# Temperature, Morbidity and Behaviour in Milder Climates

Garreth Gibney[1], Thomas K.J. McDermott[1] and John Cullinan[1*]

[1] School of Business & Economics, University of Galway.

* Corresponding author. School of Business & Economics, University of Galway, University Road, Galway, H91 TK33, Ireland. Email: john.cullinan@universityofgalway.ie. Tel: +353 (0)91 493996.

**Funding:** Funding from the College of Business, Public Policy and Law's 'Post-Covid Research Support Fund' at University of Galway supported this work and is gratefully acknowledged.

**Declaration of competing interests:** None.

**Data availability:** This paper uses publicly available data from National Health Service (NHS) England, Centre for Environmental Data Analysis (CEDA), and StatWales. The NHS England data is available for download at https://www.england.nhs.uk/statistics/statistical-work-areas/ae-waiting-times-and-activity/, the CEDA data is available for download at https://catalogue.ceda.ac.uk/uuid/97bc0b64bc354898a242a42238e1b45c, and the StatWales data is available for download at https://statswales.gov.wales/Catalogue/Population-and-Migration/Population/Estimates/Local-Authority/populationestimates-by-localauthority-year.

**Acknowledgements:** We would like to sincerely thank the Editor (Professor Angus C. Chu) and two anonymous referees for their very helpful comments and suggestions on an earlier version of this manuscript.

## 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* (Basu, 2009; Campbell et al., 2018; Deschenes, 2014), the impact on *morbidity* has received much less attention and significant gaps remain in our understanding. In particular, while a small number of previous studies have presented estimates of the effects of extreme temperatures on morbidity-related outcomes, this literature mainly focuses on countries or regions with relatively hotter climates and more extreme temperatures (Agarwal et al., 2021; Karlson and Ziebarth, 2018; White, 2017) and/or on primary care visits or hospital admissions related to specific disease categories (Fritz, 2022; Masiero et al., 2022; Rizmie et al., 2022). Our paper adds to this literature by estimating the impact of temperature on morbidity in England, a country with a temperate maritime climate and relatively mild temperature extremes[1]. The aim is to investigate if similar effects of temperature on morbidity are present in countries with milder climates as have been shown to exist in hotter countries.

Considering the temperature-morbidity relationship in temperate climates is important, as the greatest overall temperature increases from climate change are expected to occur in northern latitudes (Beusch et al., 2022; IPCC, 2021). In addition, the impacts of extreme temperatures on health outcomes in milder climates are likely to be distinct from those observed in locations with more extreme temperatures, given longer-term adaptation to existing climates (Carleton and Hsiang, 2016; Heutel et al., 2021). Estimating such impacts in countries such as England

[1] Whereas previous studies on temperature and morbidity tend to be based in regions with relatively hot climates, the highest daily maximum temperature in our sample is just 32.8°C (91.0°F). In fact, daily maximum temperatures only exceed 30.0°C (86.0°F) on 14 occasions in our data, representing fewer than 0.1% of days in the sample. In contrast, for Karlson and Ziebarth's (2018) study based in Germany, approximately 2.5% of days exceeded 30.0°C. Similarly, in White's (2017) study, which uses daily *mean* temperatures and is based on data from California, the top temperature bin of 26.7°C (80.0°F) or above accounts for 6% of the sample. In our data, the daily mean temperature never exceeds 24.5°C (76.1°F).

therefore represents an important contribution to our understanding of the overall costs of climate change. These estimates can, for example, help to inform revisions to the estimated social cost of carbon (SCC), a crucial value underpinning climate policies in many parts of the world, and an input to cost-benefit analyses for investments and policies valued in the trillions of US dollars (Aufhammer, 2018; Carleton and Greenstone, 2021; Millner and McDermott, 2016). Existing estimates of the SCC have been widely critiqued on various grounds, particularly in relation to so-called 'damage functions' that translate temperature changes into economic losses. Our study contributes new empirical evidence on important regional heterogeneity in climate impacts, as well as on non-linearities in the relationship between temperatures and human well-being, which have been highlighted as important omissions in existing SCC estimates (Carleton and Greenstone, 2021). Our estimates can also be used more directly by policymakers locally to inform healthcare provision planning, and to predict likely spikes in demand for healthcare services during future extreme weather episodes.

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, a second aim of this paper is to consider the likely role of behavioural responses to extreme temperatures in countries with milder climates. In particular, it focuses on potential short-term defensive/avoidance adaptive behaviours that may help mitigate the health impacts of extreme temperature events. Again here the setting of our study is significant, as the short-term behavioural responses to weather variation are likely to be distinct in the context of a milder climate, such as England, where for example heat-waves have often been portayed as good news stories[2].

To address these aims, we combine 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. We employ a distributed lag regression model that includes hospital, 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 A&E attendances in the same week, this effect appears to be due to the postponement of visits to subsequent weeks. In contrast, for hotter temperatures, we find evidence of substantial increases in weekly A&E attendances that are not offset by reductions over subsequent weeks.

Overall, this paper makes two specific contributions to the literature. First, our analysis shows that hotter temperatures significantly impact morbidity even in countries with relatively milder climates. In particular, we find net increases in overall A&E attendances at lower levels of hot temperature than in previous studies for hotter countries and regions, perhaps reflecting a relative lack of adaptation to heat in our context. This finding has major implications for our current understanding of the health impacts 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; IPCC, 2021).

[2] See, for example, https://www.mirror.co.uk/news/uk-news/uk-weather-met-office-delivers-26665166 (accessed 28/04/2022).

Second, our results across the temperature distribution are consistent with differences in individual-level behavioural responses and adaptation 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 and also highlights important differences in adaptation across countries. For example, our results suggest that England's population is better adapted to colder temperatures, in comparative terms, likely in part because of their generally milder climate.

The rest of this paper is organised as follows: Section 2 discusses the relevant extant literature, Section 3 describes the data, and Section 4 outlines the empirical strategy. Section 5 presents and describes the main results, while Section 6 discusses the possible behavioural mechanisms underpinning our findings. Finally, Section 7 concludes.

## 2. LITERATURE

There is a growing body of literature in economics that exploits random fluctuations in local weather to identify the effects of climate on a range of socio-economic outcomes including, for example, conflict, crime, agricultural output, labor productivity, and health[3]. Specifically in relation to health, this literature has for the most part focused on the effects of extreme temperatures on *mortality* (White, 2017). 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. Comparable 'U-shaped' results were also identified in Barreca (2012), also for the US, and in Karlsson and Ziebarth (2018) for Germany.

[3] See for example Dell et al. (2014) and Carleton and Hsiang (2016) for extensive reviews of this literature, and Hsiang et al. (2017) for an application of this empirical evidence to valuing the damages from climate change.

In a recent study using Italian data, Masiero et al. (2022) found that only hotter temperatures had a significant effect on mortality, with the effects of cold temperatures being insignificant[4].

In contrast, the relationship between temperature and *morbidity* has received much less attention from economists, with some notable recent 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 also found for hospital admissions in Germany by Karlsson and Ziebarth (2018) and in China by Agarwal et al. (2021), although the latter found extremely cold temperatures (less than -6ºC) had no effect on admissions. In contrast, Fritz (2022) found no evidence of a U-shaped relationship between temperature and daily visits to primary care facilities in Indonesia, though all-cause and non-communicable disease related visits increased substantially on days where the temperature exceeded the average. In addition, Masiero et al. (2022) found no evidence of morbidity effects from temperature when measured in absolute terms in Italy. However, similar to their mortality findings, when using relative measures of temperature, their results showed that extreme temperatures (both hot and cold) exerted significant effects on morbidities from specific conditions i.e. emergency admissions for cardiovascular and respiratory illnesses.

Importantly, whereas these previous studies have tended to be based on data from countries with hotter climates where temperature extremes occur more frequently, our study investigates the effect of temperature on morbidity in a country, England, with a relatively mild climate that experiences fewer and less extreme hot temperatures. This is both novel and important.

[4] However, using relative measures of temperature (deviations from local averages), Masiero et al. (2022) did find that extremes of both hot and cold temperatures – relative to the local climate – significantly affected mortality. This finding is suggestive of local adaptation to existing climates, a point we return to later in this section.

Previous studies have found significant regional heterogeneity in the temperature-mortality relationship (Heutel et al., 2021), while regional heterogeneity of impacts, and non-linearities, have been highlighted as important empirical gaps in assessments of the overall damage costs from climate change (Carleton and Greenstone, 2021). In addition, with the exception of White (2017), most of the other studies mentioned here measure morbidity outcomes using hospital *admissions* data, which may be affected by capacity constraints on the supply side. Our outcome measure, which is based on all-cause A&E *attendances*, is more likely to capture the totality of morbidity effects, as well as the influence of any mediating factors such as behavioural or adaptive responses to extreme temperatures.

The health impacts of climate have also been investigated from other perspectives in related disciplines. In particular, the relationship between extreme temperatures and health has been widely considered in the public health/epidemiology literature, including both mortality impacts (Braga et al., 2001; Fouillet et al., 2008; Kalkstein and Greene, 1997; Ye et al., 2001) and morbidity effects (Ebi et al., 2004; Morabito et al., 2005; Schwartz et al., 2004)[5]. Specifically for the UK, a number of studies in this literature have investigated the link between extreme temperatures and health outcomes, with several papers demonstrating a U-shaped relationship between temperature and mortality (Gasparrini et al., 2022; Hajat et al., 2006; Hajat et al., 2014)[6]. There are also a handful of studies in this literature that examine the link between temperature and morbidity from an epidemiological perspective, using UK data. Here, however, the findings are less conclusive. Two older studies found no association between temperature and emergency hospital admissions, specifically in the context of a heat-wave in Birmingham (Ellis et al., 1980) and for London (Kovats et al., 2004)[7]. Two more recent studies,

[5] McMichael et al. (2006) provide a comprehensive review of the climate-public health literature.
[6] In a related study, Iparraguirre (2015) demonstrated that 'winter fuel payments' accounted for almost half the reduction in excess winter mortality in England and Wales from 1999/2000 to 2012.
[7] The latter study did find an increace in emergency hospital admissions for specific disease catgories (i.e. respiratory and renal illnesses) amoung vunerable sub-populations (i.e. <5yrs and 75yrs+).

in contrast, found positive associations between temperatures and morbidity outcomes; for all-cause A&E attendance in London (Corcuera Hotz and Hajat, 2020) and for emergency hospital admissions in England for six specific temperature-sensitive illneses (Rizmie et al., 2022).

In summary, the existing economics literature on the morbidity impacts of extreme temperatures have mainly studied these effects for countries with relatively hot climates and more frequent temperature extremes. In the public health/epidemiology literature, there have been a small number of studies on morbidity effects of extreme temperatures based on UK data, but these have either been limited in geographic scope (to individual cities)[8], or focused on outcome measures that capture a sub-set of the overall morbidity effects and behavioural responses to extreme weather. While studies focusing on specific illnesses are important to understand biological pathways between temperature and morbidity, understanding the overall morbidity effects of temperature, as well as the influence of any mediating factors such as behavioural or adaptive responses, is key in both estimating the costs of climate change and in planning for healthcare service delivery. Thus, our paper is complementary to the existing literature discussed here and aims to fill this specific knowledge gap.

In addition, there are also a number of related strands of the empirical climate economics literature that focus on alternative outcome measures related to human well-being. Temperature, in particular, has been shown to exert significant influence over various dimensions of human well-being, including birth weight (Deschenes et al., 2009), cognitive attainment (Graff-Zivin et al., 2018), physical performance (Sexton et al., 2022), and sentiment (Baylis, 2020). A related strand of the literature relates to the mental health impacts of extreme temperatures. For example, Mullins and White (2019) found that higher temperatures increase

[8] The limited geographical scope of these studies may raise issues about the generalisability of their results, in particular in relation to the representativeness of the overall effect of temperaure on morbidity in milder climates such as England. This could be due to differences in demographics between urban and rural areas, for instance, or the relative concentration of extreme heat events in larger urban areas, such as London.

ED visits for mental illness, suicides, and self-reported days of poor mental health in California. Other studies have shown increases in suicide rates in response to higher temperatures in the US and Mexico (Burke et al., 2018), and in India, where the effects appear to operate *via* the impact of temperature on agricultural yields (Carleton, 2017). Elsewhere, higher temperatures have been shown to be associated with decreases in self-reported mental health (Obradovich et al., 2018).

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 as an adaptive response (Deschenes and Moretti, 2009). Heutel et al. (2021) demonstrated substantial variation across regions of the US in the temperature-mortality relationship, with the mortality effects of extreme heat being significantly higher in cold regions relative to warm regions. Similarly, the findings in Masiero et al. (2022), mentioned previously, that relative deviations in temperature have stronger effects on health than absolute temperatures, is suggestive of longer-term adaptation to local climates. The factors driving this heterogeneity across climate regions, however, remain unclear.

In contrast to these longer-term adaptation responses, relatively few studies have considered short-term behavioural responses to extreme temperatures. There is, however, a related literature on health and air quality, where the role of 'avoidance behaviors' has been considered. For instance, Neidell (2009) shows that hospital attendances decrease on days where air quality is forecast to be unhealthy, likely driven by avoidance behaviors. Moreover, studies using instrumental variables (IV) further demonstrate the role of avoidance behaviours in biasing OLS estimates of the health impacts of pollution towards zero. For example, Moretti and Neidell (2011) use the timing of Port of Los Angeles traffic and distance to the port as an instrument for ozone, finding IV results that are much larger than the OLS equivalent, suggesting the presence of avoidance behavior. Similarly, Knittel et al. (2016), using random traffic shocks as instruments for bad air quality, find a large and statistically significant effect of air pollution on infant mortality. However, Graff-Zivin and Neidell (2009) demonstrate a dynamic response whereby behavioural changes to smog alerts depend in part on the prior history of such alerts. Specifically, individuals appear quite responsive to alerts on the first day they are issued, but much less so on subsequent consecutive days.

Focusing on general behavioural responses to temperature, 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. However, while such responses can influence the relationship between temperature and morbidity, they are not necessarily self-protecting in nature. For instance, 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.

Undertanding these behavioural responses is important in estimating the cost of extreme temperature events and climate change. For example, Janke et al. (2009) notes "the extent to which we can use our estimates to quantify the effects of a change in pollution depends on whether individuals are likely to take actions to protect themselves from increases in pollution levels". If individuals do engage in protective behaviors, estimates of health impacts of external health threats, such as extreme temperatures, will have a downward bias i.e. empirical studies will tend to under-state the true effects of (unanticipated) temperature shocks on morbidity. On the other hand, especially in the case of extreme temperatures, short-run behavioural responses could in some cases increase an individual's exposure to temperature, leading to upward biased estimates of health effects. Therefore, a somewhat overlooked question in the literature to date is the role of short-run behavioural responses in mediating the temperature-morbidity relationship, and the relationship between health and temperature more broadly. Thus, this study also aims to address this gap in the literature by examining the potential role of behavioural responses in mediating the temperature-moribidity relationship in the context of a relatively mild climate.

## 3. 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.

### *3.1 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 A1.1 in Appendix 1), 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.

### *3.2 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°C, 4°C) takes a value of 1 if the highest daily maximum temperature in a given week is greater than or equal to 1°C but less than 4°C. Subsequent bins increase in 3°C intervals to the highest temperature indicator [28ºC, ), which takes a value of 1 if the highest daily maximum temperature in a given week is greater than or equal to 28ºC. 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).

## 4. 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:

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

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 10-13ºC bin[9], 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 10-13ºC. 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

[9] 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 60-65ºF (15.6-18.3ºC) temperature bin for California, Karlsson and Ziebarth (2018) omitted the 40-50ºF (4.4-10ºC) bin for Germany, while Agarwal et al. (2021) omitted the 9-12ºC 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 10-13ºC bin. Our results and findings are robust to alternative base categories.

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 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 a set of region-by-week ($\delta_{Region-Week}$) 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, these 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 region-by-year ($\delta_{Region-Year}$) fixed effects in our model. 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 A1.2 in Appendix 1). 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.

## 5. RESULTS

### *5.1 Main Results*

In this section we present the results of our empirical analysis. To begin, the results from 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][10]. While the estimates 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 [22ºC, 25ºC) temperature indicator bin – see Column (1) of Table 3 – is as follows: a week with a maximum temperature greater than or equal to 22ºC but less than 25ºC is associated with 2.26 additional A&E attendances per 100,000 individuals, relative to a week with maximum temperature in the [10ºC, 13ºC) base category range. 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%

[10] Additional specifications and results are reported as robustness and placebo tests in Appendices 2-7 and discussed below in Section 5.2.

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$^{o}$C, 4$^{o}$C) temperature indicator bin suggests a 4.3% decline in A&E attendances, relative to the omitted [10$^{o}$C, 13$^{o}$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$^{o}$C, 4$^{o}$C) temperature indicator bin is positive, though not statistically different from zero. A similar pattern is found for each of the other colder temperature indicator bins, up to 10$^{o}$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$^{o}$C, 28$^{o}$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$^{o}$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 percentage contemporaneous 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 percentage cumulative effect over a four-week period for each of the temperature bins, showing statistically 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[11]. 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 [16ºC, 19ºC) and above. This is a similar pattern to the 31-day cumulative effects found in California (White, 2017), where temperatures in the ranges 75-80ºF (23.8-26.7ºC) and 80+ºF (26.7+ºC) are associated with net total increases in ED attendances. Notably, however, we find net increases in A&E attendances in our data at relatively low 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 appear to be somewhat larger than those found in White (2017) and other studies. In addition, the overall shape of the estimated relationship here also differs somewhat from the U-shaped relationship generally found in the temperature-mortality (Barreca, 2012; Barreca et al., 2016; Deschenes and Greenstone, 2011) and temperature-morbidity literatures (Karlsson and Ziebarth, 2018; White, 2017). In particular, in our context, we find the relative size of the effect of a week with very hot temperatures is larger in magnitude than the effect of a week with very cold

[11] While the estimated cumulative effect for the coldest temperature bin in our data is not statistically different from zero, it is positive and 'practically significant'. The non-statistical significance may be, in part, due to a lack of statistical power as a result of relatively few observations in this temperature bin in our data. Thus, overall we conclude there is inconclusive evidence of an effect at the lowest temperatures.

temperatures, which is also much less precisely estimated.

[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[12]. In each figure the dynamic association at relatively cold temperatures, i.e. the [1°C, 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 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 statistically

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

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 statistically 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 apparent differences in the level of hotter temperatures associated with increased A&E attendance in our study, 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 (Armstrong, 2006; Basu and Samet, 2002; Braga et al., 2001; Deschenes and Moretti, 2009). 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 the contemporaneous effects are not being driven by harvesting.

### *5.2 Robustness and Placebo Tests*

In order to test the sensitivity and robustness of our results and findings, we also estimated a range of additional models and the results from these are presented in Appendices 2-6 and briefly summarised here. First, in Appendix 2, we present estimates using the unbalanced panel, which uses all available data on 429 A&E treatment facilities. Second, in Appendix 3, we present results from a model that applies analytical weights based on the average number of A&E attendances per treatment facility in our sample period. Third, in Appendix 4, we aggregate A&E attendances from hospital to broad regional level and present results from a regional model where the dependent variable is regional A&E attendances per 100,000 population. Fourth, in Appendix 5, to address the possibility that annual population levels may be endogenous with respect to temperature, we used lagged population values as the denominator in the calculation of our dependent variable. Fifth, in Appendix 6, we present results from a model employing a set of weekly maximum temperature *count* bins, as opposed to *indicator* bins, as the main independent variables of interest. Across all these additional analyses we found that our main results and conclusions were robust and qualitatively unchanged.

Finally, in Appendix 7, we also present results from a placebo test that adds a single temperature 'lead' to the model presented in Equation [1]. In particular, we present the estimated weekly effects for extreme cold (lowest) and extreme hot (highest) temperature bins from this model and, in both cases, the results show no evidence of a significant change in hospital attendances in the week *prior to* an extreme temperature occurrence. This is as expected and lends some support to a causal interpretation of our results.

## 6. BEHAVIOURAL MECHANISMS

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[13]. 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

[13] 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 (Barreca, 2012; Deschenes and Greenstone, 2011; Karlsson and Ziebarth, 2018), while in northern latitudes at least cold weather is also associated with 'flu season'.

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 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 (Barreca, 2012; Deschenes and Greenstone, 2011; 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[14].

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 these individuals 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. 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

[14] 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 $t + 1$).

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.

## 7. 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. A number of recent studies have demonstrated a link between temperature and morbidity, mostly in countries with hotter climates and more frequent extreme temperatures, and our results show clear effects of temperature on morbidity in the context of a relatively mild climate. Specifically, we find that while cold weather is associated with lower contemporaneous A&E attendances, this effect appears to be largely 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. While some caution should be exercised in comparing estimates across studies, due to differences in variables and model specifications, our results nonetheless suggest net increases in overall A&E attendances at lower levels of hot temperature than in previous studies for hotter countries and regions, perhaps reflecting a relative lack of adaptation to heat in our context. In addition, our results are consistent with differences in individual-level behavioural responses to extreme cold and hot temperatures in England.

These findings highlight the potentially significant negative consequences of climate change for countries with cooler climates in terms of health outcomes and health system capacity. At a local level, our results can help to inform health service providers and planners in anticipating spikes in demand for emergency services during increasingly frequent episodes of extreme hot weather. More generally, our results have important implications for our understanding of the costs of climate change. We find significant health effects of even relatively modest levels of heat. In terms of magnitude, these effects also appear quite large, indicating a steeper dose-response function between temperature and morbidity in the context of a relatively mild climate. In other words, our evidence points, perhaps unsurprisingly, to populations in milder climates being relatively less well adapted to heat. At the other end of the temperature distribution, our results suggest weaker effects of cold temperatures on health. Given anticipated increases in extreme temperatures, particularly in northern latitudes, our results suggest that without adaptation, more frequent heat waves are likely to result in substantial morbidity effects for populations currently living with relatively milder climates.

Finally, we acknowledge some limitations with our data and analysis. First, we do not have information on a patient's residential location, only where they were treated, necessitating analysis at hospital level as opposed to, say, local authority level. Second, unlike Karlson and Ziebarth (2018), we do not include data on pollutants in our analysis. It found that for cold temperatures, failure to account for air pollution results in downward bias, while for hot temperatures, it results in upward bias. However, the relationship and interactions between temperature, pollutants, and health outcomes is relatively complex and, we believe, unlikely to be fully captured by including pollutants as additional controls in our regressions.

**REFERENCES**


Agarwal, S., Qin, Y., Shi, L., Wei, G., Zhu, H., 2021. Impact of temperature on morbidity: New evidence from China. J. Environ. Econ. Manage. 109, 102495.

Armstrong, B., 2006. Models for the relationship between ambient temperature and daily mortality. Epidemiology. 17, 624–631.

Auffhammer, M., 2018. Quantifying economic damages from climate change. J. Econ. Perspect. 32, 33–52.

Barreca, A., 2012. Climate change, humidity, and mortality in the United States. J. Environ. Econ. Manage. 63, 19–34.

Barreca, A., Clay, K., Deschenes, O., Greenstone, M., Shapiro, J., 2016. Adapting to climate change: The remarkable decline in the US temperature-mortality relationship over the twentieth century. J. Polit. Econ. 124, 105–159.

Basu, R., 2009. High ambient temperature and mortality: A review of epidemiologic studies from 2001 to 2008. Environ. Health. 8, 1–13.

Basu, R., Samet, J.M., 2002. Relation between elevated ambient temperature and mortality: A review of the epidemiologic evidence. Epidemiol. Rev. 24, 190–202.

Baylis, P., 2020. Temperature and temperament: Evidence from Twitter. J. Public Econ. 184, 104161.

Bélanger, M., Gray-Donald, K., O'Loughlin, J., Paradis, G., Hanley, J., 2009. Influence of weather conditions and season on physical activity in adolescents. Ann. Epidemiol. 19, 180–186.

Beusch, L., Nauels, A., Gudmundsson, L., Gütschow, J., Schleussner, C.-F., Seneviratne, S.I., 2022. Responsibility of major emitters for country-level warming and extreme hot years. Commun. Earth Environ. 3, 1–7.

Braga, A.L.F., Zanobetti, A., Schwartz, J., 2001. The time course of weather-related deaths. Epidemiology. 12, 662–667.

Burke, M., González, F., Baylis, P., Heft-Neal, S., Baysan, C., Basu, S., Hsiang, S., 2018. Higher temperatures increase suicide rates in the United States and Mexico. Nat. Clim. Change. 8, 723–729.

Campbell, S., Remenyi, T.A., White, C.J., Johnston, F.H., 2018. Heatwave and health impact research: A global review. Health Place. 53, 210–218.

Carleton, T.A., 2017. Crop-damaging temperatures increase suicide rates in India. Proc. Natl. Acad. Sci. 114, 8746–8751.

Carleton, T.A., Greenstone, M., 2021. Updating the United States government's social cost of carbon. University of Chicago, Becker Friedman Institute for Economics Working Paper, 2021-04.

Carleton, T.A., Hsiang, S.M., 2016. Social and economic impacts of climate. Science. 353(6304).

Corcuera Hotz I, Hajat S., 2020. The effects of temperature on accident and emergency department attendances in London: A time-series regression analysis. Int. J. Environ. Res. Public Health. 17, 1957.

Costello, A., Abbas, M., Allen, A., Ball, S., Bell, S., Bellamy, R., Friel, S., Groce, N., Johnson, A., Kett, M., Lee, M., Levy, C., Maslin, M., McCoy, D., McGuire, B., Montgomery, H., Napier, D., Pagel, C., Patel, J., de Oliveira, J.A., Redclift, N., Rees, H., Rogger, D., Scott, J., Stephenson, J., Twigg, J., Wolff, J., Patterson, C., 2009. Managing the health effects of climate change: Lancet and University College London Institute for Global Health Commission. Lancet. 373, 1693–1733.

Dell, M., Jones, B.F., Olken, B.A., 2014. What do we learn from the weather? The new climate-economy literature. J. Econ. Lit. 52, 740–98.

Deschenes, O., 2014. Temperature, human health, and adaptation: A review of the empirical literature. Energy Econ. 46, 606–619.

Deschenes, O., Greenstone, M., 2011. Climate change, mortality, and adaptation: Evidence from annual fluctuations in weather in the US. Am. Econ. J. Appl. Econ. 3, 152–85.

Deschenes, O., Greenstone, M., Guryan, J., 2009. Climate change and birth weight. Am. Econ. Rev. 99, 211–17.

Deschenes, O., Moretti, E., 2009. Extreme weather events, mortality, and migration. Rev. Econ. Stat. 91, 659–681.

Ebi, K.L., Exuzides, K.A., Lau, E., Kelsh, M., Barnston, A., 2004. Weather changes associated with hospitalizations for cardiovascular diseases and stroke in California, 1983-1998. Int. J. Biometeorol. 49, 48–58.

Ellis, F.P., Prince, H.P., Lovatt, G., Whittington, R.M., 1980. Mortality and morbidity in Birmingham during the 1976 heatwave. QJM-Int. J. Med. 49, 1–8.

Fouillet, A., Rey, G., Wagner, V., Laaidi, K., Empereur-Bissonnet, P., Le Tertre, A., Frayssinet, P., Bessemoulin, P., Laurent, F., De Crouy-Chanel, P., Jougla, E., 2008. Has the impact of heat waves on mortality changed in France since the European heat wave of summer 2003? A study of the 2006 heat wave. Int. J. Epidemiol. 37, 309–317.

Fritz, M., 2022. Temperature and non-communicable diseases: Evidence from Indonesia's primary health care system. Health Econ. In press. https://doi.org/10.1002/hec.4590.

Gasparrini, A., Masselot, P., Scortichini, M., Schneider, R., Mistry, M.N., Sera, F., Macintyre, H.L., Phalkey, R., Vicedo-Cabrera, A.M., 2022. Small-area assessment of temperature-related mortality risks in England and Wales: A case time series analysis. Lancet Planet. Health. 6, e557–e564.

Graff Zivin, J., Hsiang, S.M., Neidell, M., 2018. Temperature and human capital in the short and long run. J. Assoc. Environ. Resour. Econ. 5, 77–105.

Graff Zivin, J., Neidell, M., 2009. Days of haze: Environmental information disclosure and intertemporal avoidance behavior. J. Environ. Econ. Manage. 58, 119–128.

Graff Zivin, J., Neidell, M., 2014. Temperature and the allocation of time: Implications for climate change. J. Labor Econ. 32, 1–26.

Hajat, S., Armstrong, B., Baccini, M., Biggeri, A., Bisanti, L., Russo, A., Paldy, A., Menne, B., Kosatsky, T., 2006. Impact of high temperatures on mortality: Is there an added heat wave effect? Epidemiology. 17, 632–638.

Hajat, S., Vardoulakis, S., Heaviside, C., Eggen, B., 2014. Climate change effects on human health: Projections of temperature-related mortality for the UK during the 2020s, 2050s and 2080s. J. Epidemiol. Community Health. 68, 641–648.

Hampton, M., Clark, M., Baxter, I., Stevens, R., Flatt, E., Murray, J., Wembridge, K., 2020. The effects of a UK lockdown on orthopaedic trauma admissions and surgical cases: A multicentre comparative study. Bone Joint J. 1, 137–143.

Heutel, G., Miller, N.H., Molitor, D., 2021. Adaptation and the mortality effects of temperature across US climate regions. Rev. Econ. Stat. 103, 740–753.

Hsiang, S., Kopp, R., Jina, A., Rising, J., Delgado, M., Mohan, S., Rasmussen, D.J., Muir-Wood, R., Wilson, P., Oppenheimer, M., Larsen, K., Houser, T., 2017. Estimating economic damage from climate change in the United States. Science. 356, 1362–1369.

Iparraguirre, J., 2015. Have winter fuel payments reduced excess winter mortality in England and Wales? J. Public Health. 37, 26–33.

IPCC, 2021. Summary for Policymakers. In: Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change [Masson-Delmotte, V., P. Zhai, A. Pirani, S.L. Connors, C. Péan, S. Berger, N. Caud, Y. Chen, L. Goldfarb, M.I. Gomis, M. Huang, K. Leitzell, E. Lonnoy, J.B.R. Matthews, T.K. Maycock, T. Waterfield, O. Yelekçi, R. Yu, B. Zhou (eds.)]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA, pp. 3−32, doi:10.1017/9781009157896.001.

Janke, K., Propper, C., Henderson, J., 2009. Do current levels of air pollution kill? The impact of air pollution on population mortality in England. Health Econ. 18, 1031–1055.

Kalkstein, L.S., Greene, J.S., 1997. An evaluation of climate/mortality relationships in large US cities and the possible impacts of a climate change. Environ. Health Perspect. 105, 84–93.

Karlsson, M., Ziebarth, N.R., 2018. Population health effects and health-related costs of extreme temperatures: Comprehensive evidence from Germany. J. Environ. Econ. Manage. 91, 93–117.

Kiszewski, A., Mellinger, A., Spielman, A., Malaney, P., Sachs, S.E., Sachs, J., 2004. A global index representing the stability of malaria transmission. Am. J. Trop. Med. Hyg. 70, 486–498.

Knittel, C.R., Miller, D.L., Sanders, N.J., 2016. Caution, drivers! Children present: Traffic, pollution, and infant health. Rev. Econ. Stat. 98, 350–366.

Kovats, R.S., Hajat, S., Wilkinson, P., 2004. Contrasting patterns of mortality and hospital admissions during hot weather and heat waves in Greater London, UK. Occup. Environ. Med. 61, 893–898.

Kuitunen, I., Ponkilainen, V.T., Launonen, A.P., Reito, A., Hevonkorpi, T.P., Paloneva, J., Mattila, V.M., 2020. The effect of national lockdown due to COVID-19 on emergency department visits. Scand. J. Trauma, Resusc. Emerg. Med. 28, 1–8.

Masiero, G., Mazzonna, F., Santarossa, M., 2022. The effect of absolute versus relative temperature on health and the role of social care. Health Econ. 31, 1228–1248.

McMichael, A.J., Woodruff, R.E., Hales, S., 2006. Climate change and human health: present and future risks. Lancet. 367, 859–869.

Met Office, Hollis, D., McCarthy, M., Kendon, M., Legg, T., Simpson, I., 2021. HadUK-Grid Climate Observations by Administrative Regions over the UK, v1.0.3.0 (1862-2020). NERC EDS Centre for Environmental Data Analysis, 08 September 2021.

Millner, A., McDermott, T., 2016. Model confirmation in climate economics. Proc. Natl. Acad. Sci. 113, 8675–8680.

Morabito, M., Modesti, P.A., Cecchi, L., Crisci, A., Orlandini, S., Maracchi, G., Gensini, G.F., 2005. Relationships between weather and myocardial infarction: A biometeorological approach. Int. J. Cardiol. 105, 288–293.

Moretti, E., Neidell, M., 2011. Pollution, health, and avoidance behaviour: Evidence from the ports of Los Angeles. J. Hum. Resour. 46, 154–175.

Mullins, J.T., White, C., 2019. Temperature and mental health: Evidence from the spectrum of mental health outcomes. J. Health Econ. 68, 102240.

National Health Service England (NHS) (2022) *A&E Attendances and Emergency Admissions*. (Accessed on 01/03/2022 at: https://www.england.nhs.uk/statistics/statistical-work-areas/ae-waiting-times-and-activity/).

Neidell, M., 2009. Information, avoidance behavior, and health: The effect of ozone on asthma hospitalizations. J. Hum. Resour. 44, 450–478.

Obradovich, N., Migliorini, R., Paulus, M.P., Rahwan, I., 2018. Empirical evidence of mental health risks posed by climate change. Proc. Natl. Acad. Sci. 115, 10953–10958.

Rizmie, D., de Preux, L., Miraldo, M., Atun, R., 2022. Impact of extreme temperatures on emergency hospital admissions by age and socio-economic deprivation in England. Soc. Sci. Med. 308, 115193.

Schwartz, J., Samet, J.M., Patz, J.A., 2004. Hospital admissions for heart disease: The effects of temperature and humidity. Epidemiology. 15, 755–761.

Sexton, S., Wang, Z., Mullins, J.T., 2022. Heat adaptation and human performance in a warming climate. J. Assoc. Environ. Resour. Econ. 9, 141–163.

StatWales (2022) *Population Estimates by Local Authority and Year.* (Accessed on 01/03/2022 at: https://statswales.gov.wales/Catalogue/Population-and-Migration/Population/Estimates/Local-Authority/populationestimates-by-localauthority-year).

Van de Vliert, E., 2007. Climatoeconomic roots of survival versus self-expression cultures. J. Cross-Cult. Psychol. 38, 156–172.

White, C., 2017. The dynamic relationship between temperature and morbidity. J. Assoc. Environ. Resour. Econ, 4, 1155–1198.

Ye, F., Piver, W.T., Ando, M., Portier, C.J., 2001. Effects of temperature and air pollutants on cardiovascular and respiratory diseases for males and females older than 65 years of age in Tokyo, July and August 1980-1995. Environ. Health Perspect. 109, 355–359.

## 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: Main Model Results – Balanced Panel

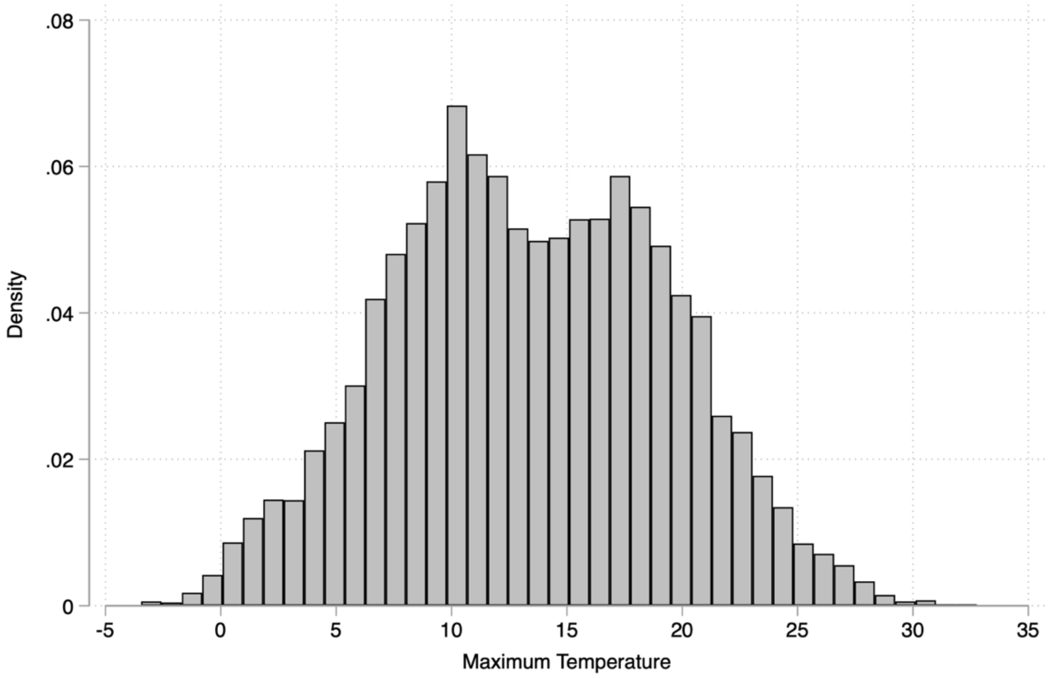
| Temperature Bins | (1) Contemporaneous Effects | (2) Cumulative Effects |
|---|---|---|
| [1ºC, 4ºC) | -1.512*** | 1.589 |
| | (0.445) | (0.987) |
| [4ºC, 7ºC) | -0.819*** | 0.245 |
| | (0.157) | (0.383) |
| [7ºC, 10ºC) | -0.369* | 0.032 |
| | (0.171) | (0.438) |
| [10ºC, 13ºC) | Base Category | Base Category |
| | - | - |
| [13ºC, 16ºC) | 0.569*** | 0.998* |
| | (0.167) | (0.507) |
| [16ºC, 19ºC) | 1.102*** | 1.527*** |
| | (0.238) | (0.279) |
| [19ºC, 22ºC) | 1.590*** | 1.960*** |
| | (0.296) | (0.288) |
| [22ºC, 25ºC) | 2.256*** | 2.830*** |
| | (0.336) | (0.380) |
| [25ºC, 28ºC) | 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 |
| Region-Week FEs | Yes | Yes |
| Region-Year FEs | Yes | Yes |
| Treatment Facility FEs | Yes | Yes |
| Error Cluster | One-way | One-way |
| N | 37,433 | 37,433 |

Notes: Table 3 presents results from the distributed lag regression model presented in Equation [1] in the form of (1) contemporaneous effects and (2) cumulative effects. The dependent variable is the weekly A&E treatment facility attendance rate per 100,000 regional population and the model is estimated using the balanced panel. The contemporaneous effects represent the impact of each weekly maximum temperature bin on A&E attendances in the same week, while the cumulative effects measure the impact on both current and subsequent A&E weekly attendances. Standard errors are clustered at the region level. *** denotes significant at the 1% level, ** denotes significant at the 5% level, and * denotes significant at the 10% level.

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

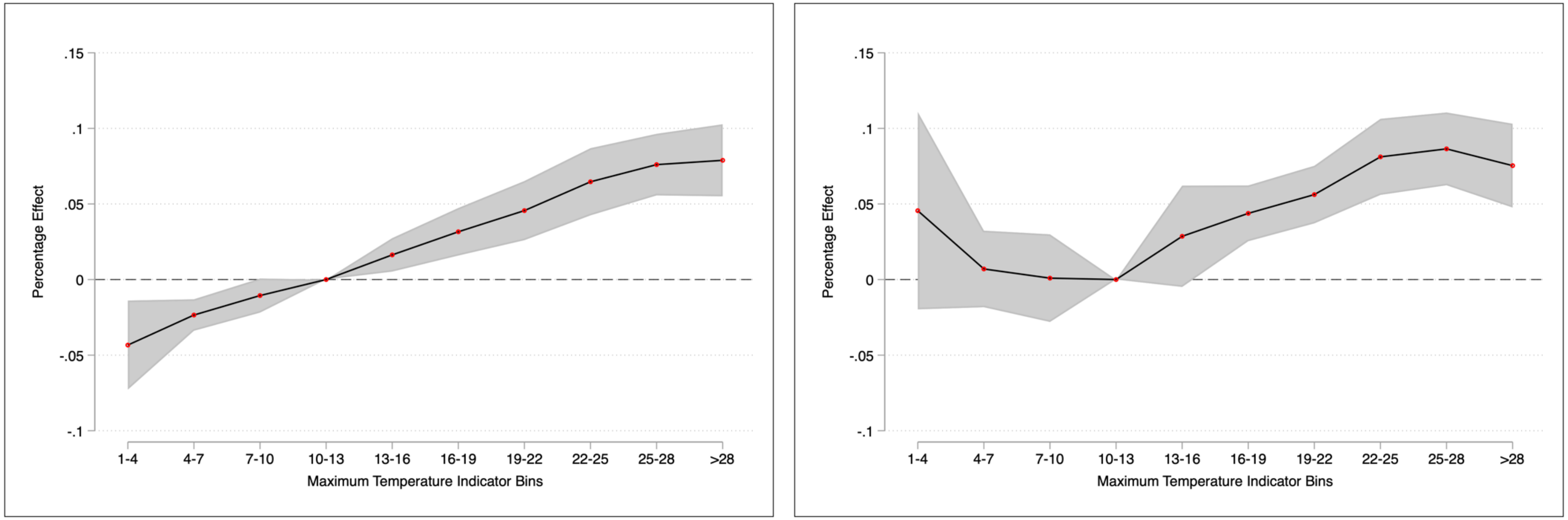
## Figures

Figure 1: Distribution of Daily Maximum Temperatures




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

Figure 2: Estimated Percentage Contemporaneous and Cumulative Effects

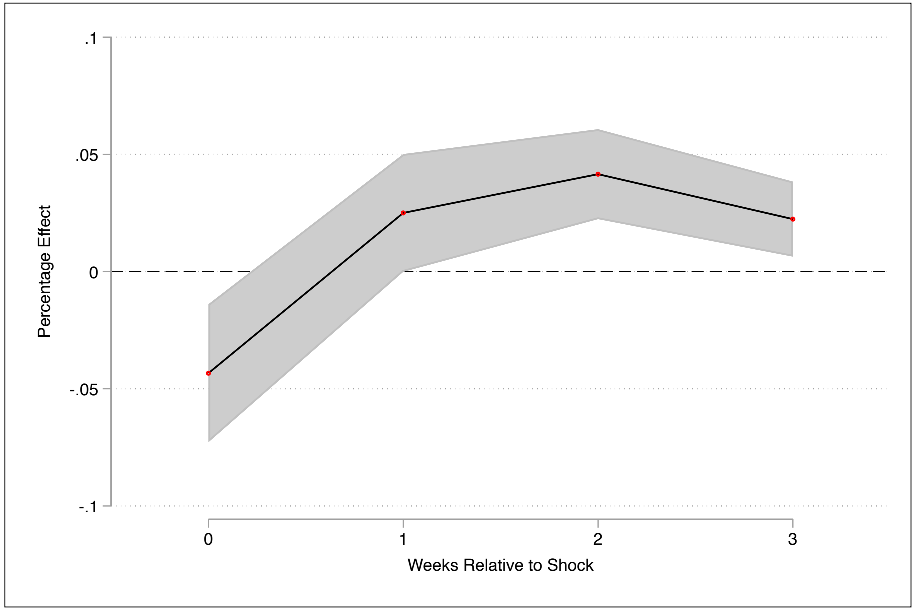



**(A) Contemporaneous Effects** **(B) Cumulative Effects**

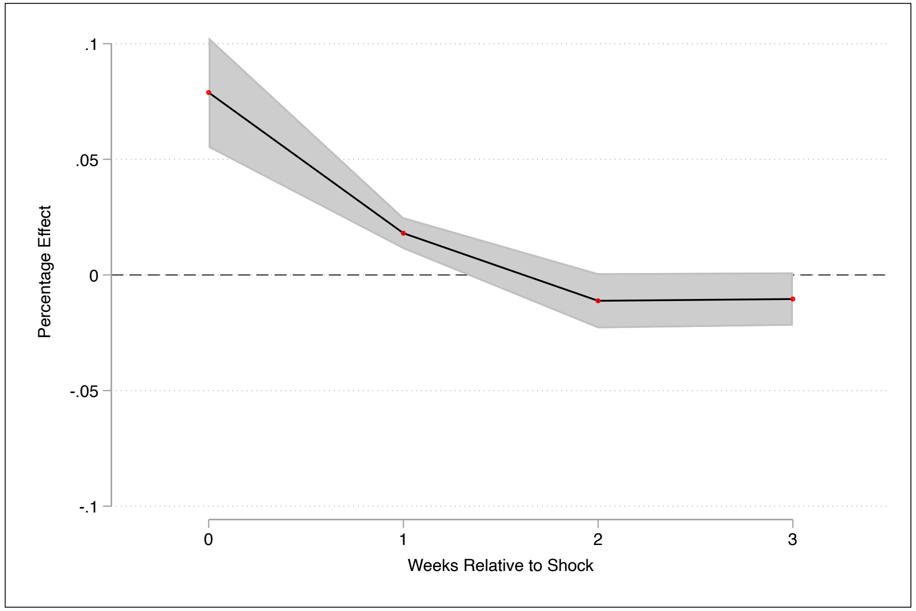
Notes: Figure 2 presents estimated contemporaneous and cumulative effects on weekly A&E attendance rates in percentage terms for each temperature indicator bin. All effects are based on the model presented in Equation [1] and estimated using the balanced panel. The contemporaneous effects in Panel (A) represent the percentage effect of each weekly maximum temperature bin on A&E attendances in the same week, while the cumulative effects in Panel (B) measure the percentage effect on both current and subsequent A&E weekly attendances. 95% confidence intervals are represented by the shaded regions.

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

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




**(A) 1-4$^{o}$C**

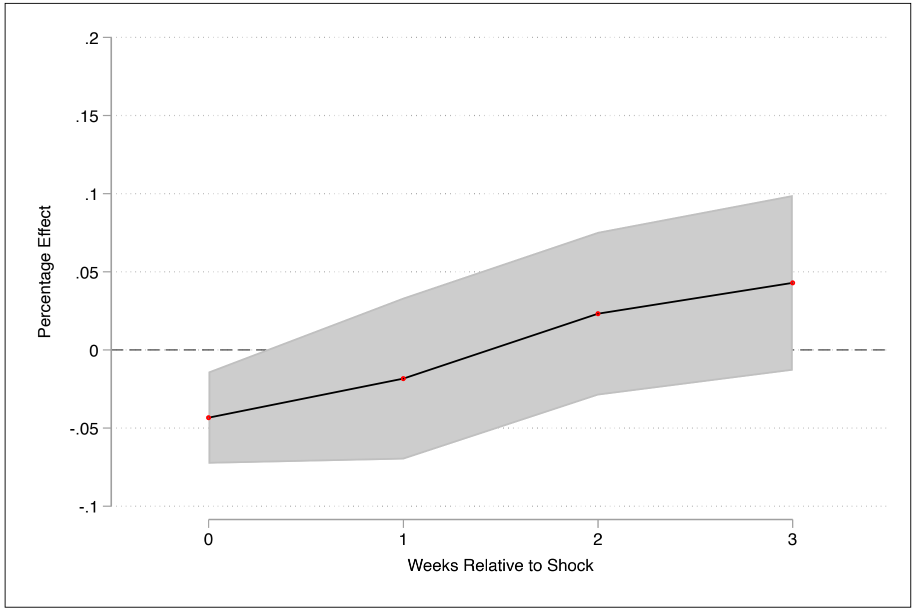



**(B) 28+$^{o}$C**

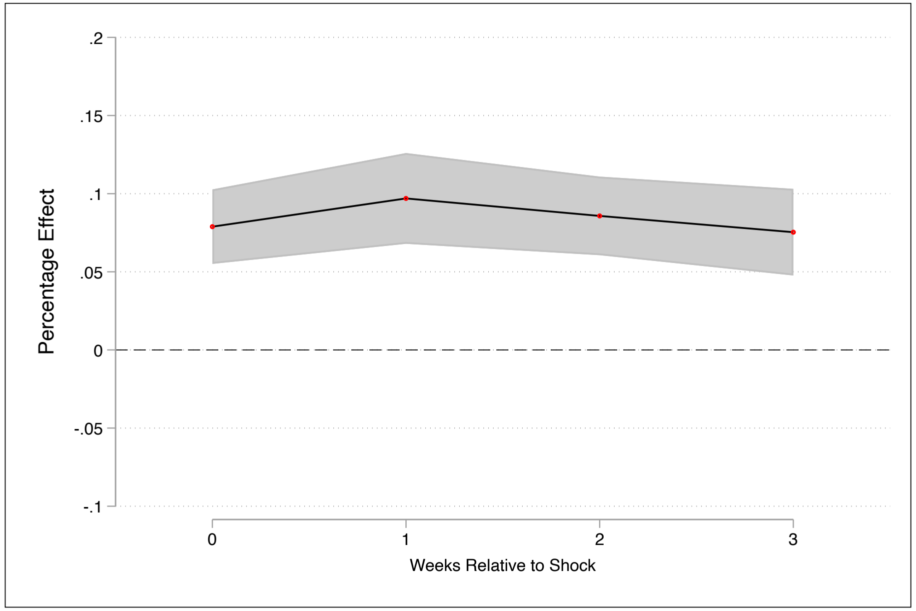
Notes: Figure 3 presents the estimated percentage weekly effects on A&E attendance rates for each week relative to the temperature shock for the (A) lowest and (B) highest temperature bins. The contemporaneous effect is represented by $t = 0$ on the $x$-axis. All effects are based on the model presented in Equation [1] and estimated using the balanced panel. 95% confidence intervals are represented by the shaded regions.

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

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




**(A) 1-4$^{o}$C**



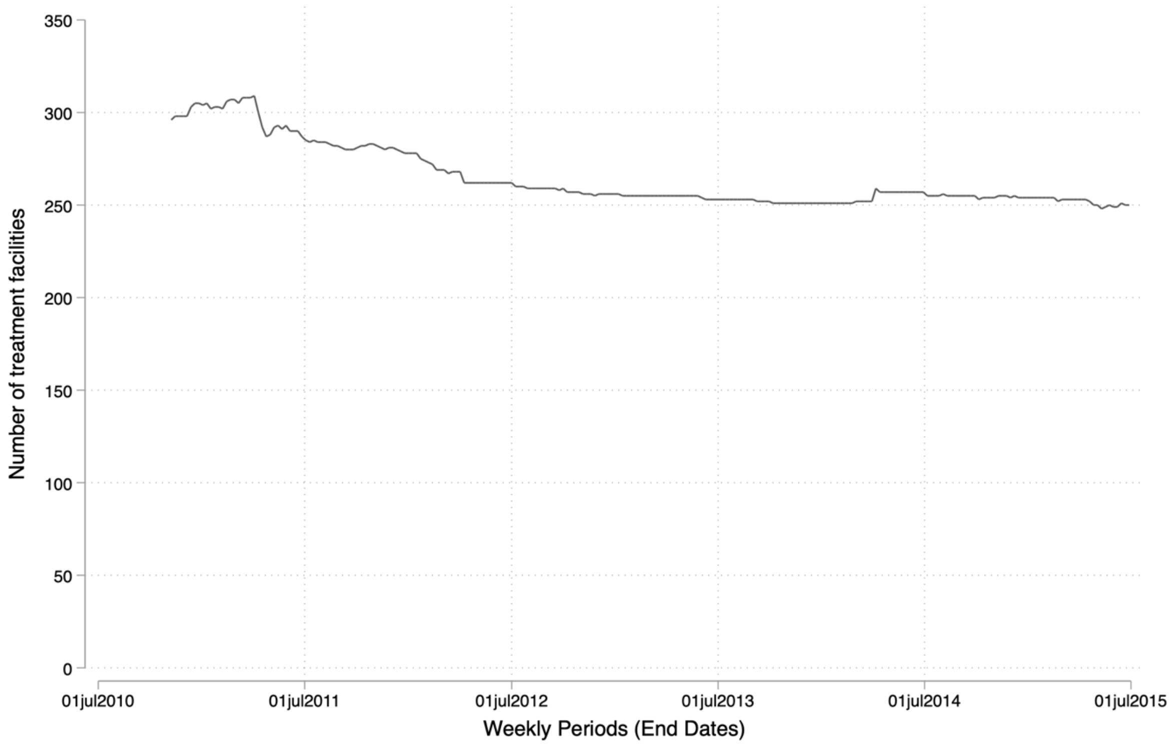

**(B) 28+$^{o}$C**

Notes: Figure 4 presents the sum of all estimated percentage weekly effects on A&E attendance rates up to and including a given week relative to the temperature shock for the (A) lowest and (B) highest temperature bins. The contemporaneous effect is represented by $t = 0$ on the $x$-axis. All effects are based on the model presented in Equation [1] and estimated using the balanced panel. 95% confidence intervals are represented by the shaded regions.

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

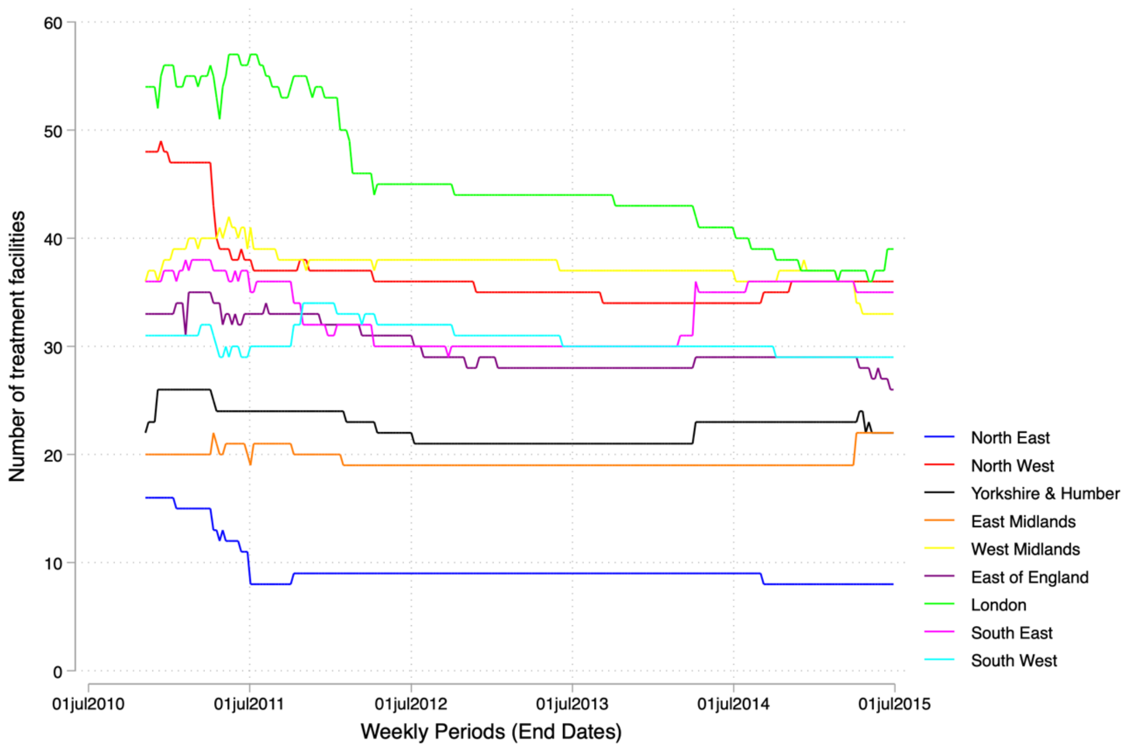
## Appendix 1: Changes in Number of Treatment Facilities in Data over Study Period

Figure A1.1: Number of Treatment Facilities in NHS Data over Study Period




Source: Analysis of data from NHS (2022).

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




Source: Analysis of data from NHS (2022).

## Appendix 2: Robustness Test – Unbalanced Panel Model

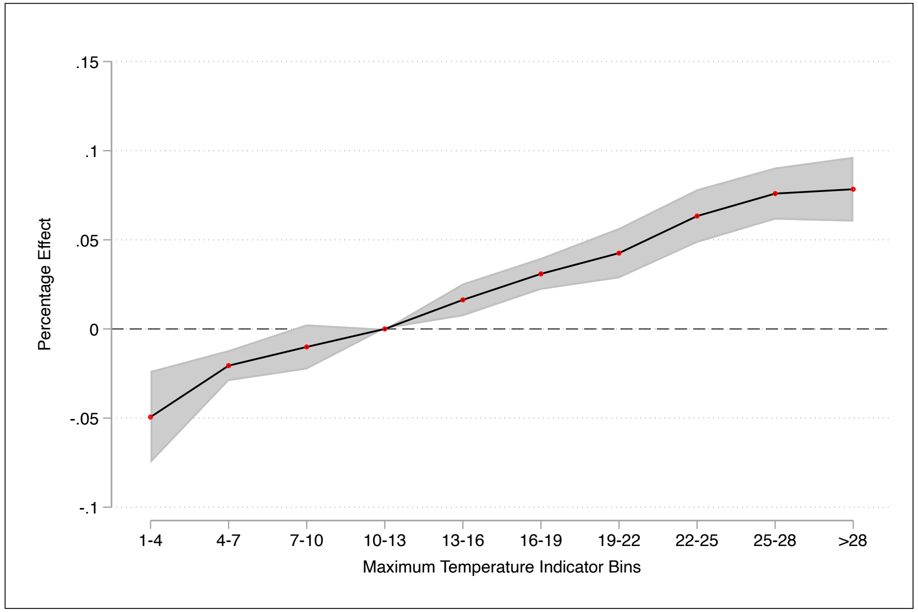
Table A2.1: Main Model Results – Unbalanced Panel

| **Temperature Bins** | **(1) Contemporaneous Effects** | **(2) Cumulative Effects** |
|---|---|---|
| [1ºC, 4ºC) | -1.310*** | 1.498* |
| | (0.296) | (0.658) |
| [4ºC, 7ºC) | -0.545*** | 0.783* |
| | (0.100) | (0.370) |
| [7ºC, 10ºC) | -0.267 | 0.157 |
| | (0.145) | (0.394) |
| [10ºC, 13ºC) | Base Category | Base Category |
| | - | - |
| [13ºC, 16ºC) | 0.432*** | 0.858** |
| | (0.105) | (0.269) |
| [16ºC, 19ºC) | 0.819*** | 1.307*** |
| | (0.102) | (0.225) |
| [19ºC, 22ºC) | 1.127*** | 1.524*** |
| | (0.162) | (0.193) |
| [22ºC, 25ºC) | 1.678*** | 2.368*** |
| | (0.172) | (0.164) |
| [25ºC, 28ºC) | 2.012*** | 2.692*** |
| | (0.168) | (0.248) |
| [28ºC, ) | 2.077*** | 2.274*** |
| | (0.208) | (0.314) |
| | | |
| Mean Dependent Variable | 26.54 | 26.54 |
| Rainfall Controls | Yes | Yes |
| Region-Week FEs | Yes | Yes |
| Region-Year FEs | Yes | Yes |
| Treatment Facility FEs | Yes | Yes |
| Error Cluster | One-way | One-way |
| N | 62,845 | 62,845 |

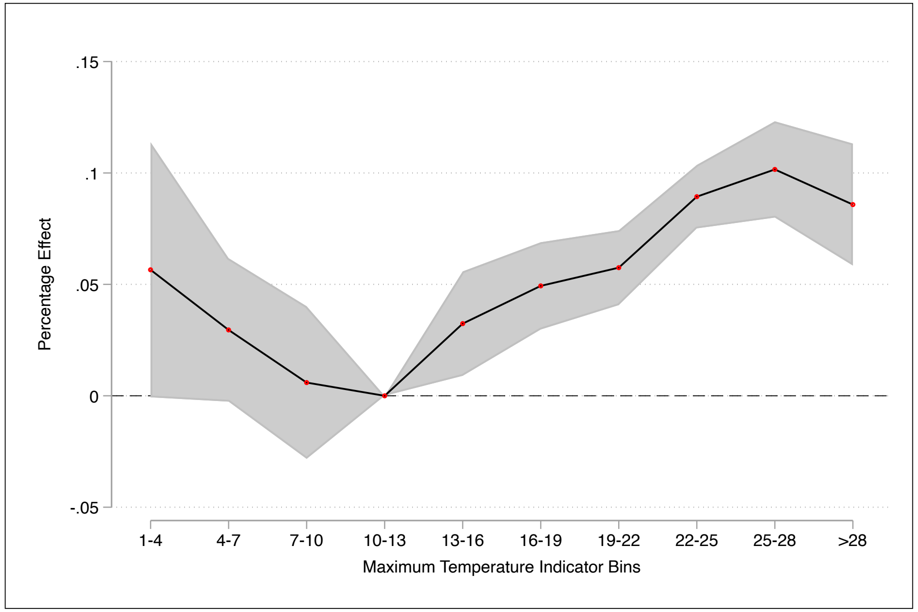
Notes: Table A2.1 presents results from the distributed lag regression model presented in Equation [1] in the form of (1) contemporaneous effects and (2) cumulative effects. The dependent variable is the weekly A&E treatment facility attendance rate per 100,000 regional population and the model is estimated using the unbalanced panel. The contemporaneous effects represent the impact of each weekly maximum temperature bin on A&E attendances in the same week, while the cumulative effects measure the impact on both current and subsequent A&E weekly attendances. Standard errors are clustered at the region level. *** denotes significant at the 1% level, ** denotes significant at the 5% level, and * denotes significant at the 10% level.

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

Figure A2.1: Estimated Percentage Contemporaneous and Cumulative Effects – Unbalanced Panel




**(A) Contemporaneous Effects**




**(B) Cumulative Effects**

Notes: Figure A2.1 presents estimated contemporaneous and cumulative effects on weekly A&E attendance rates in percentage terms for each temperature indicator bin. All effects are based on the model presented in Equation [1] and estimated using the unbalanced panel. The contemporaneous effects in Panel (A) represent the percentage effect of each weekly maximum temperature bin on A&E attendances in the same week, while the cumulative effects in Panel (B) measure the percentage effect on both current and subsequent A&E weekly attendances. 95% confidence intervals are represented by the shaded regions.

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

## Appendix 3: Robustness Test – Weighted Model

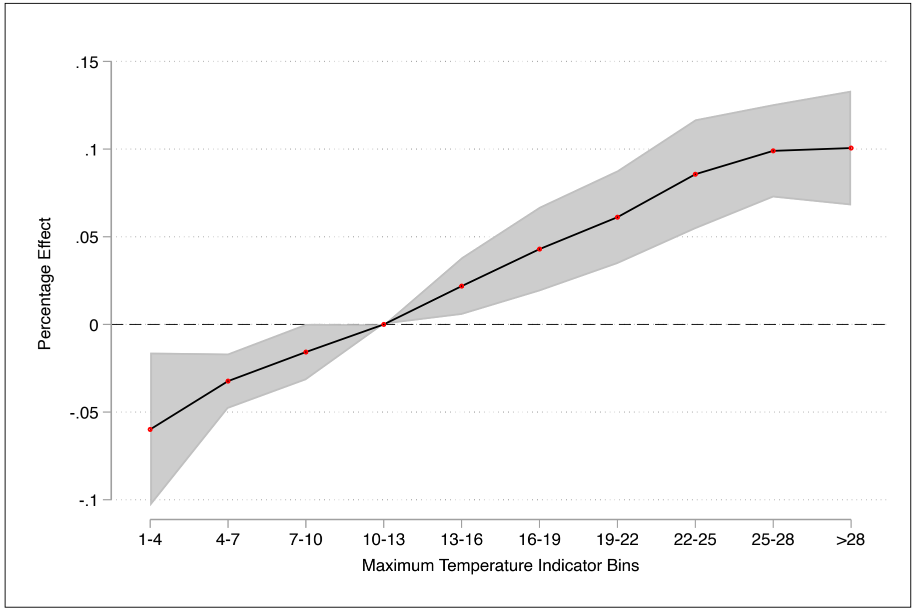
Table A3.1: Weighted Model Results

| Temperature Bins | (1) Contemporaneous Effects | (2) Cumulative Effects |
|---|---|---|
| [1ºC, 4ºC) | -2.089** | 1.504 |
| | (0.662) | (1.783) |
| [4ºC, 7ºC) | -1.128*** | 0.023 |
| | (0.238) | (0.622) |
| [7ºC, 10ºC) | -0.550* | -0.139 |
| | (0.242) | (0.595) |
| [10ºC, 13ºC) | Base Category | Base Category |
| | - | - |
| [13ºC, 16ºC) | 0.762** | 1.445 |
| | (0.248) | (0.817) |
| [16ºC, 19ºC) | 1.498*** | 2.041*** |
| | (0.364) | (0.403) |
| [19ºC, 22ºC) | 2.133*** | 2.457*** |
| | (0.403) | (0.386) |
| [22ºC, 25ºC) | 2.987*** | 3.645*** |
| | (0.473) | (0.471) |
| [25ºC, 28ºC) | 3.452*** | 3.753*** |
| | (0.402) | (0.536) |
| [28ºC, ) | 3.508*** | 3.185*** |
| | (0.495) | (0.507) |
| | | |
| Mean Dependent Variable | 34.87 | 34.87 |
| Rainfall Controls | Yes | Yes |
| Region-Week FEs | Yes | Yes |
| Region-Year FEs | Yes | Yes |
| Treatment Facility FEs | Yes | Yes |
| Error Cluster | One-way | One-way |
| N | 37,433 | 37,433 |

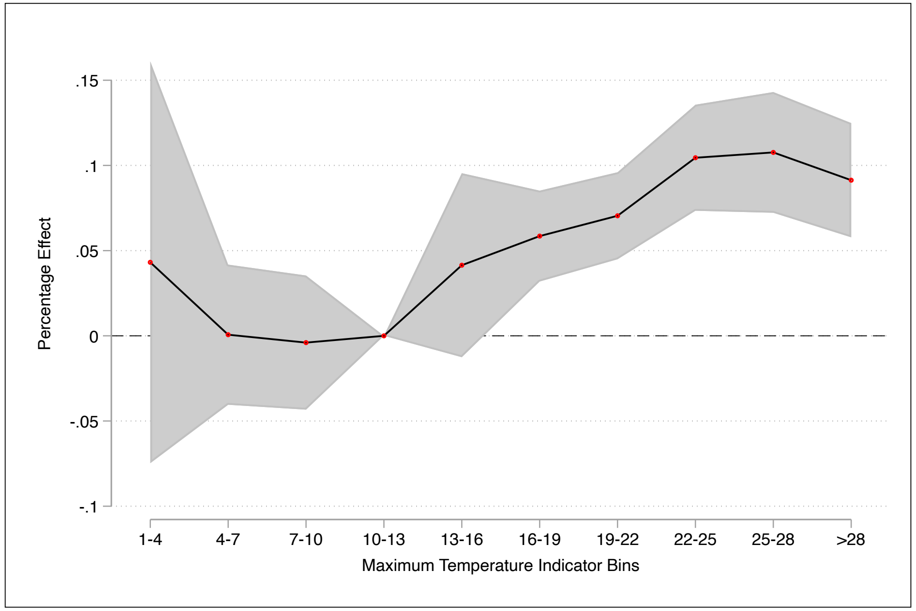
Notes: Table A3.1 presents results from the distributed lag regression model presented in Equation [1] in the form of (1) contemporaneous effects and (2) cumulative effects, applying analytical weights based on the average number of A&E attendances per treatment facility over the sample period. The dependent variable is the weekly A&E treatment facility attendance rate per 100,000 regional population and the model is estimated using the unbalanced panel. The contemporaneous effects represent the impact of each weekly maximum temperature bin on A&E attendances in the same week, while the cumulative effects measure the impact on both current and subsequent A&E weekly attendances. Standard errors are clustered at the region level. *** denotes significant at the 1% level, ** denotes significant at the 5% level, and * denotes significant at the 10% level.

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

Figure A3.1: Estimated Percentage Contemporaneous and Cumulative Effects – Weighted Model




**(A) Contemporaneous Effects**




**(B) Cumulative Effects**

Notes: Figure A3.1 presents estimated contemporaneous and cumulative effects on weekly A&E attendance rates in percentage terms for each temperature indicator bin. All effects are based on the model presented in Equation [1] estimated using the unbalanced panel and applying analytical weights based on the average number of A&E attendances per treatment facility over the sample period. The contemporaneous effects in Panel (A) represent the percentage effect of each weekly maximum temperature bin on A&E attendances in the same week, while the cumulative effects in Panel (B) measure the percentage effect on both current and subsequent A&E weekly attendances. 95% confidence intervals are represented by the shaded regions.

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

## Appendix 4: Robustness Test – Regional Model

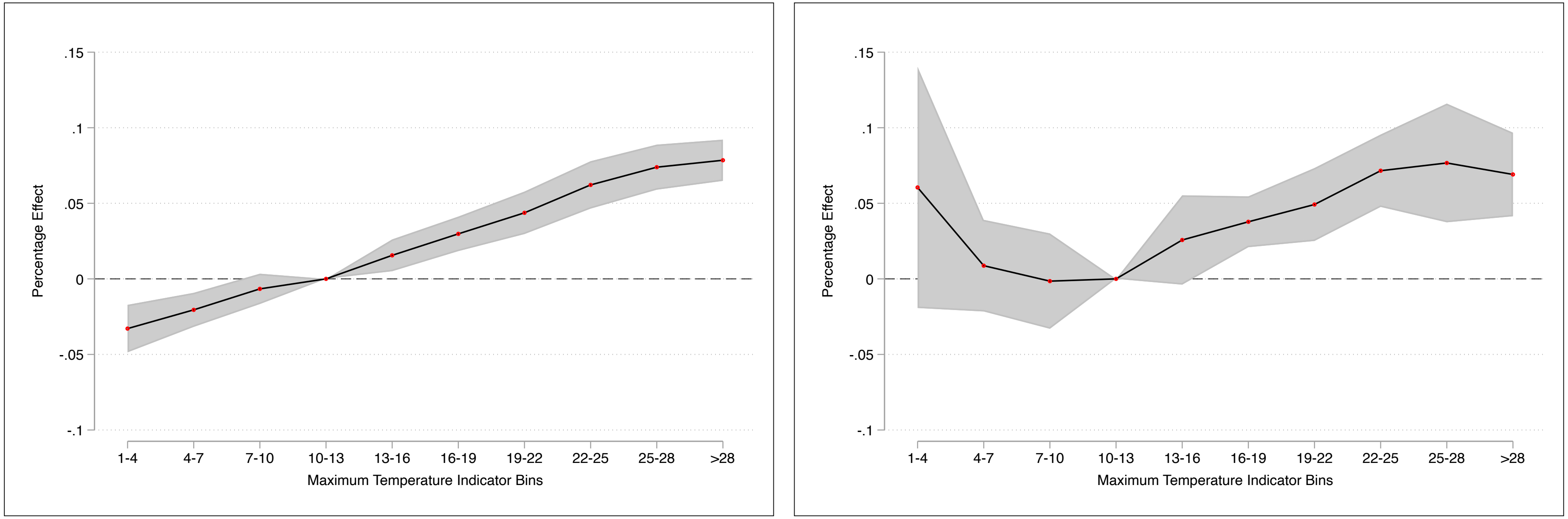
Table A4.1: Regional Model Results

| Temperature Bins | (1) Contemporaneous Effects | (2) Cumulative Effects |
|---|---|---|
| [1ºC, 4ºC) | -19.963*** | 36.706 |
| | (4.136) | (20.994) |
| [4ºC, 7ºC) | -12.441*** | 5.301 |
| | (2.969) | (7.980) |
| [7ºC, 10ºC) | -4.016 | -0.900 |
| | (2.643) | (8.307) |
| [10ºC, 13ºC) | Base Category | Base Category |
| | - | - |
| [13ºC, 16ºC) | 9.454*** | 15.612* |
| | (2.770) | (7.781) |
| [16ºC, 19ºC) | 18.072*** | 22.918*** |
| | (3.008) | (4.428) |
| [19ºC, 22ºC) | 26.520*** | 29.858*** |
| | (3.702) | (6.353) |
| [22ºC, 25ºC) | 37.728*** | 43.422*** |
| | (4.130) | (6.306) |
| [25ºC, 28ºC) | 44.846*** | 46.541*** |
| | (3.926) | (10.339) |
| [28ºC, ) | 47.626*** | 41.922*** |
| | (3.593) | (7.283) |
| | | |
| Mean Dependent Variable | 606.75 | 606.75 |
| Rainfall Controls | Yes | Yes |
| Region-Week FEs | Yes | Yes |
| Region-Year FEs | Yes | Yes |
| Treatment Facility FEs | Yes | Yes |
| Error Cluster | One-way | One-way |
| N | 2,124 | 2,124 |

Notes: Table A4.1 presents results from a regional version of the distributed lag regression model presented in Equation [1] in the form of (1) contemporaneous effects and (2) cumulative effects. The dependent variable is the regional weekly A&E attendance rate per 100,000 population and the model is estimated using the balanced panel. The contemporaneous effects represent the impact of each weekly maximum temperature bin on A&E attendances in the same week, while the cumulative effects measure the impact on both current and subsequent A&E weekly attendances. Standard errors are clustered at the region level. *** denotes significant at the 1% level, ** denotes significant at the 5% level, and * denotes significant at the 10% level.

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

Figure A4.1: Estimated Percentage Contemporaneous and Cumulative Effects – Regional Model




**(A) Contemporaneous Effects** **(B) Cumulative Effects**

Notes: Figure A4.1 presents estimated contemporaneous and cumulative effects on weekly A&E attendance rates in percentage terms for each temperature indicator bin. All effects are based on a regional version of the model presented in Equation [1] and estimated at regional level using the balanced panel. The contemporaneous effects in Panel (A) represent the percentage effect of each weekly maximum temperature bin on A&E attendances in the same week, while the cumulative effects in Panel (B) measure the percentage effect on both current and subsequent A&E weekly attendances. 95% confidence intervals are represented by the shaded regions.

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

## Appendix 5: Robustness Test – Lagged Denominator Model

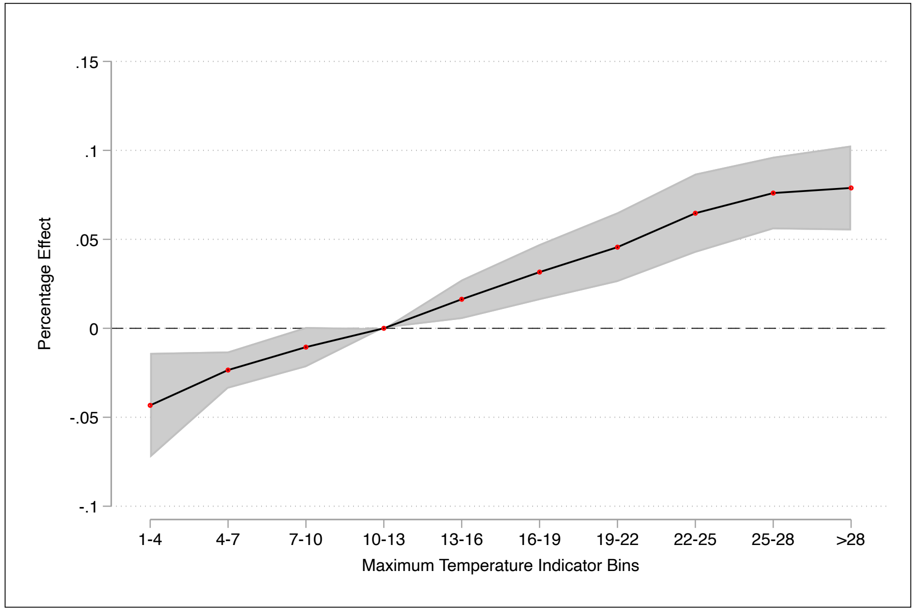
Table A5.1: Lagged Denominator Model Results

| Temperature Bins | (1) Contemporaneous Effects | (2) Cumulative Effects |
|---|---|---|
| [1ºC, 4ºC) | -1.510*** | 1.599 |
| | (0.445) | (0.988) |
| [4ºC, 7ºC) | -0.818*** | 0.250 |
| | (0.158) | (0.385) |
| [7ºC, 10ºC) | -0.369* | 0.033 |
| | (0.170) | (0.438) |
| [10ºC, 13ºC) | Base Category | Base Category |
| | - | - |
| [13ºC, 16ºC) | 0.569*** | 0.999* |
| | (0.168) | (0.507) |
| [16ºC, 19ºC) | 1.102*** | 1.528*** |
| | (0.238) | (0.279) |
| [19ºC, 22ºC) | 1.590*** | 1.960*** |
| | (0.296) | (0.288) |
| [22ºC, 25ºC) | 2.256*** | 2.830*** |
| | (0.336) | (0.381) |
| [25ºC, 28ºC) | 2.651*** | 3.015*** |
| | (0.308) | (0.365) |
| [28ºC, ) | 2.751*** | 2.628*** |
| | (0.361) | (0.419) |
| | | |
| Mean Dependent Variable | 34.87 | 34.87 |
| Rainfall Controls | Yes | Yes |
| Region-Week FEs | Yes | Yes |
| Region-Year FEs | Yes | Yes |
| Treatment Facility FEs | Yes | Yes |
| Error Cluster | One-way | One-way |
| N | 37,433 | 37,433 |

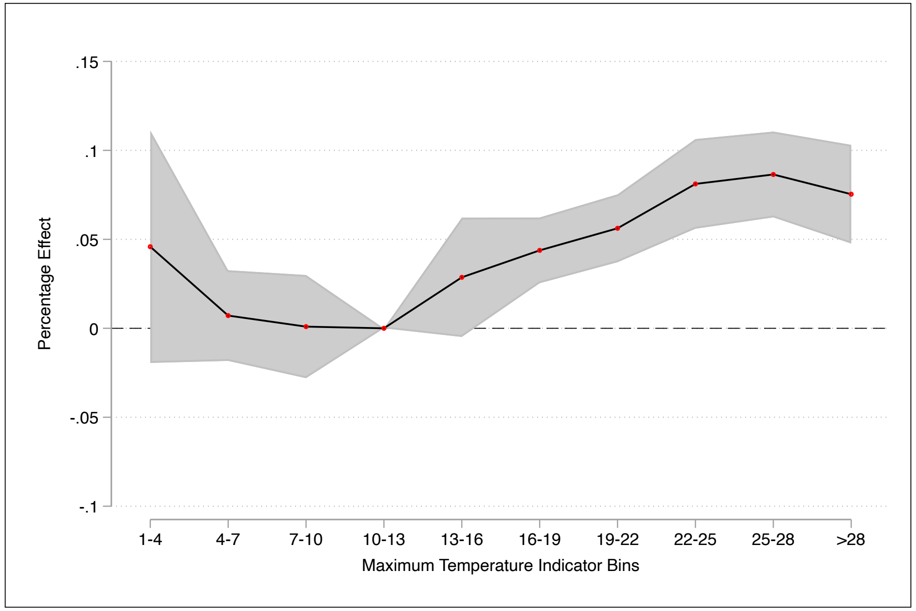
Notes: Table A5.1 presents results from the distributed lag regression model presented in Equation [1] in the form of (1) contemporaneous effects and (2) cumulative effects. The dependent variable is the weekly A&E attendance rate per 100,000 population in the previous year and the model is estimated using the balanced panel. The contemporaneous effects represent the impact of each weekly maximum temperature bin on A&E attendances in the same week, while the cumulative effects measure the impact on both current and subsequent A&E weekly attendances. Standard errors are clustered at the region level. *** denotes significant at the 1% level, ** denotes significant at the 5% level, and * denotes significant at the 10% level.

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

Figure A5.1: Estimated Percentage Contemporaneous and Cumulative Effects – Lagged Denominator Model




**(A) Contemporaneous Effects**




**(B) Cumulative Effects**

Notes: Figure A5.1 presents estimated contemporaneous and cumulative effects on regional weekly A&E attendance rates in percentage terms for each temperature indicator bin. All effects are based on the model presented in Equation [1] and estimated using the population in the previous year as the denominator in the dependent variable and the balanced panel. The contemporaneous effects in Panel (A) represent the percentage effect of each weekly maximum temperature bin on A&E attendances in the same week, while the cumulative effects in Panel (B) measure the percentage effect on both current and subsequent A&E weekly attendances. 95% confidence intervals are represented by the shaded regions.

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

## Appendix 6: Robustness Test – Temperature Count Bin Model

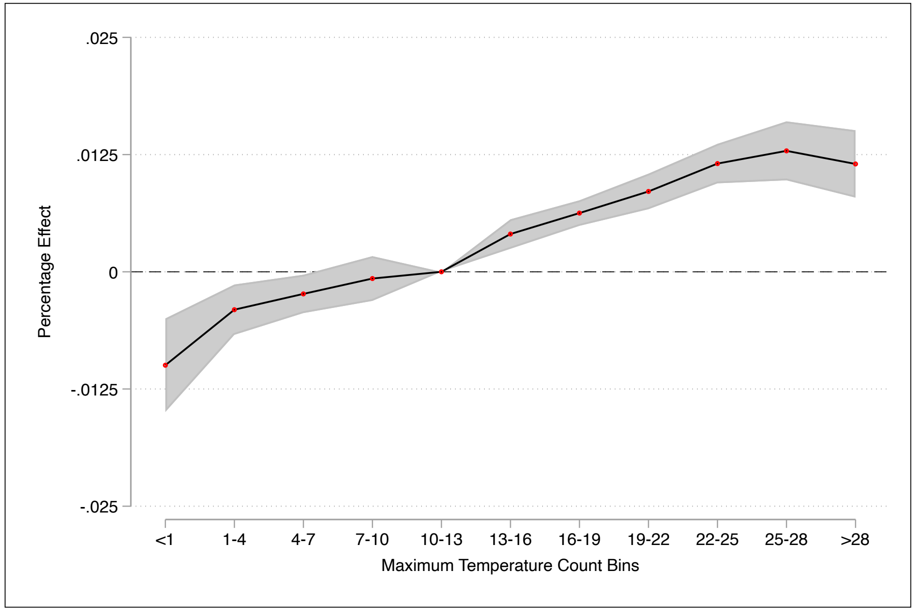
Table A6.1: Temperature Count Bin Model Results

| Temperature Bins | (1) Contemporaneous Effects | (2) Cumulative Effects |
|---|---|---|
| ( , 1ºC) | -0.331*** | 0.196 |
| | (0.078) | (0.198) |
| [1ºC, 4ºC) | -0.202** | 0.089 |
| | (0.072) | (0.127) |
| [4ºC, 7ºC) | -0.116*** | -0.060 |
| | (0.033) | (0.086) |
| [7ºC, 10ºC) | -0.046 | -0.026 |
| | (0.046) | (0.114) |
| [10ºC, 13ºC) | Base Category | Base Category |
| | - | - |
| [13ºC, 16ºC) | 0.183*** | 0.239** |
| | (0.036) | (0.080) |
| [16ºC, 19ºC) | 0.306*** | 0.434*** |
| | (0.046) | (0.074) |
| [19ºC, 22ºC) | 0.414*** | 0.367** |
| | (0.045) | (0.155) |
| [22ºC, 25ºC) | 0.544*** | 0.591*** |
| | (0.066) | (0.090) |
| [25ºC, 28ºC) | 0.582*** | 0.613*** |
| | (0.075) | (0.161) |
| [28ºC, ) | 0.505*** | 0.185 |
| | (0.095) | (0.189) |
| | | |
| Mean Dependent Variable | 34.87 | 34.87 |
| Rainfall Controls | Yes | Yes |
| Region-Week FEs | Yes | Yes |
| Region-Year FEs | Yes | Yes |
| Treatment Facility FEs | Yes | Yes |
| Error Cluster | One-way | One-way |
| N | 37,433 | 37,433 |

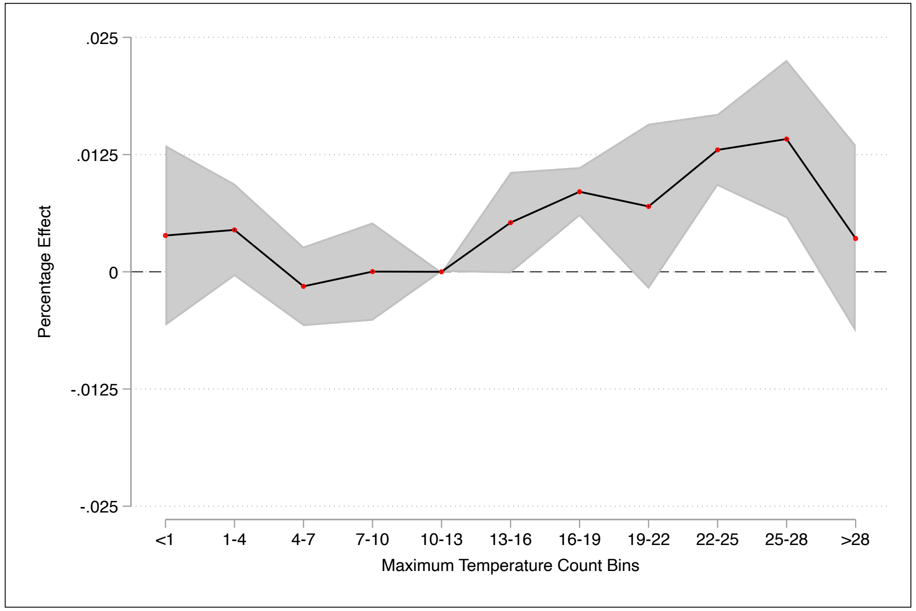
Notes: Table A6.1 presents results from a count bin version of the distributed lag regression model presented in Equation [1] in the form of (1) contemporaneous effects and (2) cumulative effects. The dependent variable is the weekly A&E treatment facility attendance rate per 100,000 regional population and the model is estimated using the balanced panel. This model includes temperature count bin variables defined as the number of days in a week with daily maximum temperatures falling within the range of one of the three-degree temperature bins. The contemporaneous effects represent the impact of each additional day falling within a specific temperature range on A&E attendances in the same week, while the cumulative effects measure the impact on both current and subsequent A&E weekly attendances. Standard errors are clustered at the region level. *** denotes significant at the 1% level, ** denotes significant at the 5% level, and * denotes significant at the 10% level.

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

Figure A6.1: Estimated Percentage Contemporaneous and Cumulative Effects – Temperature Count Bin Model




**(A) Contemporaneous Effects**




**(B) Cumulative Effects**

Notes: Figure A6.1 presents estimated contemporaneous and cumulative effects on weekly A&E attendance rates in percentage terms for each temperature count bin. All effects are based on the model presented in Equation [1] and estimated using the balanced panel. The temperature count bin variables are defined as the number of days in a week with daily maximum temperatures falling within the range of one of the three-degree temperature bins. The contemporaneous effects in Panel (A) represent the impact of each additional day falling within a specific temperature range on A&E attendances in the same week, while the cumulative effects in Panel (B) measure the impact on both current and subsequent A&E weekly attendances. 95% confidence intervals are represented by the shaded regions.

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

## Appendix 7: Placebo Test – Model with Tempertaure Lead

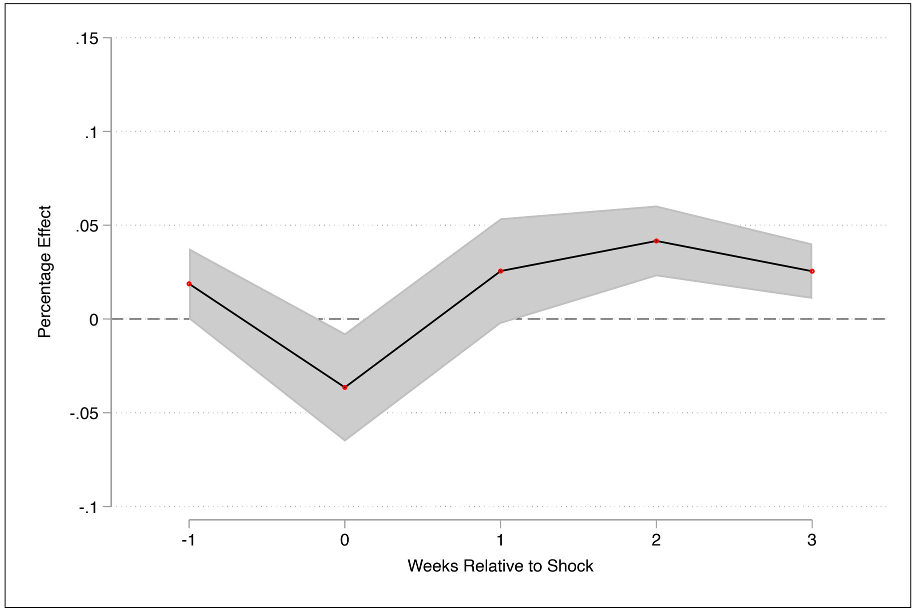
Table A7.1: Placebo Test Model Results

| Temperature Bins | (1) Contemporaneous Effects | (2) Cumulative Effects | (3) Lead Effects |
|---|---|---|---|
| [1ºC, 4ºC) | -1.273** | 1.958* | 0.655* |
| | (0.436) | (1.016) | (0.285) |
| [4ºC, 7ºC) | -0.833*** | 0.241 | 0.068 |
| | (0.159) | (0.388) | (0.248) |
| [7ºC, 10ºC) | -0.311* | 0.170 | -0.217 |
| | (0.143) | (0.409) | (0.194) |
| [10ºC, 13ºC) | Base Category | Base Category | Base Category |
| | - | - | - |
| [13ºC, 16ºC) | 0.559*** | 1.045* | 0.144* |
| | (0.162) | (0.543) | (0.070) |
| [16ºC, 19ºC) | 1.067*** | 1.562*** | 0.105 |
| | (0.226) | (0.275) | (0.099) |
| [19ºC, 22ºC) | 1.557*** | 1.972*** | 0.173 |
| | (0.289) | (0.286) | (0.115) |
| [22ºC, 25ºC) | 2.184*** | 2.804*** | 0.426** |
| | (0.328) | (0.397) | (0.156) |
| [25ºC, 28ºC) | 2.587*** | 3.048*** | 0.402* |
| | (0.308) | (0.333) | (0.176) |
| [28ºC, ) | 2.674*** | 2.519*** | 0.327 |
| | (0.328) | (0.366) | (0.248) |
| | | | |
| Mean Dependent Variable | 34.87 | 34.87 | 34.87 |
| Rainfall Controls | Yes | Yes | Yes |
| Region-Week FEs | Yes | Yes | Yes |
| Region-Year FEs | Yes | Yes | Yes |
| Treatment Facility FEs | Yes | Yes | Yes |
| Error Cluster | One-way | One-way | One-way |
| N | 37,433 | 37,433 | 37,433 |

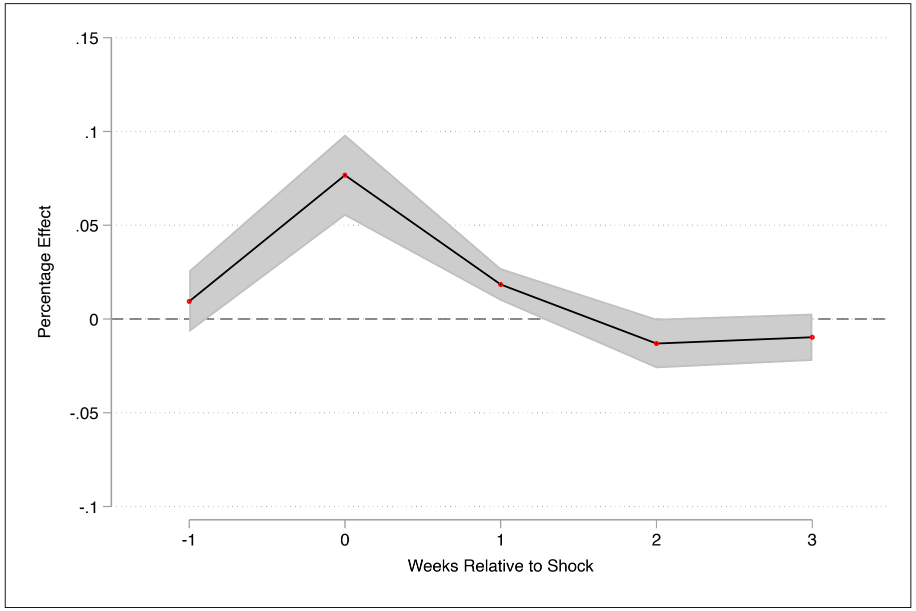
Notes: Table A7.1 presents results from the distributed lag regression model presented in Equation [1], with a single lead added to the model, in the form of (1) contemporaneous effects, (2) cumulative effects, and (3) lead effects. The dependent variable is the weekly A&E treatment facility attendance rate per 100,000 regional population and the model is estimated using the balanced panel. The contemporaneous effects represent the impact of each weekly maximum temperature bin on A&E attendances in the same week, the cumulative effects measure the impact on both current and subsequent A&E weekly attendances, while the lead effects represent the effect on attendances in the week prior (i.e. the placebo test). Standard errors are clustered at the region level. *** denotes significant at the 1% level, ** denotes significant at the 5% level, and * denotes significant at the 10% level.

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

Figure A7.1: Estimated Percentage Weekly Effects – Model with Single Temperature Lead – Lowest and Highest Temperature Bins




**(A) 1-4°C**




**(B) 28+°C**

Notes: Figure A7.1 presents the estimated percentage weekly effects on A&E attendance rates for each week relative to the temperature shock for the (A) lowest and (B) highest temperature bins. All effects are based on the model presented in Equation [1] with a single lead added to the model and estimated using the balanced panel. The contemporaneous effect is represented by $t = 0$ on the *x*-axis and $t = -1$ represents the week prior to the temperature shock (i.e. the placebo test). 95% confidence intervals are represented by the shaded regions.

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