $\beta_{j,t-h}$ represent the marginal effect of a week with maximum temperature in bin *j* relative to a week with maximum temperature in the range 10-13°C. Controls for weekly precipitation $Precip_{j,r,t-h}$, including lags, are also included in the form of 10mm rainfall bins, with the 0-10mm bin omitted. Given the nature of our weather data, standard errors are clustered at the region level.

The model in Equation [1] allows us to estimate a range of different effects. First, the 'contemporaneous effect' $\beta_{j,t}$ represents the impact of a weekly maximum temperature bin *j* on A&E attendances in the same week, controlling for weekly maximum temperatures for every other week in the 4-week period. Second, the 'cumulative effect' measures the total effect of a temperature bin i.e. the impact on both current and subsequent A&E weekly attendances. It is calculated as the sum of all coefficients (including lags) for each temperature bin, $\sum_{h=0}^{3}\beta_{j,t-h}$, and captures the total 'net effect' of temperature on A&E attendances over four weeks. Third, the pattern of the dynamic relationship between temperature and A&E attendances over the 4-week period can also be considered using the separate lagged

[1] A variety of omitted bins have been used in the literature, depending on the context of each region or country's underlying climate. For example, White (2017) omitted the 60-65°F (15.6-18.3°C) temperature bin for California, Karlsson and Ziebarth (2018) omitted the 40-50°F (4.4-10°C) bin for Germany, while Agarwal et al. (2021) omitted the 9-12°C bin for China. As noted in Agarwal et al. (2021), the literature generally uses the ideal or most comfortable temperature as the reference group and we have chosen the modal 10-13°C bin. Our results and findings are robustness to alternative base categories.

coefficients and their linear combinations.

In terms of identification, our strategy relies on the inclusion of a comprehensive set of fixed effects in our distributed lag model. First, it is necessary to account for the fact that both A&E attendances and weather are likely to vary together seasonally and our model includes both week-of-year (δ_{Week}) and region-by-week ($\delta_{Region-Wee}$) fixed effects. This allows seasonality to vary at a relatively fine scale (weekly) and for seasonality effects to vary by region, which is important if changes in health are driven by behaviour (White, 2017). In addition, region-by-week fixed effects control for differences in the climate across England and thus capture any potential correlation in the seasonality of both weather and health across regions.

We also include year (δ_{Year}) and region-by-year ($\delta_{Region-Yea}$) fixed effects. This controls flexibly both for annual factors across England and annual factors that vary by region including, for example, variations in regional health policy or demographic changes. The region-by-year fixed effects are particularly important for identification in our model, as health policy varies significantly across each of our nine regions. For example, London saw a much greater level of attrition among treatment facilities during our sample period compared with other regions (see Figure A2 in the Appendix). While we restrict attention in our main analysis to a balanced panel (i.e. only including facilities that are present throughout the sample period), the closure of treatment facilities within a given region could nonetheless increase demands on all other healthcare facilities in the same region. We also include treatment facility fixed effects ($\delta_{Treat\_Facility}$) to account for any time-invariant differences across observational units in A&E attendance rates.

Finally, it is important to note that our empirical strategy faces some limitations as a result of data availability. For example, we do not include day-of-the-week effects and national holiday controls since our A&E attendance records are aggregated at a weekly level. However, since weather is independent of both the day-of-the-week and national holidays conditional on our seasonal controls, the exclusion of these controls does not necessarily threaten identification, but is likely to decrease the precision of our estimates.

4. RESULTS

In this section we present the results of our empirical analysis. The results for our preferred specification are presented in Table 3 in the form of contemporaneous and cumulative effects and are based on the model presented in Equation [1]. Additional specifications are reported as robustness checks in Appendix Tables A1 and A2. While the results are reported in levels in the tables, much of the subsequent discussion focuses on percentage changes for ease of interpretation. These are calculated by dividing the relevant estimated coefficient (or sum of coefficients) by the mean weekly attendance rate. For example, the interpretation of the contemporaneous effect for the 22-25°C temperature indicator bin – see Column (1) of Table 3 – is as follows: a week with a maximum temperature greater than or equal to 22°C but less than 25°C is associated with 2.26 additional A&E attendances per 100,000 individuals, relative to a week with maximum temperature in the range 10-13°C. The percentage change is then calculated by dividing the estimated coefficient by the mean weekly A&E attendance rate (34.87 attendances per 100,000 individuals), giving an estimated 6.5% increase in weekly A&E attendances (2.26/34.87=6.5%).

[Insert Table 3 about here]

Taking the estimates of contemporaneous effects first, the results reported in Column (1) indicate significant effects of temperature variation on A&E attendance rates in England. They also suggest a contrast in the effects of low and high temperatures, with negative coefficients (i.e. reductions in A&E attendances) estimated for cold temperature bins, and positive coefficients (i.e. increases in A&E attendances) estimated for higher temperature bins. The results in Column (1) also show a monotonic increase in the magnitudes of the estimated contemporaneous effects.

These results seem to indicate that population health in England benefits considerably from colder weather. For example, the estimated contemporaneous effect of the 1-4°C temperature indicator bin suggests a 4.3% decline in A&E attendances, relative to the omitted 10-13°C category. However, the results in Column (2), which account for the cumulative effect on hospital attendance rates up to three weeks after the weather shock, indicate that the initial decline in attendance is offset in the subsequent weeks; the cumulative effect of the 1-4°C temperature indicator bin is not statistically different from zero. A similar pattern is found for each of the other colder temperature indicator bins, up to 10°C.

In contrast, hotter temperatures are associated with increases in A&E attendances that persist up to three weeks after the shock. For example, weekly maximum temperatures in the 25-28°C range are associated with a contemporaneous increase of 7.6% in A&E attendances that if anything intensifies slightly in subsequent weeks, with a net total increase of 8.6%. The highest temperature indicator bin [28°C,) is associated with a 7.9% increase in A&E attendances and a net total effect of 7.5% over four weeks.

Our main results are summarised visually in Figure 2. First, Panel A displays the contemporaneous percentage effect of each of the weekly maximum temperature indicator bins, showing a near linear relationship between temperature and contemporaneous weekly A&E attendances. In contrast, Panel B displays the cumulative percentage effect over a four-week period for each of the temperature bins, showing significant effects only for higher temperature bins. In particular, we find no evidence of a statistically significant effect of colder temperatures on A&E attendances when allowing for the effects of the cold weather shock to play out over a period of four weeks. On the other hand, for hotter temperatures, Panel B illustrates a net total increase (over the 4-week cumulative period) for weekly maximum temperature in the ranges 16-19°C and above. This is similar to the 31-day cumulative effects found in California (White, 2017), where temperatures in the ranges 75-80°F (23.8-26.7°C) and 80+°F (26.7+°C) are associated with net total increases in ED attendances. Notably, however, we find net increases in A&E attendances in our data at lower levels of temperature, perhaps reflecting a relative lack of adaptation to heat in our context. The magnitudes of the net (cumulative) effects that we estimate are also somewhat larger in percentage terms than those found in White (2017). The overall shape of the estimated relationship here also differs somewhat from the U-shaped relationship generally found in the temperature-mortality (Deschenes and Greenstone, 2011; Barreca, 2012; Barreca et al., 2016) and temperature-morbidity literatures (White, 2017; Karlsson and Ziebarth (2018).

[Insert Figure 2 about here]

The analysis so far has focused on summarising the dynamic relationship between temperature and morbidity by reporting the contemporaneous and cumulative effects. However, it is also informative to consider the nature of the dynamic relationship over the 4-week window that we study and Figures 3 and 4 illustrate how A&E attendances are affected in the weeks following a temperature shock[2]. In each figure the dynamic association at relatively cold temperatures, i.e. the 1-4°C temperature indicator bin, is presented in Panel (A), while the same dynamic association for our hottest temperature category, the 28+°C temperature indicator bin, is presented in Panel (B). Figure 3 plots the estimated effects (reported in percentages, as described previously) for each week, with the contemporaneous effect represented by $t = 0$ on the x-axis. Figure 4, on the other hand, plots the sum of all effects (again reported in

[2] These figures mimic the presentation of results in White (2017) to facilitate comparison of our findings with existing literature in a different climate context.

percentages) up to and including the relevant lag. For example, the point corresponding to one week after the temperature shock represents the sum of effects on contemporaneous temperature and the first temperature lag.

[Insert Figures 3 and 4 about here]

Starting with Panel (A) of Figures 3 and 4, the contemporaneous decline in A&E attendances for colder temperatures is clearly illustrated (note that the estimates at $t = 0$ are equivalent across both figures). Figure 3 illustrates that this initial decline in attendances for weeks with cold temperatures is followed by increases in A&E attendances in subsequent weeks, while Figure 4 demonstrates how this translates into total net changes in A&E attendances over the 4-week period. The initial decline in A&E attendances for weeks with cold temperatures is compensated by subsequent increases in attendances, such that the net effect is indistinguishable from zero in the weeks after the initial cold temperature shock.

Turning to Panel (B) of Figures 3 and 4, where we focus on the hottest temperature bin, we see a large contemporaneous increase in A&E attendances followed by a much smaller but still statistically significant increase in the week following the hot temperature shock. In the subsequent two weeks the estimated coefficients are slightly negative but not statistically different from zero. Figure 4 shows how these weekly coefficients translate into net total A&E attendances over the 4 weeks. In contrast to the pattern observed for cold temperatures, the initial increase in A&E attendances for weeks with high maximum temperatures is not compensated by subsequent declines. In fact, we observe a compounding effect initially, as the net increase in A&E attendances following the hot weather shock is actually larger one week after the initial temperature shock. Over the subsequent two weeks the net effect declines somewhat, but remains positive and significantly different from zero.

This pattern of effects for hotter temperatures on morbidity is similar to that observed by White

(2017) for ED visits in California, albeit with some notable differences in the level of hotter temperatures associated with increased A&E attendance in our study, and slightly larger magnitude effects (in percentage terms), as noted previously. However, this pattern of effects is quite distinct from the dynamic observations in several previous temperature-mortality studies. Essentially, the literature on temperature and mortality has found evidence of 'harvesting', whereby an initial increase in mortality is offset by subsequent decreases, as the temperature shock brings forward by a short interval the mortality of some vulnerable persons (Deschenes and Moretti, 2009; Armstrong, 2006; Basu and Samet, 2002; Braga et al., 2001). Harvesting has also been found to play a role in the relationship between extremely hot temperatures and hospital admissions for heart diseases (Schwartz et al., 2004). We find some modest evidence of harvesting as the total estimated net effect of a hot temperature shock (after 3 weeks) is smaller than the peak effect (after a week) and somewhat smaller than the contemporaneous effect, as demonstrated in Panel (b) of Figure 4. However, the net effect of a hot weather shock on A&E attendance remains substantial after three weeks, indicating that these effects are not primarily driven by harvesting.

In Appendix Tables A1 and A2 we present the results of a series of robustness tests on our main findings. In Table A1, we compare results for the balanced and unbalanced panels. The results for the unbalanced panel, which uses all available data on 429 A&E facilities, remain qualitatively unchanged from our balanced panel model. In Table A2, we compare results from our baseline model with a version that includes analytical weights based on the average number of A&E attendances in our sample period. Again, the results are qualitatively very similar. Indeed, across all specifications considered in various other robustness checks, the broad pattern of results holds, with contrasting findings at either end of the temperature distribution.

5. DISCUSSION

How do we reconcile and interpret these contrasting results across the temperature distribution? In this section, we discuss the possible behavioural mechanisms that could underpin the contrasting dynamic relationship between the extremes of heat and cold, and A&E attendances, that we observe in our data. A behavioural interpretation seems warranted here, particularly for the results on the effects of colder temperatures, where the initial decline in A&E attendances, followed by a compensating increase in attendances over subsequent weeks, seems difficult to reconcile with purely biological or physiological responses to cold weather.

The estimated reductions that we observe in A&E attendances for weeks with colder weather, if driven by purely physiological responses, would suggest that cold weather is on average health improving at a population level, which seems unlikely[3]. Instead, it may be that the observed effects are driven primarily by behavioural responses to colder temperatures. This interpretation is reinforced by the findings in relation to the cumulative effects, which show that the initial reduction in A&E attendances during spells of colder weather is fully offset by increases in attendances in the subsequent weeks. In other words, the evidence is consistent with A&E visits being postponed during bouts of cold weather – a kind of 'reverse-harvesting' effect.

In this context, two distinct behavioural effects could plausibly be associated with the outcomes we observe. The first is changes in willingness or propensity to attend A&E in response to variations in the weather. The second is differences in the composition of activities that people

[3] It has been observed in some cross-sectional studies comparing locations around the world that extremes of cold can be associated with better health environments, since frosts can kill pathogens leading to a lower prevalence of some diseases (Kiszewski et al., 2004). However, these are likely much more long-term effects of climate on disease environments. For short-run variations in weather, such as the weekly temperatures we study here, it seems more plausible to expect that cold weather might be damaging to health, for example because extremes of temperature (either cold or hot) place additional strain on the human body (Van de Vliert, 2007). Cold snaps are generally associated with increases in mortality (Deschenes and Greenstone, 2011; Barreca, 2012; Karlsson and Ziebarth, 2018), while in northern latitudes at least cold weather is also associated with 'flu season'.

engage in during periods of hot and cold weather. Taking the former effect first, any factor that increases the cost of treatment will tend to decrease the rate at which treatment is sought (White, 2017). This may include cold weather, if extremes of cold disrupt transport systems, or more generally if people experience disutility from going outside in colder weather. As a result, there may be a decreased willingness to seek treatment during periods of colder weather. This interpretation would be consistent with the idea of individuals delaying A&E visits during colder weather, and would seem to fit the pattern of results that we find in relation to the effects of cold weather on A&E attendances.

The postponement of A&E attendances to periods with more favourable weather conditions might also help explain the observed increase in A&E attendances for hotter temperatures – in this case if people bring forward their attendance for treatment during warmer weather. Here, however, postponement cannot account for the totality of the results we observe at hotter temperatures. In particular, the monotonic increase in A&E attendance for progressively hotter temperature intervals seems unlikely to correspond to individuals preferring to attend for treatment as temperatures get progressively hotter. Similarly, if the results we find for hotter temperatures were largely due to temporal shifts in when people choose to seek treatment, we would expect to see initial increases in A&E attendances during periods of hotter weather offset by subsequent declines (as in the harvesting phenomenon observed in the temperature-mortality literature). But this is not what we observe. If anything, the effect of hot weather on A&E attendance rates appears to intensify in the week after the hot weather shock and the cumulative effect remains large and statistically significant three weeks after the initial temperature shock (as per Panel (B) of Figure 4).

Instead, it seems more plausible that the effects of hotter temperatures that we observe reflect actual changes in morbidity. This likely reflects, at least in part, the well-documented physiological effects of heat, which are also widely cited as being behind the observed temperature-mortality relationship, particularly at the upper end of the temperature distribution (Deschenes and Greenstone, 2011; Barreca, 2012; Karlsson and Ziebarth, 2018). But genuine morbidity effects could also manifest in response to weather fluctuations as a result of the second behavioural effect that we consider – that is, if the overall composition of activities that people engage in changes in response to the weather.

Previous research has shown that individuals' time use responds significantly to the weather, with, for example, people found to substitute indoor activity for outdoor activity during periods of extremes of cold or hot weather (Graff-Zivin and Neidell, 2014) and levels of physical activity engaged in by adolescents found to increase modestly with temperature (Bélanger et al., 2009). While time spent outdoors and physical activity are widely acknowledged to be health promoting, at least in the medium to longer-term, the avoidance of these activities during periods of extreme temperatures might be thought of as health-preserving behaviour. Certainly it seems plausible that fewer accidents and physical injuries are likely to occur if people are spending more time at home and/or indoors (Kuitunen et al., 2020; Hampton et al., 2020). This postponement of activities could again be part of the underlying mechanism behind the results we observe in relation to the effects of cold weather on A&E attendance.

For periods of hot weather, this behavioural effect seems less plausible given that we observe increases in A&E attendance during periods of hotter weather. The modest intensification of the effect of hot weather in the week after the temperature shock could be evidence of this type of postponement behaviour (of riskier activity), but it could equally be the result of symptoms or illnesses caused by hotter temperatures in some cases not appearing until a week after the temperature shock[4].

Instead, it may be that in our context periods of hotter weather are associated with behaviours that are not health-preserving. Comparing the results that we observe for the dynamic relationship between extremes of heat and cold with A&E attendances suggests a differential behavioural response of individuals in England across the temperature distribution (as illustrated in Figure 2). It may be that individuals in England are not engaging in health-preserving behaviours at the same rate for extremely hot temperatures as they do for extremely cold temperatures. Of course, this difference across extremes of heat and cold could partly be explained by the degree of longer-term adaptation to underlying climate conditions. For instance, individuals may be limited in their adaptive capacity due to current building standards being made to protect against cold weather but limited in terms of protection against the effects of extremely hot weather.

An alternative, more behavioural explanation, may be that heatwaves often tend to be seen as 'good news' stories in the UK[5]. As a result, behavioural responses to hotter weather in this context may involve increased activities that lead to higher exposure to extremely hot temperatures (i.e. socialising, going to the beach, etc.), and an associated increase in accidents, physical injuries, and illness. Of course, one should note that such activities, despite being potentially damaging to health, may still increase an individual's utility.

The discussion in this section is somewhat speculative; given limitations in the available data, such as a lack of information on disease category or reason for attendance, we are unable to test explicitly the behavioural mechanisms that we propose here. However, we can conclude

[4] This might be more likely in our data given the aggregation to weekly observations. For example, if the maximum weekly temperature for week t happened to be on the last day of the week, this could conceivably show up in an increase in A&E attendances at the start of the following week (i.e. in week $t + 1$).
[5] See, for example, https://www.mirror.co.uk/news/uk-news/uk-weather-met-office-delivers-26665166 (accessed 28/04/2022).

by suggesting that the dynamic relationship we observe between cold weather shocks and A&E attendances appears likely to be driven largely by behavioural responses to colder weather, leading to 'missing' or postponed attendances in the week of the cold weather shock. For periods with hotter weather, on the other hand, it seems more plausible that the effects we observe derive from a combination of direct physiological effects of heat and behavioural responses to hotter weather. Further research is required to investigate the extent to which these behavioural interpretations of our findings are supported by the data.

6. CONCLUSION

This paper investigates the relationship between temperature and morbidity using data on the near-universe of A&E attendances in England for the period 2010-2015. We find that while cold weather is associated with lower contemporaneous A&E attendances, this effect appears to be entirely attributable to displacement of A&E visits to subsequent weeks. In contrast, for hotter temperatures, we find evidence of substantial contemporaneous increases in weekly A&E attendances that are not offset by subsequent reductions. Overall our results are consistent with differences in individual-level behavioural responses to extreme cold and hot temperatures in England. They also demonstrate, for the first time, a significant effect of hot temperatures on human health in a country with a relatively temperate climate. This highlights the potentially significant negative consequences of climate change for countries with cooler climates in terms of health outcomes and health system capacity.

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Tables

Table 1: Descriptive Statistics – A&E Attendances – Balanced Panel

Variable Name	Description	Descriptive Statistics
A&E_Rate	Weekly A&E treatment facility attendance rate per 100,000 regional population (Mean (SD))	34.87 (27.65)
A&E_Attendances	Number of A&E attendances (Total)	76,732,480
Region	= East Midlands (% of Total)	6.51%
	= East of England (% of Total)	9.99%
	= London (% of Total)	16.72%
	= Northeast (% of Total)	7.39%
	= Northwest (% of Total)	17.20%
	= Southeast (% of Total)	12.17%
	= Southwest (% of Total)	7.77%
	= West Midlands (% of Total)	11.15%
	= Yorkshire & Humber (% of Total)	11.10%
Number of treatment facilities		156
Number of weekly observations		37,897

Source: Analysis of data from NHS (2022) and StatWales (2022).

Table 2: Descriptive Statistics – Temperature Variables

Temperature Bins	**Description**	**Percentage of Weekly Maximum Temperatures**
[1ºC, 4ºC)	= 1 if weekly maximum temperature is greater than or equal to 1ºC but less than 4ºC, 0 otherwise	1.2%
[4ºC, 7ºC)	= 1 if weekly maximum temperature is greater than or equal to 4ºC but less than 7ºC, 0 otherwise	2.9%
[7ºC, 10ºC)	= 1 if weekly maximum temperature is greater than or equal to 7ºC but less than 10ºC, 0 otherwise	10.6%
[10ºC, 13ºC)	= 1 if weekly maximum temperature is greater than or equal to 10ºC but less than 13ºC, 0 otherwise	20.4%
[13ºC, 16ºC)	= 1 if weekly maximum temperature is greater than or equal to 13ºC but less than 16ºC, 0 otherwise	14.1%
[16ºC, 19ºC)	= 1 if weekly maximum temperature is greater than or equal to 16ºC but less than 19ºC, 0 otherwise	15.5%
[19ºC, 22ºC)	= 1 if weekly maximum temperature is greater than or equal to 19ºC but less than 22ºC, 0 otherwise	15.5%
[22ºC, 25ºC)	= 1 if weekly maximum temperature is greater than or equal to 22ºC but less than 25ºC, 0 otherwise	12.3%
[25ºC, 28ºC)	= 1 if weekly maximum temperature is greater than or equal to 25ºC but less than 28ºC, 0 otherwise	5.2%
[28ºC,)	= 1 if weekly maximum temperature is greater than or equal to 28ºC, 0 otherwise	2.3%

Source: Analysis of data from Met Office et al. (2021).

Table 3: Baseline Model Results – Balanced Panel

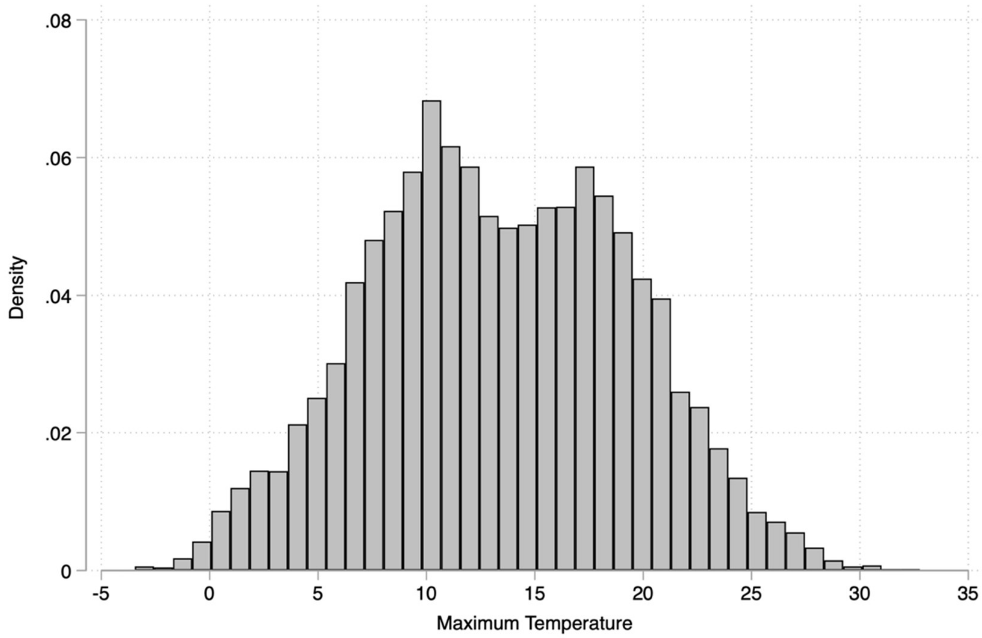
Temperature Bins	**(1) Contemporaneous Effects**	**(2) Cumulative Effects**
[1ºC, 4ºC)	-1.512***	1.589
	(0.445)	(0.987)
[4ºC, 7ºC)	-0.819***	0.245
	(0.157)	(0.383)
[7ºC, 10ºC)	-0.369	0.032
	(0.171)	(0.438)
[10ºC, 13ºC)	Base Category	Base Category
	-	-
[13ºC, 16ºC)	0.569***	0.998
	(0.167)	(0.507)
[16ºC, 19 ºC)	1.102***	1.527***
	(0.238)	(0.279)
[19ºC, 22 ºC)	1.590***	1.960***
	(0.296)	(0.288)
[22ºC, 25 ºC)	2.256***	2.830***
	(0.336)	(0.380)
[25 ºC, 28 ºC)	2.651***	3.014***
	(0.308)	(0.364)
[28ºC,)	2.751***	2.628***
	(0.360)	(0.419)
Mean Dependent Variable	34.87	34.87
Rainfall Controls	Yes	Yes
Hospital FEs	Yes	Yes
Week & Region-Week FEs	Yes	Yes
Year & Region-Year FEs	Yes	Yes
Error Cluster	One-way	One-way
N	37,433	37,433

Source: Analysis of data from NHS (2022), StatWales (2022) and Met Office et al. (2021).

Notes: Standard errors are clustered at the region level. *** significant at the 1% level.

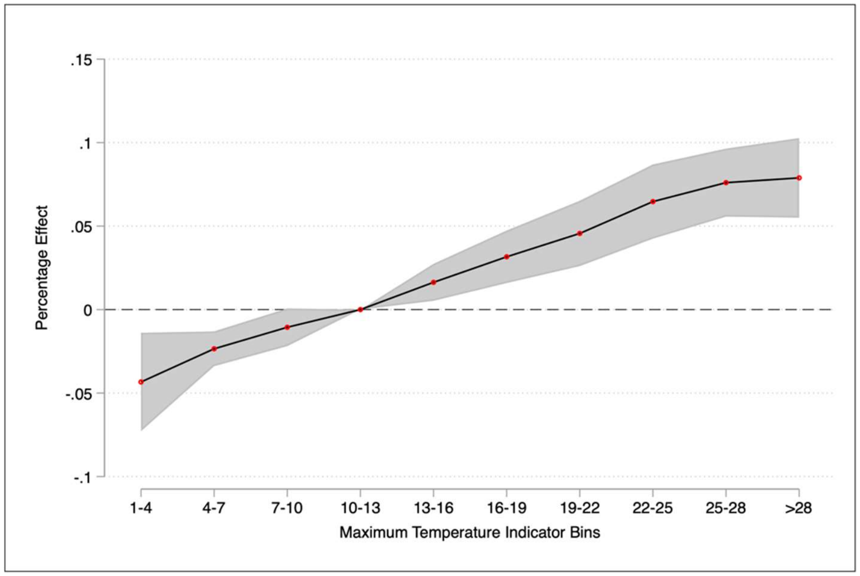
Figures

Figure 1: Distribution of Daily Maximum Temperatures

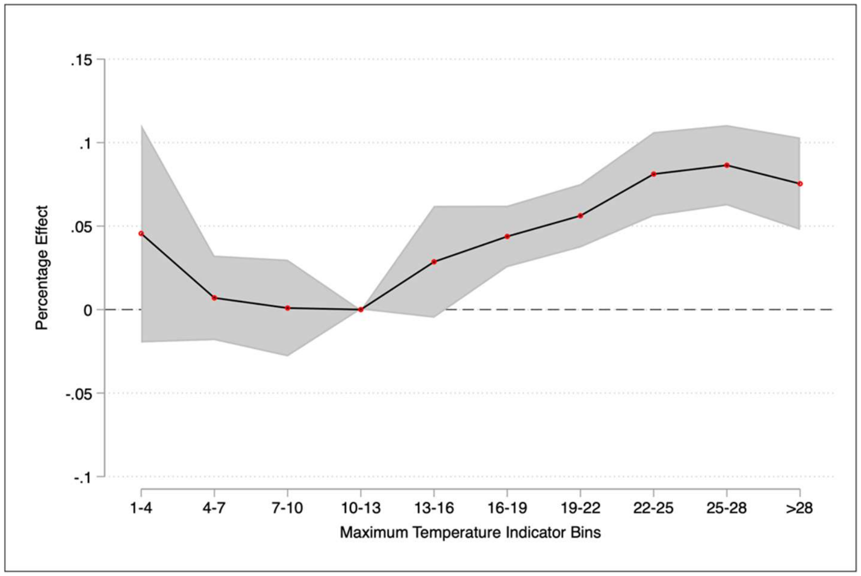


Source: Analysis of data from Met Office et al. (2021).

Figure 2: Estimated Contemporaneous and Cumulative Effects



(A) Contemporaneous Effects

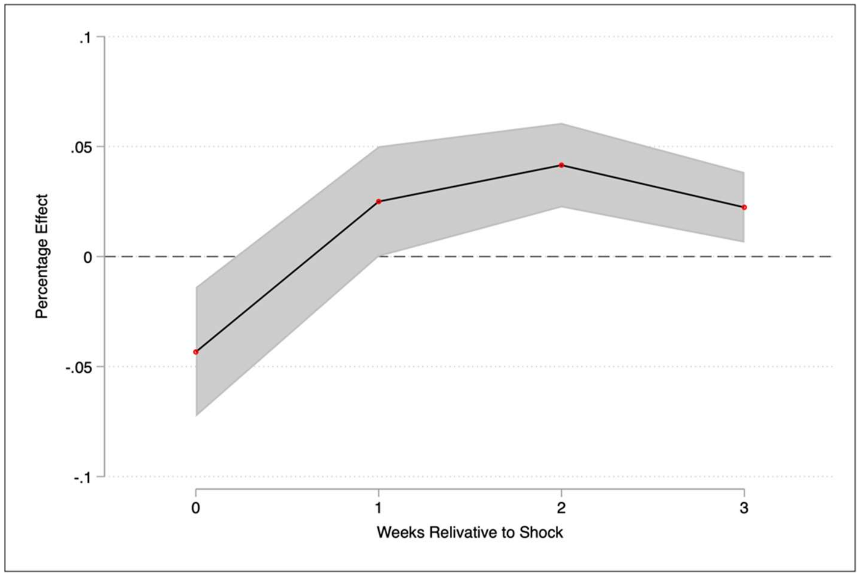


(B) Cumulative Effects

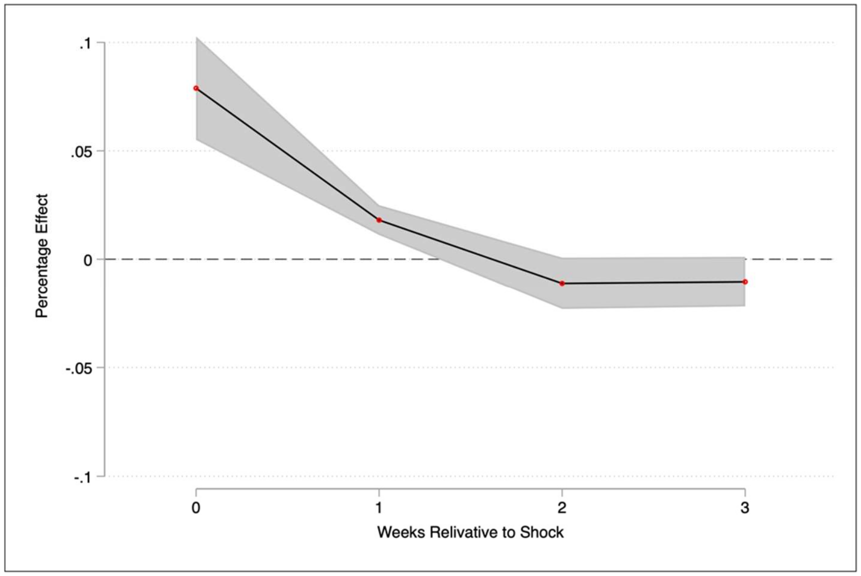
Source: Analysis of data from NHS (2022), StatWales (2022) and Met Office et al. (2021).

Note: 95% confidence intervals represented by shaded region.

Figure 3: Estimated Weekly Effects – Lowest and Highest Temperature Bins



(A) 1-4°C

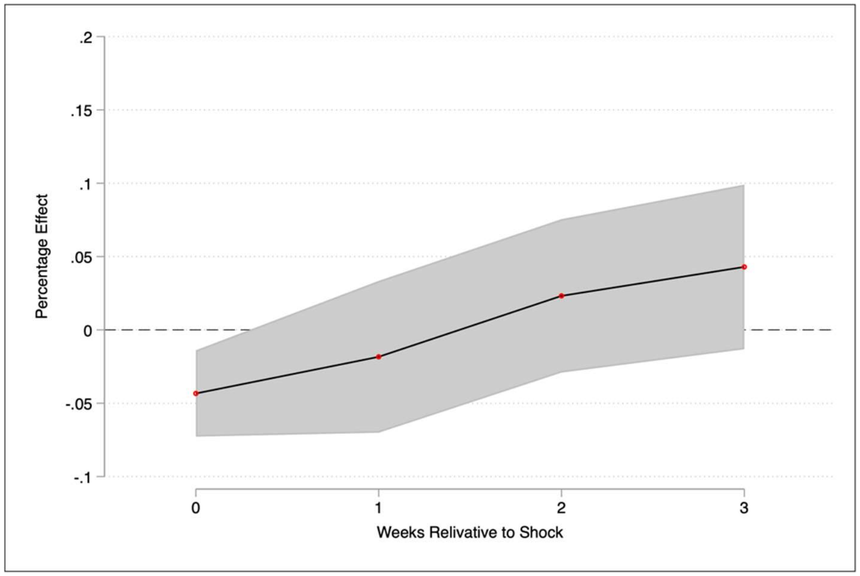


(B) 28+°C

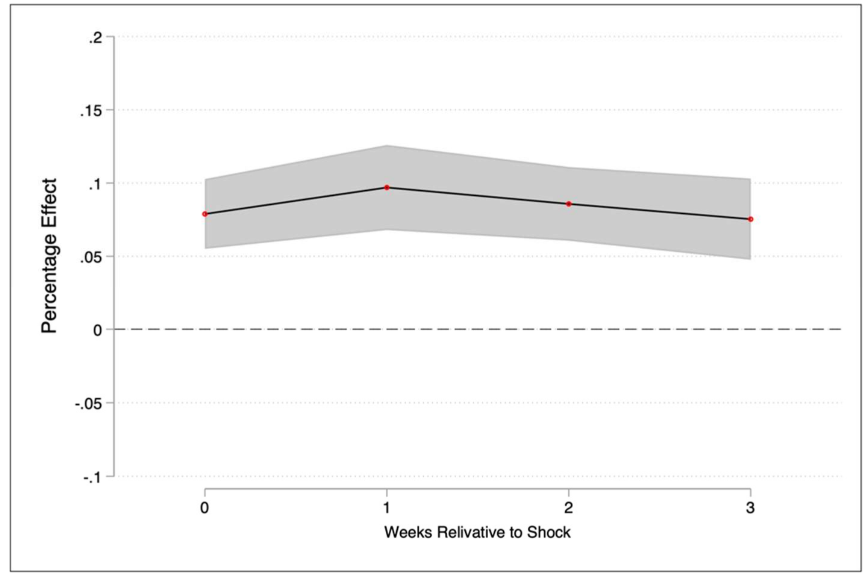
Source: Analysis of data from NHS (2022), StatWales (2022) and Met Office et al. (2021).

Note: 95% confidence intervals represented by shaded region.

Figure 4: Estimated Cumulative Effects – Lowest and Highest Temperature Bins



(A) 1-4^{o}C



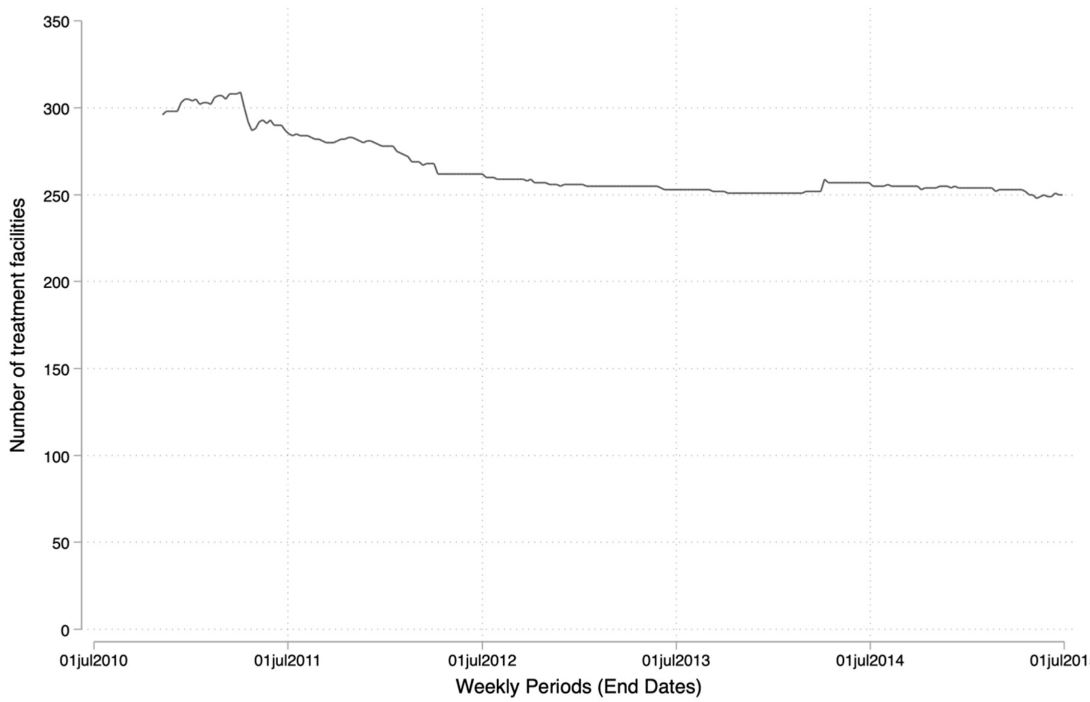
(B) 28+^{o}C

Source: Analysis of data from NHS (2022), StatWales (2022) and Met Office et al. (2021).

Note: 95% confidence intervals represented by shaded region.

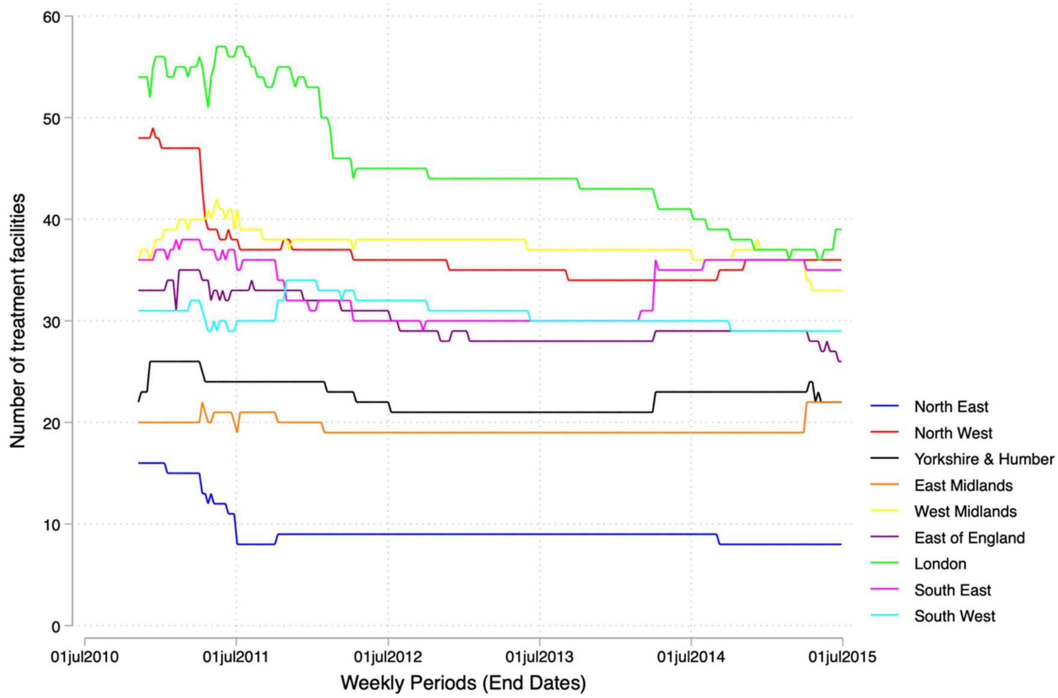
Appendix

Figure A1: Number of Treatment Facilities in NHS Data over the Study Period



Source: Analysis of data from NHS (2022).

Figure A2: Number of Treatment Facilities in NHS Data over the Study Period by Region



Source: Analysis of data from NHS (2022).

Table A1: Robustness Test – Balanced versus Unbalanced Panels

	Balanced Panel		**Unbalanced Panel**	
Temperature Bins	**Contemporaneous Effects**	**Cumulative Effects**	**Contemporaneous Effects**	**Cumulative Effects**
[1ºC, 4ºC)	-1.512***	1.589	-1.310***	1.498
	(0.445)	(0.987)	(0.296)	(0.658)
[4ºC, 7ºC)	-0.819***	0.245	-0.545***	0.783
	(0.157)	(0.383)	(0.100)	(0.370)
[7ºC, 10ºC)	-0.369	0.032	-0.267	0.157
	(0.171)	(0.438)	(0.145)	(0.394)
[10ºC, 13ºC)	Base Category	Base Category	Base Category	Base Category
	-	-	-	-
[13ºC, 16ºC)	0.569***	0.998	0.432***	0.858**
	(0.167)	(0.507)	(0.105)	(0.269)
[16ºC, 19 ºC)	1.102***	1.527***	0.819***	1.307***
	(0.238)	(0.279)	(0.102)	(0.225)
[19ºC, 22 ºC)	1.590***	1.960***	1.127***	1.524***
	(0.296)	(0.288)	(0.162)	(0.193)
[22ºC, 25 ºC)	2.256***	2.830***	1.678***	2.368***
	(0.336)	(0.380)	(0.172)	(0.164)
[25 ºC, 28 ºC)	2.651***	3.014***	2.012***	2.692***
	(0.308)	(0.364)	(0.168)	(0.248)
[28ºC,)	2.751***	2.628***	2.077***	2.274***
	(0.360)	(0.419)	(0.208)	(0.314)
Mean Dep. Var.	34.87	34.87	26.54	26.54
Rainfall Controls	Yes	Yes	Yes	Yes
Hospital FEs	Yes	Yes	Yes	Yes
Week & Region-Week FEs	Yes	Yes	Yes	Yes
Year & Region-Year FEs	Yes	Yes	Yes	Yes
Error Cluster	One-way	One-way	One-way	One-way
N	37,433	37,433	62,845	62,845

Source: Analysis of data from NHS (2022), StatWales (2022) and Met Office et al. (2021).

Notes: Standard errors are clustered at the region level. *** significant at the 1% level. ** significant at the 5% level.

Table A2: Robustness Test – Weighted versus Unweighted Models

	Unweighted		**Weighted by Hospital Size**	
Temperature Bins	**Contemporaneous Effects**	**Cumulative Effects**	**Contemporaneous Effects**	**Cumulative Effects**
[1ºC, 4ºC)	-1.512***	1.589	-2.089**	1.504
	(0.445)	(0.987)	(0.662)	(1.783)
[4ºC, 7ºC)	-0.819***	0.245	-1.128***	0.023
	(0.157)	(0.383)	(0.238)	(0.622)
[7ºC, 10ºC)	-0.369	0.032	-0.550*	-0.139
	(0.171)	(0.438)	(0.242)	(0.595)
[10ºC, 13ºC)	Base Category	Base Category	Base Category	Base Category
	-	-	-	-
[13ºC, 16ºC)	0.569***	0.998	0.762**	1.445
	(0.167)	(0.507)	(0.248)	(0.817)
[16ºC, 19 ºC)	1.102***	1.527***	1.498***	2.041***
	(0.238)	(0.279)	(0.364)	(0.403)
[19ºC, 22 ºC)	1.590***	1.960***	2.133***	2.457***
	(0.296)	(0.288)	(0.403)	(0.386)
[22ºC, 25 ºC)	2.256***	2.830***	2.987***	3.645***
	(0.336)	(0.380)	(0.473)	(0.471)
[25 ºC, 28 ºC)	2.651***	3.014***	3.452***	3.753***
	(0.308)	(0.364)	(0.402)	(0.536)
[28ºC,)	2.751***	2.628***	3.508***	3.185***
	(0.360)	(0.419)	(0.495)	(0.507)
Mean Dep. Var.	34.87	34.87	34.87	34.87
Rainfall Controls	Yes	Yes	Yes	Yes
Hospital FEs	Yes	Yes	Yes	Yes
Week & Region-Week FEs	Yes	Yes	Yes	Yes
Year & Region-Year FEs	Yes	Yes	Yes	Yes
Error Cluster	One-way	One-way	One-way	One-way
N	37,433	37,433	37,433	37,433

Source: Analysis of data from NHS (2022), StatWales (2022) and Met Office et al. (2021).

Notes: Standard errors are clustered at the region level. *** significant at the 1% level. ** significant at the 5% level. * significant at the 10% level.