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The effect of absolute versus relative temperature on health and the role of social care

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Abstract

We investigate the effect of extreme temperatures on mortality and emergency hospital admissions, and whether local social care allows to mitigate their adverse effects. We merge monthly administrative data on mortality and hospital discharge from Italian municipalities for the period 2001–2015 with daily data on local weather conditions, and yearly data on disaggregated municipal expenditure. We compare two different measures of temperature shocks, one using the conventional approach based on absolute levels (without accounting for regional heterogeneity) and the other based on deviations from local mean temperatures. The former approach shows noisy evidence of an increase in mortality due to extremely hot days while the latter approach shows a large increase in mortality and hospital admissions for cardiovascular and respiratory diseases due to both cold and hot days. These effects are mostly driven by the oldest age group and partially by young children. Then, we report evidence of a mitigating effect of social expenditure on the impact of extremely hot and cold days on both emergency hospital admission and mortality rates. A back of the envelope calculation suggests that the additional social care expenditure is fully compensated by the benefits arising from the lower impact of temperature shocks.

KEYWORDS
hospital admissions, mortality, social expenditure, temperature shocks

JEL CLASSIFICATION
I18, Q51, Q54

1 | INTRODUCTION

Global warming as a result of increasing greenhouse gas emissions is associated with a rise in the intensity and the frequency of extreme weather events (Stott, 2016) with harmful effects on human well-being, especially health and longevity. These effects are likely exacerbated by population aging that enlarges the share of the vulnerable population. The design of (costly) policy measures meant to reduce greenhouse gas emissions, and so the potential impact on population health, relies on precise estimates of the effects of extreme weather conditions that vary over time and across space. To this end, the recent literature has shown that a decline in the mortality effects of extreme temperature is moderated by human adaptation through the adoption of

currently existing technologies (e.g., Barreca et al., 2016). However, most of this literature assumes a homogeneous relationship between temperature and population health across space, failing to account for the heterogeneity in local resilience (and adaptation) to extreme weather conditions. This might lead to a substantial underestimation of the population health cost of temperature shocks or to wrong predictions about the geographic distribution of the health effects of climate change (Heutel et al., 2021). Also, the optimal policy response might include the identification of other policy interventions, such as local social services, that can mitigate the adverse health consequences of extreme climate conditions and reduce the utilization of expensive health care services.

In this paper, we address these concerns investigating the effect of extreme temperatures on mortality and emergency hospital admission rates, and whether social care provided by local governments—targeted at the most vulnerable population— allows to mitigate their adverse effects. To this aim, we build up an extensive dataset that merges monthly administrative data on mortality from Italian provinces (which have an average size comparable to that of US counties) and hospital discharge data from Italian municipalities for the period 2001–2015, with daily data on local weather conditions and yearly data on disaggregated municipal expenditure. The fine geographical detail of our dataset and the relatively long observation window allow us to credibly and precisely estimate the non-linear relationship between extreme temperature events and population health, as well as the potential mediating role of municipal social expenditure.

Our empirical investigation follows two steps. In the first step, we identify the effect of temperature shocks on mortality and emergency hospital admission rates by comparing two different measures of temperature, one using the conventional approach based on absolute levels (without accounting for regional heterogeneity) and the other based on deviations from local mean temperatures. As standard in the literature (e.g., Barreca et al., 2016; Dell et al., 2014), we use a non-parametric temperature-bin regression model that controls for precipitation, province-specific time trends, *municipality-by-month* and *year-by-month* fixed effects. Then, we investigate the mitigating effect of social care on temperature-related mortality and hospital admission surges. We do so by comparing the effect of extreme temperatures among groups of municipalities or provinces identified by quintiles of the year-specific distribution of per capita local government social expenditure (lagged by 1 year).

When using absolute temperature bins, we only find (noisy) evidence of an increase in mortality due to extremely hot days and somewhat counter-intuitive reduction in hospital admissions due to extremely cold days. Conversely, when using bins based on standard deviations from local mean temperature, we find a large increase in mortality and hospital admissions (for cardiovascular and respiratory diseases) due to both cold and hot days. For instance, one additional day with temperature above 1.5 (2) standard deviations from the local mean increases mortality rates by 0.63% (1.67%). These effects are mostly driven by the most vulnerable part of the population, the oldest age group (above 65 years), and partially by young children (0–4). Then, we find some suggestive evidence of a mitigating effect of social expenditure on the impact of extremely hot and cold days on both emergency hospital admission and mortality rates. This result is driven by the beneficial effects of social expenditure for the elderly, who are among the main consumers of social care services and the most vulnerable when extreme temperatures hit a region.

Building on our results, we provide an assessment of the health costs associated to our measure of extreme temperature. We find that temperatures above or below 1.5 standard deviations (from their local mean) generate a yearly cost up to 884 Euros per capita in the 65+ population. We then calculate the potential savings generated by higher local social expenditure. Moving from the lowest to the highest quintile of municipal social expenditure allows to save up to 155 Euros per capita, which fully offsets the additional expenditure for older adults of the highest quintile (117 Euros).

Temperature peaks have relevant effects on the cardiovascular and the respiratory systems. Indeed, these systems are the most subject to stress during hot periods, leading to diseases such as stroke, myocardial infarction, hypothermia and pneumonia (Basu & Samet, 2002). In particular, cold temperatures increase respiratory diseases due to the reduced resistance of the immune system to infections. Similarly, cold temperatures exacerbate cardiovascular diseases, such as ischemic heart and cerebrovascular illness, because of the higher risk of thrombosis and other cold-driven cardiovascular reflexes (The Eurowinter Group, 1997). The elderly and children, in particular those aged less than 5 years, are more vulnerable to extreme weather conditions because their body temperature regulation is less responsive as compared to other people, and they are more likely to depend on others for the regulation of environmental temperature levels (Basagaña et al., 2011; Basu & Ostro, 2008). While the literature provides evidence of heat-related surges in hospital admission and mortality rates, the effect of cold temperatures on these health outcomes is still inconclusive (Karlsson & Ziebarth, 2018).

The economic literature analyzes the impact of temperature shocks on a variety of aspects, including health.[1] Deschênes and Moretti (2009) and Deschênes and Greenstone (2011) find that average daily temperatures above 80°F or below 30°F increase mortality rates in the US. Similarly, Mullins and White (2019) find that higher temperatures increase suicides, visits to emergency departments for mental illness, and self-reported days of poor mental health. Other studies show that long-run exposure to high or cold temperatures makes the population resilient against weather conditions and reduces mortality rates.

The effect of hot temperatures is mitigated by the adoption of air conditioning systems (Barreca et al., 2016), but outdoor workers are exposed to a higher risk of facing heat-related diseases (Dillender, 2019). Also, extreme temperatures may anticipate adverse health outcomes (harvesting effect), which would have occurred shortly afterward (up to 30 days) even in the absence of temperature shocks (Deschênes & Moretti, 2009). Closely related to our paper is a recent study by Heutel et al. (2021) who estimate how mortality effects of extreme temperatures vary across US regions. They show that accounting for regional heterogeneity substantially affects the mortality estimates of climate change.

The evidence on the impact of temperature shocks on health outcomes is very rich also in the epidemiological and public health literature (e.g., Anderson & Bell, 2009; Nordio et al., 2015; Son et al., 2014). These studies, however, use quite different parametric models (hierarchical Poisson models with smooth splines of the date) and often focus on data from a relatively small number of cities.[2]

Evidence relating the supply of social services to health outcomes and health care services utilization is spurious (e.g., Bradley et al., 2011; Dunn et al., 2005; Stuckler et al., 2010). Of relevance is the recent study by Costa-Font et al. (2018) who exploit a policy on the introduction of social care subsidies in Spain to show that hospital care utilization and costs decrease because they are replaced by cheaper social care services. Indeed, this might be one of the potential mechanisms behind our results. The increase of social care services at home may improve the continuity of care allowing faster and more effective primary assistance, and may improve compliance to follow advices and protect fragile people during exceptionally hot and cold days. Another prevention effect comes from the integration of home care assistance with health care services, which allows to monitor more closely elderly people during extremely hot/cold periods.[3]

We provide two main contributions to the literature. First, similar to Heutel et al. (2021), we remark the importance of accounting for regional heterogeneity in the resilience to extreme weather conditions. For instance, if people in places that are more often affected by high temperatures are more likely to follow offsetting behaviors and adapt, the conventional approach based on absolute temperatures might underestimate the adverse effects of hot temperature shocks. While Heutel et al. (2021) account for regional heterogeneity by interacting the absolute temperature bins with dummies for climate regions, we use measures of temperature shocks based on within-area mean and standard deviation to account for local "anomalies." Although our model might lead to estimates that are more difficult to interpret than a model based on absolute temperature bins, it is more parsimonious because it requires a smaller number of parameters to be estimated.[4]

Second, we shed light on the role of social expenditure in mitigating the adverse health outcomes and hospital care utilization in Italy. Although we do not leverage on a quasi-experimental variation in social expenditure, a set of additional results arguably show that our findings are not driven by other unobserved confounding municipal characteristics. In particular, using per capita municipal expenditure for the general administration, instead of municipal social expenditure, we do not find any evidence of mitigating effects. We can also exclude the possibility of reverse causality since temperature shocks are predictable only in the very short-run, while the local government expenditure to prevent surges in mortality and emergency hospital admissions is set at the beginning of the year. Moreover, the identification of temperature shocks based on local temperature anomalies prevents the possibility that municipalities usually affected by extreme temperatures respond by constantly spending more on social care services. Related to this contribution, we also quantify the costs and benefits associated to higher local social expenditure.

The remainder of the paper is structured as follows. Section 2 describes the hospital care system and the role of social expenditure in Italy. Section 3 explains the data used in the study, how temperature shocks are measured and the identification strategy. Section 4 reports the results on the impact of temperature shocks on health outcomes, and analyzes the mitigating effect of social expenditure. At the end of this section, we also provide a back-of-the envelope calculation assessing the net benefits of social care. Section 5 concludes.

2 | INSTITUTIONAL SETTING

2.1 | Hospital care in Italy

The Italian National Health Service (NHS) was established in 1978 and builds on the principles of universal coverage, solidarity and human dignity (Italian law 833/1978). The NHS is subdivided into regional health services (RHSs) which are responsible for the local provision of health care services. The NHS, together with the central government, establishes the essential benefit package that RHSs deliver to the population, and provides the financial resources to fund the services. Both elective and emergency hospital care is included in the essential benefit package. Hospital care is generally provided at zero fee or against a limited out-of-pocket contribution in order to mitigate inefficient hospital utilization. Waiting lists serve as a tool to match

scarce supply with the excess of demand for elective hospital admissions generated by free access, although the gatekeeping role exerted by general practitioners ensures, at least partially, that hospital referrals are based on medical needs.

Conversely, emergencies are treated in emergency wards that are organized across the country according to a hub-and-spoke model. Residents can access emergency wards across the entire country for free when in need.[5] The order in which patients are treated in emergency wards is related to the severity of their illness, with the more severe cases having the highest priority over less urgent cases. If urgency does not allow the person in need to reach the emergency ward, an emergency call center can be contacted for free and an ambulance reaches the sick individual, provides first aid and carry him/her to the closest hospital.

2.2 | Social care in Italy

The organization and the provision of social assistance is delegated to local public authorities, namely regions, provinces (whose size is on average comparable to the US counties) and municipalities. Municipalities are the main providers and funders of social care services and have administrative and organizational responsibilities on the provision of social assistance and charity.[6]

Since 2000, municipalities have to plan, achieve and organize the local network of social care, and to provide economic and non-economic services to the community.[7] In practice, social care is often provided by consortia of municipalities (*Unioni di comuni*) or mountain communities (*Comunità montane*), especially for small municipalities, and is funded by transfers from member municipalities to achieve a more efficient provision of services. In addition, local health authorities (LHAs) can integrate the provision of social care with health care services, as it happens for instance in the Lombardy region.

In 2015, total social expenditure in Italy amounted to almost 7 billion Euro, which corresponds to about 112 Euro per individual. About 67% of total social expenditure is funded by local governments, consortia of municipalities and mountain communities. Social services provided by municipalities are mainly addressed to two groups: families with children and the elderly/disabled (mostly aged 65+), who absorb 38.5% and 44.3% of the social care budget, respectively. The remaining 17.2% of the resources is allocated to the poor (7%), immigrants (4.2%), the addicted (0.4%) and the administration (5.6%; Istat, 2017).

The resources allocated to families with children are mainly used for subsidies (32.8%) and semi-residential services (32.0%). Among the resources allocated to the elderly/disabled, 44.2% are used to provide services at home (mainly home care) and 25.3% for residential services (mainly from nursing home providers). The remaining resources are devoted to subsidize income, to help families treating the elderly at home, and to reimburse nursing home and home care fees (15.5%), and to provide other professional services (7.4%).

3 | METHODS

3.1 | Data

3.1.1 | Mortality

We collect data on the monthly number of deaths by province and 5-year age groups for the period 2001–2015 from the Italian Institute for Statistics (ISTAT). We express mortality rates as the number of deaths per 10,000 individuals both for the total and the age-group-specific population.[8]

3.1.2 | Hospital statistics

We collect data on the universe of hospital discharge records relative to hospital admissions for cardiovascular and respiratory diseases for the period 2001–2015 provided by the Italian Ministry of Health. These data include personal information on patients (age, gender, and municipality of residence) and on the hospitalization (day of admission, ICD9 code of the primary disease and type of admission, namely emergency or elective). In this study, we focus on emergency hospital admissions because temperature shocks likely have an immediate effect on health, while we use elective hospitalizations as a placebo. We aggregate hospital admissions by municipality and month, and express them in rates per 10,000 individuals, both for the total and the age-group-specific population, using yearly population data from the ISTAT.[9]

3.1.3 | Weather statistics

Data on daily weather conditions for the period 2001–2015 are provided by the National Climatic Data Center. In particular, we use data from the Global Surface Summary of the Day. These data include information on average daily temperature and precipitation rates by weather station. On average, the number of weather stations are 110 (about one per province), but the number varies over time. We describe how we measure temperatures at provincial and municipal level in the next section. Moreover, we obtain data on pollution for the period 2001–2015 from the European air quality database (AirBase). This database collects daily station-level data on a large number of pollutants. Following Lagravinese et al. (2014), the pollutants that we consider are ozone (O_3), nitrogen dioxide (NO_2), carbon monoxide (CO) and particulate matter with a diameter below 10 μm (PM10). See the next section for a description of pollution measurement at municipal level.

3.1.4 | Municipal data

Ideally, we would measure social care by means of data on social services provided by each municipality. Unfortunately, precise data are not available and are missing for many municipalities and years. One alternative would be to exploit limited data on home care services (ADI or Assistenza domiciliare integrata, in Italian) provided by LHAs and aggregate them at province level. These data are available only for about 40% of provinces from 2011, and 70% of provinces from 2012. Moreover, data do not include social services provided at local (municipal) level. A valid alternative to measure social care at local level is therefore provided by municipal social expenditure. Yearly balance sheet data of Italian municipal governments are obtained from the Italian Ministry of the Interior for the period 2000–2015. The spending category of interest, *social expenditure*, aggregates expenditure for the universe of social services, which are classified into fixed and centrally defined sub-categories.[10]

   Finally, we collect data on yearly personal income at municipal level for the period 2001–2015 from the Ministry of Economics and Finance. Note that both income and social expenditure are expressed in Euro per capita and deflated using the consumer price index to obtain real values at 2010 prices.

3.2 | Measurement of temperature shocks

Starting from daily weather station data, we generate monthly temperature measures at municipal and province level. In what follows, the term *area* refers to both institutional levels. First, we calculate the average daily temperature in an area as the distance-weighted average daily temperature measured at weather stations located within a radius of 40 and 100 km from area centroid. For areas where the distance between the centroid and the closest weather station exceeds the threshold (20% of the municipal sample, none of the provincial sample), we assign the average daily temperature of the closest weather station.[11] The average temperature in area i on day d is given by the following equation:

$$T_{id} = \sum_k w_{ik} T_{kd} / \sum_k w_{ik} \tag{1}$$

with T_{kd} being the average temperature registered by the weather station k on day d, and w_{ik} being the inverse of the distance between the centroid of area i and the weather station k. Note that we use this approach also to measure monthly precipitation rates and pollution at municipal and provincial levels.

   Figure 1 illustrates average temperatures for the period 2001–2015 by municipality. We clearly observe some spatial correlation in temperatures between neighboring municipalities, which is due to the construction of temperature measures based on data from a limited number of weather stations. Average temperatures vary remarkably across the country, from 37.6°F to 68°F. Temperatures tend to be higher in the South of Italy, especially on the sea side, and on the Islands (Sicily and Sardinia), while temperatures tend to be colder in the North and along the Apennine chain.

   Following the previous economic literature (e.g., Barreca, 2012; Barreca et al., 2016), we classify daily temperatures into temperature bins and collapse the data by month, so that each bin measures the number of days per month falling within the specified temperature range. We employ two approaches to define temperature ranges. First, as standard in the previous literature, we classify temperatures into 10°F bins, from 20°F to 90°F. Days with temperatures falling below 20°F or above 90°F are grouped into separate variables. This approach allows us to measure the objective exposure of population to temperature levels,
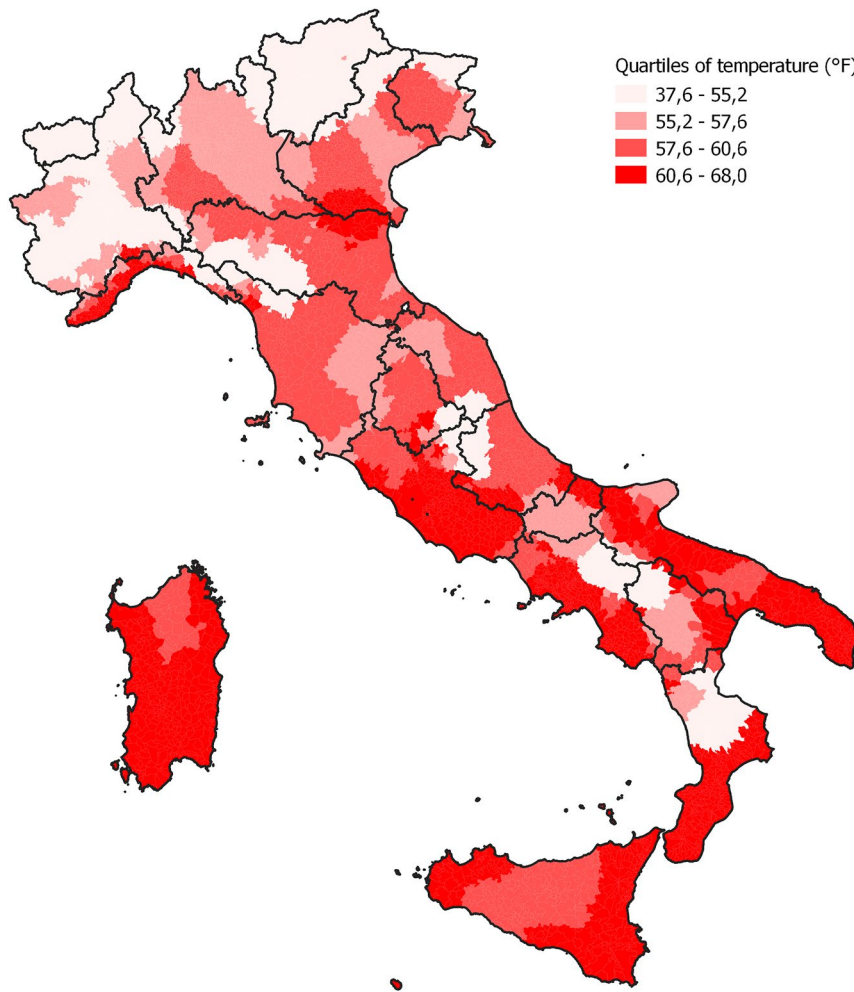
but cannot take into account the heterogeneous effects of temperature on population health generated by the local resilience to weather conditions due to adaptation and offsetting behaviors.

In the second approach, we classify daily temperatures based on deviations from area-specific average temperatures for the period 2001–2015. More specifically, we create a set of variables measuring the number of days per month with temperature falling within 0.5 standard deviation (SD) bins relative to the area-specific temperature. Our temperature bins range from −2 SDs to +2 SDs. As for absolute temperatures above, days with temperature falling below and above these thresholds are grouped into separate variables. Note that a day with average temperature deviating by more (or less) than +2 SDs (or −2 SDs) from the area-specific mean implies that the daily temperature exceeds the percentile 97.7 (or falls below the percentile 2.3) of the local temperature distribution. This corresponds approximately to the definition of extremely hot (or cold) days provided in previous epidemiology studies (e.g., Gasparrini et al., 2015; Karlsson & Ziebarth, 2018). Moreover, average temperature levels in the most extreme bins (±2 SD), which are equal to 26.5°F and 82.5°F for negative and positive deviations respectively (see Table 1), are close to the thresholds adopted in the economic literature to identify hot (above 80°F) and cold days (below 30°F), but show much more variability. Indeed, Table 1 shows that temperature level ranges largely overlap between temperature deviation bins. The minimum temperature in the highest-deviation bin (above 2 SDs) is only 6°F above the maximum temperature in the lowest deviation bin (below −2 SDs).[12] This confirms that different areas of the country are exposed to heterogeneous temperature levels (e.g., North vs. South, mountain vs. valley, rural vs. urban areas), and suggests that temperature deviations may be preferable to temperature levels to measure weather shocks at local level.

As a robustness check, we extend the temperature-deviation approach to account for seasonal heterogeneity in temperatures across areas. To this aim, we generate negative temperature deviation bins relative to the area-specific mean temperature during Autumn/Winter months (October–March), and positive temperature deviation bins relative to the area-specific mean temperature during Spring/Summer months (April–September). Relative to the baseline temperature deviation approach, the use of

TABLE 1 Descriptive statistics of temperature levels by temperature deviation bin

	Mean	SD	Min	Max
$T < -2$ SD	27.51	9.03	−0.4	52
-2 SD $\leqslant T < -1.5$ SD	34.48	7.05	6.5	56
-1.5 SD $\leqslant T < -1$ SD	40.90	6.58	14	60
-1 SD $\leqslant T < -0.5$ SD	47.66	6.52	21	65
-0.5 SD $\leqslant T < 0$ SD	54.02	6.16	27	71
0 SD $\leqslant T < 0.5$ SD	60.73	6.00	34	76
0.5 SD $\leqslant T < 1$ SD	67.50	5.80	41	83
1 SD $\leqslant T < 1.5$ SD	74.74	5.81	47	91
1.5 SD $\leqslant T < 2$ SD	80.10	6.06	52	99
$T \geqslant 2$ SD	82.70	7.85	58	106

Note: The table reports descriptive statistics of temperature levels (in °F) by temperature deviation bin, with each bin representing deviation ranges from the municipality-specific average temperature for the period 2001–2015.

seasonal deviations further accounts for the fact that season-specific temperatures may be heterogeneous across areas, but the variability in temperature deviations may be reduced.

3.3 | Descriptive statistics

Since disaggregated data on mortality are available only at provincial level, we work with two datasets. The provincial-level dataset includes 19,800 *province × year × month* observations for the period 2001–2015, but we drop 180 observations from the province of Aosta in the region Valle d'Aosta for the reason described above. The municipal-level dataset is composed of 1,436,568 *municipality × year × month* observations for the period 2001–2015. We exclude observations from municipalities located in the region Valle d'Aosta, since in this region social care is provided at provincial level (see Section 2.2). We further drop municipalities with incomplete data on weather, pollution, personal income and municipal government social expenditure. This leaves us with a final sample composed of 1,304,928 observations.

3.3.1 | Health outcomes

Panel A of Table 2 reports descriptive statistics of mortality rates and emergency hospital admission rates per 10,000 individuals.[13] Emergency hospital admission rates show more variability than mortality rates. This is partly due to the fact that mortality rates are aggregated by province while hospital admission rates by municipality.

There is clear evidence of substantial geographical variation (Figure 2). Mortality rates are very heterogeneous across the country with the South and the Islands showing lower mortality rates as compared to the other regions, except for the regions Trentino Alto Adige and parts of Lombardia and Veneto (Figure 2a). For hospital admissions the North-South gradient is less clear, but overall there is large heterogeneity also within regions.

In the Appendix, we report additional evidence on temporal variation in mortality and emergency hospital admission (Figure A.1 and Figure A.2). It is worth noting that the mortality rate shows three clear spikes in 2003, 2012 and 2015, which correspond to three hot waves in Italy. Both mortality and hospital admission rates show some evidence of seasonal cycle with peaks in winter months (December–February). This cycle is particularly pronounced for respiratory diseases with rates exceeding the mean by more than 30% in January.

3.3.2 | Temperatures

Panel B of Table 2 reports descriptive statistics for the number of days per month in each temperature level bin, while Panel C reports descriptive statistics of the number of days per month in each temperature deviation bin. More than 85% of days have average temperatures ranging between 40°F and 80°F, or between −1.5 SDs below the municipality-specific mean and 1.5 SDs

TABLE 2 Descriptive statistics

	Obs	Mean	SD	Min	Max
Panel A: Health outcomes per 10,000 individuals					
Mortality	19,620	8.220	1.518	1.36895	19
Hospital admission—Cardiovascular	1,293,571	11.462	5.467	0	444
Hospital admission—Respiratory	1,293,571	5.920	3.702	0	417
Panel B: Temperature level bins (no. of days per month)					
<20°F	1,293,571	0.045	0.603	0	21
20–30°F	1,293,571	0.367	1.771	0	29
30–40°F	1,293,571	2.675	5.800	0	30
40–50°F	1,293,571	5.367	7.274	0	31
50–60°F	1,293,571	6.943	8.186	0	31
60–70°F	1,293,571	7.106	8.183	0	31
70–80°F	1,293,571	5.985	8.645	0	31
80–90°F	1,293,571	1.897	4.870	0	31
⩾90°F	1,293,571	0.049	0.563	0	21
Panel C: Temperature deviation bins (no. of days per month)					
$T < -2$ SD	1,293,571	0.168	0.821	0	17
$-2 \geqslant T < -1.5$ SD	1,293,571	1.449	3.088	0	22
$-1.5 \geqslant T < -1$ SD	1,293,571	4.372	6.493	0	29
$-1 \geqslant T < -0.5$ SD	1,293,571	4.695	5.723	0	31
$-0.5 \geqslant T < 0$ SD	1,293,571	4.649	5.836	0	29
$0 \geqslant T < 0.5$ SD	1,293,571	4.521	5.908	0	30
$0.5 \geqslant T < 1$ SD	1,293,571	4.378	5.920	0	31
$1 \geqslant T < 1.5$ SD	1,293,571	4.450	7.024	0	30
$1.5 \geqslant T < 2$ SD	1,293,571	1.674	3.707	0	27
$T \geqslant 2$ SD	1,293,571	0.077	0.454	0	10

Note: Panel A reports descriptive statistics of mortality rates at provincial level and emergency hospital admission rates by type of disease at municipal level per 10,000 individuals for the period 2001–2015. Panel B reports statistics on the number of days per month with average daily temperature falling into 10°F bins at municipal level. Panel C reports statistics on the number of days per month with average daily temperature falling into 0.5 standard deviation bins relative to the municipality-specific mean temperature at municipal level for the period 2001–2015. Statistics are weighted by the province- or municipality-specific population according to the level of aggregation of the data.

above. Finally, it is worth noting that extreme bins for temperature below 20°F and above 90°F have lower temperature mean and higher maximum values than extreme bins for temperature deviations (± 2SD). This indicates a lower within-month variation in temperature level bins as compared to temperature deviation bins.

3.4 | Identification strategy

To identify the causal impact of temperature shocks on health outcomes, we specify the following flexible temperature-bin Ordinary Least Squares (OLS) regression model[14]:

$$H_{imy} = \sum_j \beta_j T_{jimy} + X'_{imy}\gamma + \alpha_{im} + \theta_{my} + \delta_i PrTr_{imy} + \varepsilon_{imy} \tag{2}$$

with H_{imy} being the emergency hospital admission rate per 10,000 individuals for cardiovascular or respiratory diseases in municipality i, and month m of year y. For the mortality rate, we estimate an equivalent model using Equation (2) at province level because of the data restriction described before.

T_{jimy} is the number of days in month m of year y with average temperature falling into temperature bin j, and β_j is its parameter. This flexible specification of population exposure to temperature allows us to identify a non-linear relationship between

(a) Mortality

(b) Hospital admissions - Cardiovascular
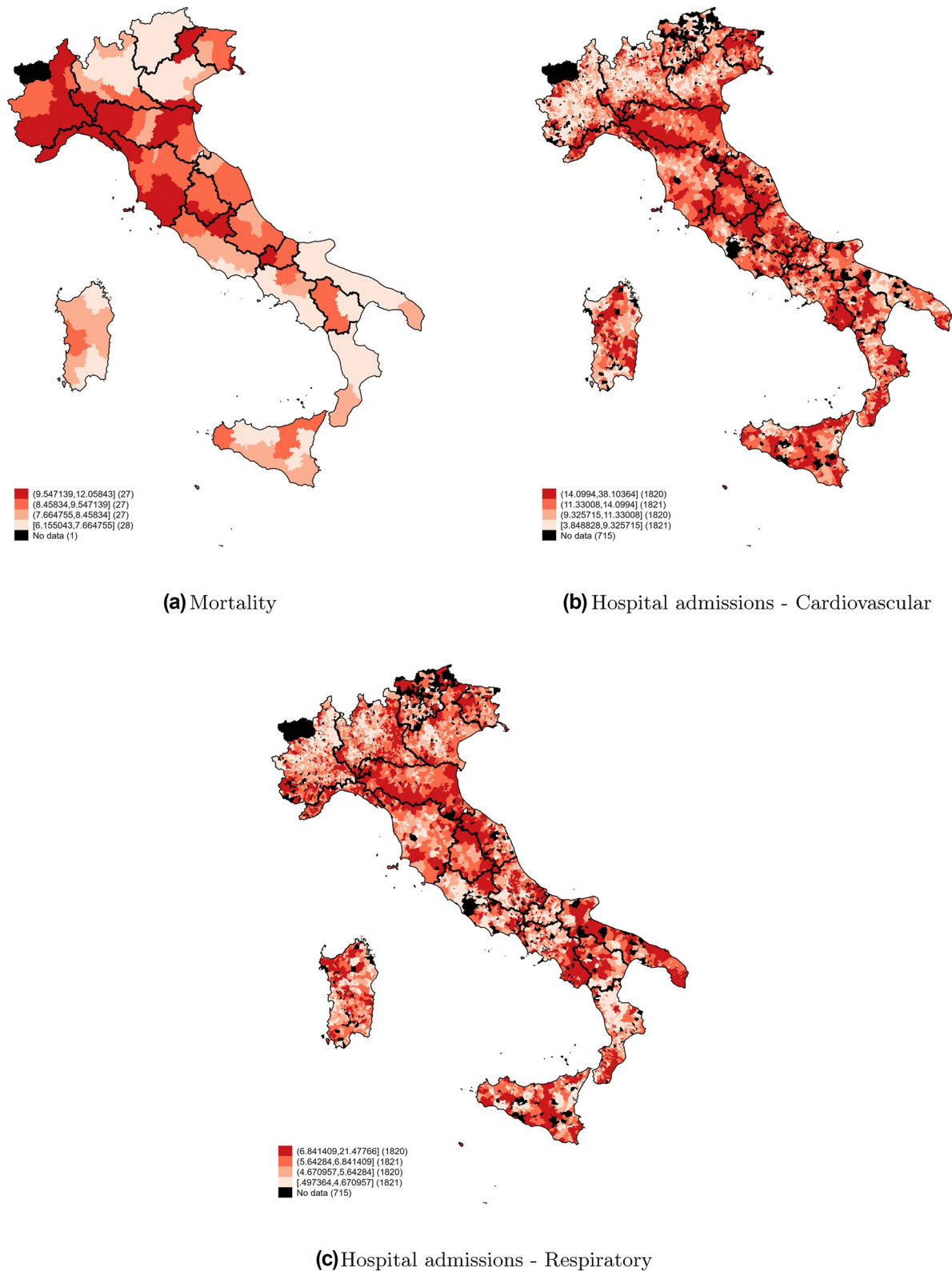
(c) Hospital admissions - Respiratory

FIGURE 2 Monthly mortality and hospital admission rates by municipality. The figures show maps of average monthly mortality rates by province (a), and emergency hospital admission rates per 10,000 individuals by municipality for the period 2001–2015, respectively for cardiovascular diseases (b) and respiratory diseases (c). The darker the color, the higher is the prevalence of mortality and hospital admissions. Black areas indicate excluded areas or areas with missing data. Mortality and hospital admission rates are weighted by the population. *Source*: Our elaboration on mortality data aggregated by province for the period 2001–2015 provided by Italian Institute for Statistics (ISTAT) and hospital discharge data for the period 2001–2015 provided by the Italian Ministry of Health. The shapemap of the 2016 administrative borders is provided by ISTAT.

weather conditions and mortality rates. As described in Section 3.2, temperature bins are either 10°F bins or 0.5 SD bins relative to the municipality-specific mean temperature for the period 2001–2015. When we use bins based on temperature levels, the reference temperature effect is provided by the 50–60°F bin. When we use bins based on temperature deviations, the reference effect of temperature deviations is provided by the two bins from −0.5 to 0.5 SDs. In this way, the model controls for 8 temperature bins independently from the adopted measurement approach. However, to ensure a comparison between the two approaches, we extend Equation (2) to estimate a combined model that controls for both types of temperature deviation measurement.

X'_{imy} is a vector of time-varying control variables, namely the average monthly precipitation rate and, only as robustness check, average monthly pollution (O_3, NO_2, CO, and PM10) and the natural logarithm of the yearly average personal income.[15] α_{im} are *municipality* × *month* fixed effects to capture unobserved municipality-specific characteristics that determine heterogeneity in hospital admission rates at monthly level. θ_{my} are *month* × *year* fixed effects and capture period-specific shocks common to all municipalities, including the yearly cycles in mortality described in Section 3.3, and in temperature levels and deviations. We also control for province-specific linear trends ($PrTr_{imy}$) to account for heterogeneity in yearly cycles and trends in mortality rates between provinces. Finally, ε_{imy} is an *iid* error term.

The parameters of main interest are the β_j s, which measure the causal effect of temperatures on health outcomes. In particular, they measure the effect of one additional day with average temperature in bin j on mortality and hospital admission rates. The validity of our identification strategy is ensured by the inclusion of temporal and spatial fixed effects, which account for unobservable differences characterizing heterogeneity in health outcomes and exposure to extreme temperatures between municipalities and over time. Clearly, cold shocks may be more frequent in mountain areas in Winter periods, while hot shocks in the South and in large urban centers during Summer. This issue justifies the inclusion of a large set of fixed effects. Indeed, *municipality* × *month* fixed effects capture fixed heterogeneity in health outcomes and temperature variations within (e.g., January vs. June in the city of Bergamo) and between municipalities (e.g., June in the city of Bergamo vs. June in the city of Palermo). This includes offsetting behaviors such as migration to areas that allow to avoid extreme temperatures. Also, *month* × *year* fixed effects capture seasonal differences in mortality and hospital admission rates (e.g., January vs. June), and differences across months of various years (e.g., January 2001 vs. June 2003) common to all areas. Finally, province-specific time trends allow for heterogeneous tendency in mortality and hospital admission rates across provinces.[16]

By construction, weather shocks are spatially correlated because temperature measures are weighted sums of temperatures gathered at weather stations nearby (see Section 3.2). This concern is particularly relevant when the model is estimated at municipal level since number of weather stations is relatively low as compared to the number of municipalities. Conversely, all provinces have at least one weather station located within the specified radius of 100 km, and 80% of them within a radius of 40 km. Therefore, to account for spatial and serial correlation within provinces we use robust standard errors clustered by province. Moreover, since municipalities differ in size and, therefore, in the amount of people exposed to extreme temperatures, we follow previous studies (e.g., Barreca et al., 2015; Deschênes & Moretti, 2009) and weight our regressions by the population.

The effect of temperatures on health outcomes likely differs by the degree of vulnerability of the population. Hence, we repeat the estimation of Equation (2) by age group. In particular, we analyze the impact of temperatures on the age groups 0–4, 5–24, 25–44, 45–64, and over 65 years. We weight the regressions by the age-group-specific population. This strategy allows us to check also the robustness of our estimation strategy since less vulnerable age groups, such as the 25–44 age group, should face less adverse effects on health when temperature shocks occur.

As in previous literature (Barreca et al., 2015; Heutel et al., 2021), we also estimate an extended version of the conventional model based on absolute temperatures that allows for regional heterogeneity. More specifically, we divide the Italian municipalities into terciles of the distributions of the number of cold ($T \leq 30°F$) and hot days ($T > 80°F$) over the observation window. Then, temperature bins below 50°F are interacted with terciles of the distributions of the number of cold days, while temperature bins above 60°F with terciles of hot days.

To further ensure the validity of our identification strategy, we run several robustness checks. First, we check the sensitiveness of our results to short-term displacement (or harvesting) in health outcomes. Several studies show that health problems are anticipated by extreme weather shocks, and would have occurred shortly afterward even in the absence of adverse weather events (e.g., Barreca, 2012; Deschênes & Moretti, 2009). Second, we estimate the impact of extreme temperatures on elective hospital admission rates for cardiovascular and respiratory diseases. Elective hospital admissions are not expected to be affected by temperature variations conditional on *month* × *year* and *municipality* × *month* fixed effects, because these admissions are planned and regulated by waiting lists (see Section 2.1). Finally, note that the models specified in Equation (2) provide an intrinsic robustness check for the effect of temperatures on health outcomes. The central temperature bins should not cause significant effects on health, and the effect should grow as days become hotter or colder. Therefore, the coefficients

of temperature bins close to the reference bin should be lower in magnitude as compared to coefficients of bins more distant from the reference bin.

3.4.1 | The mediating role of local social expenditure

The availability of (local) social services may allow to take care of the vulnerable population at home or in dedicated social care units (either called social, community, or recreation centers), and hence to prevent the adverse effects of extreme weather conditions on health. To explore these effects, we analyze whether areas with higher social expenditure face lower mortality and emergency hospital admission rates when extreme temperature shocks occur. We first split our sample into five equal-sized groups based on quintiles of the year-specific distribution of per capita province or municipal government social expenditure lagged by 1 year (see Table A.1). Then, we re-estimate Equation (2) separately for the first, the central (second to fourth) and fifth groups of social expenditure quintiles, and for each age group and type of disease.[17] Since we repeat the classification of municipalities in each year, we can create time-varying groups, and therefore account for social expenditure adjustment over time.[18] Indeed, generating time-invariant groups would require to assume that municipalities do not adjust social expenditure levels over the 15-year period, which is very unlikely since policies and budget constraints have changed between 2001 and 2015. If the group composed by the lowest-spending municipalities shows higher effects of extreme temperatures on mortality and hospital admission rates as compared to groups composed by higher-spending municipalities, this would suggest that social expenditure has a mitigating effect on adverse health outcomes.
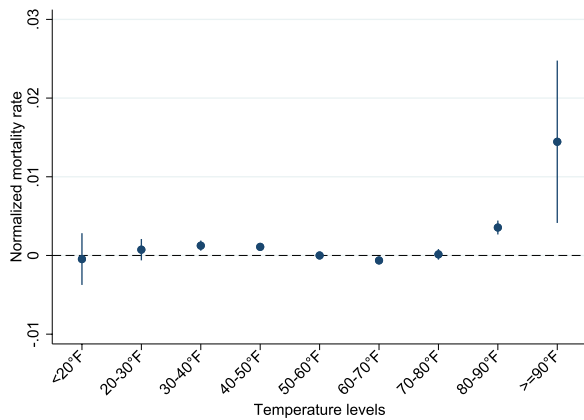
It is worth noting that the results of this analysis should be interpreted with caution since we do not exploit any clear source of exogenous variation in social expenditure. However, we try to account for confounding effects and test alternative explanations for our results. First, since extreme temperature shocks are predictable only in the very short-run (about 1 week of prediction), municipal governments cannot adjust social expenditure to prevent surges in mortality and emergency hospital admission rates. Indeed, decisions on the provision of social care services are taken before the occurrence of temperature shocks. Second, the use of a large set of municipal fixed effects allows us to get rid of many time-varying confounders. Third, to ensure that we are not confounding the effect of local social expenditure with other municipality characteristics, we repeat the heterogeneity analysis using the per capita municipal expenditure for the general administration. Since the general administration does not provide services related to health or social care, this is not expected to affect health outcomes when extreme temperature shocks occur. It is also worth noting that social expenditure targets mostly the oldest and the youngest population (see Section 2.2). As a result, other age groups provide a sort of placebo test.
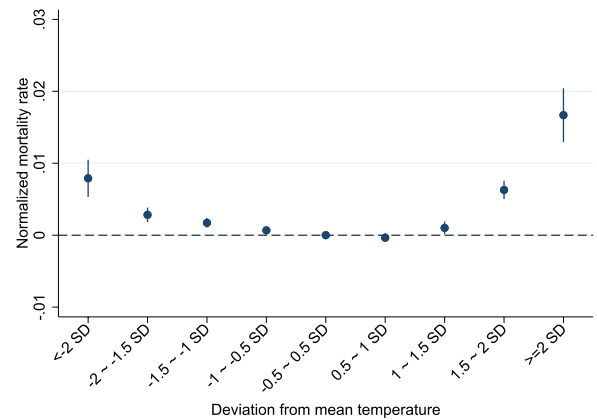
4 | RESULTS

4.1 | Effect of temperatures on emergency hospital admissions and mortality

Figure 3 illustrates the estimated effects of temperature level and deviation bins on mortality (3a,b) and emergency hospital admission rates for cardiovascular (3c,d) and respiratory diseases (3e,f). In each graph, the dots represent the estimated coefficients of temperature bins while the vertical lines indicate their 95% confidence intervals. Each coefficient measures the impact of one additional day in a temperature bin on health outcomes relative to the impact of 1 day in the reference bin (50–60°F for temperature levels and −0.5 SDs to 0.5 SDs for temperature deviations). To facilitate the interpretation of the results and their comparability, the coefficients have been standardized (divided by the population-weighted mean), and so can be interpreted as percentage changes.[19]
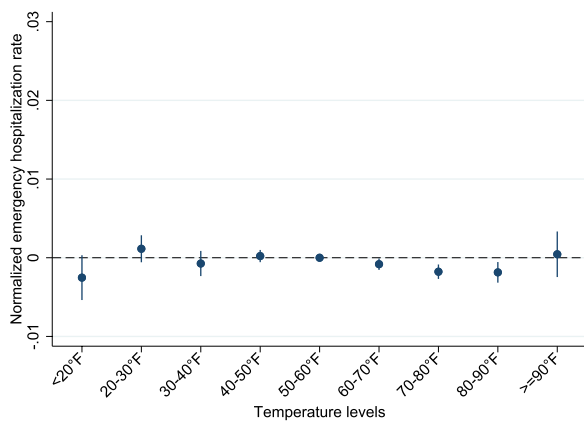
Starting from the absolute temperature estimates, we find that mortality rates significantly increase when average temperature exceed 80°F (Figure 3a). One additional day with average temperature between 80°F and 90°F increases the mortality rate by 0.36%, and the effect increases to 1.44% (with very large standard errors) when temperatures exceed 90°F. The estimated effect of hot days are slightly larger than the effect estimated in the US (e.g., Barreca et al., 2016; Deschênes & Greenstone, 2011), and lower than the effect estimated in Germany (Karlsson & Ziebarth, 2018).[20] Conversely, cold days do not show significant effects on mortality. Moreover, emergency hospital admission rates for cardiovascular (Figure 3c) and respiratory diseases (Figure 3e) do not show significant variations when temperature levels grow. A bit surprisingly, we find a decrease in hospital admissions for cardiovascular diseases when the average temperature falls below 20°F. The negative impact of cold temperatures on hospitalizations might be rationalized by the fact that cold temperatures are associated to decreased willingness to seek care, as suggested by White (2017), likely because of snowfalls or ice conditions that limit access to hospitals. However,
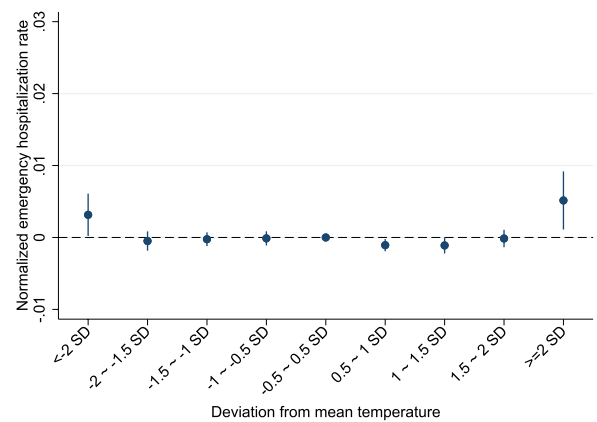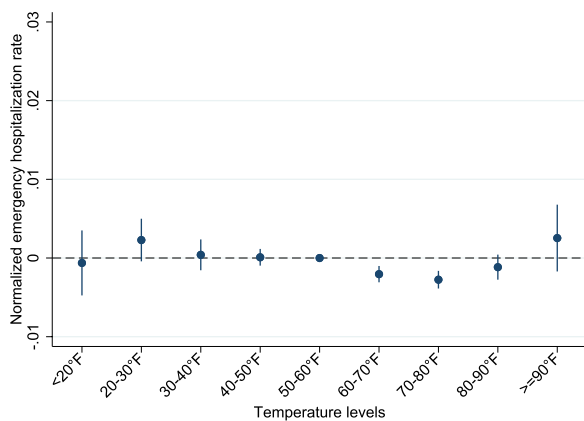
(a) Mortality - Levels
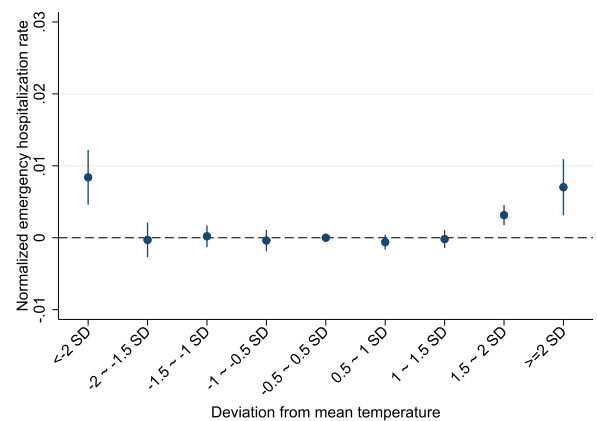

(b) Mortality - Deviations

(c) Cardiovascular - Levels

(d) Cardiovascular - Deviations

(e) Respiratory - Levels

(f) Respiratory - Deviations

the fact that we do not find a corresponding increase in mortality, nor do we find a similar effect on elective hospitalizations, does not provide much support for this explanation.

The results are quite different when using temperature deviation bins. More precisely, extreme temperature (both hot and cold) show significant effects on all health outcomes. The effects of positive temperature deviations on mortality rates are significant when temperatures exceed the local mean by more than 1.5 SDs (Figure 3b). In particular, the effects of one

additional day with temperature above 1.5 and 2 SDs are equal to 0.63% and 1.67%, respectively. Also, negative deviations show significant and increasing effects on mortality as temperatures fall. The effects of one additional day with temperature below −1, −1.5, and −2 SDs are equal to 0.17%, 0.28%, and 0.79%, respectively. Similar evidence is found for hospital admissions, though the estimated effects for hot days are lower in magnitude and, as expected, admissions for respiratory diseases are particularly sensitive to negative temperature deviations. It is also reassuring that temperature deviation bins close to the reference bin do not show any significant effect on hospital admission rates, and the magnitude and significance of this effect grow with deviations of temperature from the mean.

The different evidence provided by the two approaches might be explained by the fact that estimates based on absolute temperature bins are confounded by local adaptation and offsetting behavior that mitigate the impact of extreme weather conditions. To provide a better comparison of the two approaches, we also estimate a model that controls for both temperature measures. The results of the combined regression are reported in Figure 4. The estimated effects for deviation bins are basically unchanged. As for absolute temperature bins, the results somewhat change for mortality. In particular, we now estimate a negative effect of cold temperatures (previously null effect) and a descrease in the effect of temperatures above 90°F (of about 40%) which is no longer statistically significant at conventional levels.

We also estimate a modified version of the conventional approach allowing for geographical heterogeneity. As in Heutel et al. (2021), we interact the absolute temperature bins with terciles based on the frequency of hot days (>80°F) and cold days (≤30°F). The results for this model are reported in the Appendix (Figure A.3). Point estimates for mortality are consistent with the model based on deviations from mean temperatures, since the estimated adverse effects (i.e., an increase in mortality) of hot (cold) temperatures are larger in areas that are less frequently exposed to them. The evidence for hospital admissions is instead less clear cut. More generally, all estimates are quite noisy, likely because of the additional number of parameter to be estimated (i.e., the interaction terms). Results are even noisier if we use more extreme temperatures (e.g., 90°/30°F) to calculate the terciles, or if we use smaller quantiles (quartiles or quintiles) for the frequency of hot and cold days.
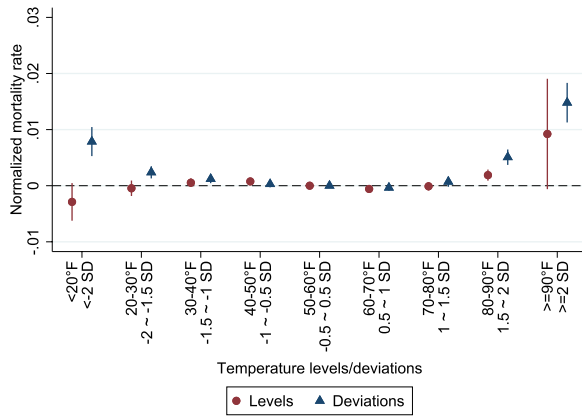
4.2 | Analysis by age group

The impact of extreme temperatures on health outcomes may differ across age groups because some of them, such as children and the elderly, are relatively more vulnerable to extreme weather conditions. This is due to the fact that their body is less responsive to temperature changes as compared to the body of adults, and they depend on other people for the regulation of environmental temperature. Therefore, we re-estimate Equation (2) for the age groups 0–4, 5–24, 25–44, 45–64, and over 65 years using the temperature deviation approach. The results are summarized in Table 3 for the most extreme deviation bins (+2 SDs and −2 SDs), that is those that cause the largest and the most significant effects on the entire population, according to our estimates (see Section 4.1).
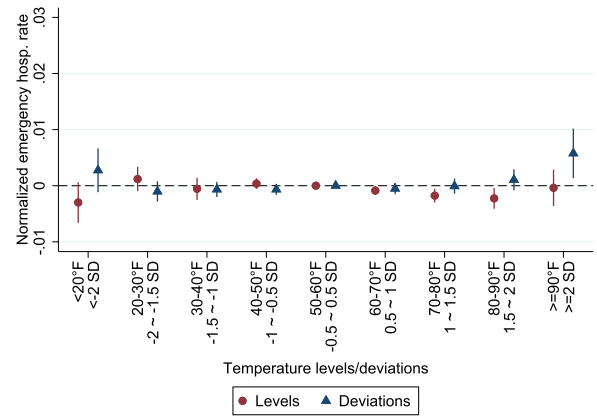
Cold days significantly increase mortality rates only for the oldest age group. Conversely, extremely hot days affect mortality rates of the population aged 25 years or older. The result on mortality for the younger age groups is consistent with Dillender (2019), who shows that outdoor working conditions exposes them to weather shocks with limited possibility of prevention.

The impact of extreme temperaturxes on emergency hospital admission rates for cardiovascular and respiratory diseases shows significant effects mainly on the oldest age group. The only two exceptions are children and people aged 45–64 who face significant surges in hospital admissions for respiratory diseases when cold days occur.
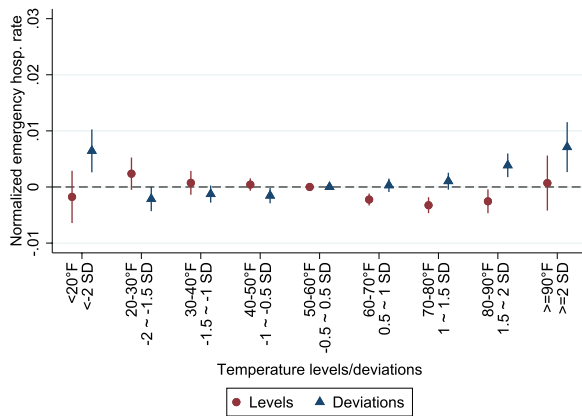

FIGURE 3 Regression results of temperature level and deviation bins on mortality and emergency hospital admission rates. The figures illustrate regression results of temperature level and deviation bins on monthly mortality rates by province (a) and (b) and emergency hospital admission rates per 10,000 individuals by municipality, respectively for cardiovascular (c) and (d) and respiratory diseases (e) and (f), for the period 2001–2015. The dots represent the normalized coefficients of temperature bins, and the vertical lines represent the 95% confidence intervals. In (a), (c), and (e), the temperature bins measure the number of days per month with average temperature falling within 10°F bins, with the baseline being the number of days with temperatures between 50°F and 60°F. In (b), (d), and (f), the temperature bins measure the number of days per month with average temperature falling within 0.5 standard deviation (SD) bins relative to the municipality-specific average temperature for the period 2001–2015, with the baseline being the number of days with temperatures deviating from the mean between −0.5 SDs and +0.5 SDs. All models control for month × year fixed effects, province-specific time trends, monthly precipitation and population age structure. Models of hospital admission rates further control for municipality × month fixed effects, and models of mortality rates further control province × month fixed effects. Standard errors are robust and clustered by province. All regressions are weighted by the population. *Source*: Our elaboration on mortality data for the period 2001–2015 provided by Italian Institute for Statistics (ISTAT), hospital discharge data for the period 2001–2015 provided by the Italian Ministry of Health and Global Surface Summary of the Day (GSOD) weather data provided by NCDC.

(a) Mortality - Combined

(b) Cardiovascular - Combined

(c) Respiratory - Combined

FIGURE 4   Regression results of combined temperature and deviation bins on mortality and emergency hospital admission rates. The figures illustrate regression results of combined temperature and deviation bins on monthly mortality rates by province (a) and emergency hospital admission rates per 10,000 individuals by municipality, respectively for cardiovascular (b) and respiratory diseases (c), for the period 2001–2015. The dots and triangles represent the normalized coefficients of temperature level and deviation bins, respectively, and the vertical lines represent the 95% confidence intervals. All models control for month × year fixed effects, province-specific time trends, monthly precipitation and population age structure. Models of hospital admission rates further control for municipality × month fixed effects, and models of mortality rates further control for province × month fixed effects. Standard errors are robust and clustered by province. All regressions are weighted by the population. *Source*: Our elaboration on mortality data for the period 2001–2015 provided by Italian Institute for Statistics (ISTAT), hospital discharge data for the period 2001–2015 provided by the Italian Ministry of Health and Global Surface Summary of the Day (GSOD) weather data provided by NCDC.

4.3 | The role of local social expenditure

We now investigate whether (local) social expenditure allows to mitigate the adverse health effect of extreme weather conditions. Following the strategy described in Section 3.4, we split the sample into five equal-sized groups based on quintiles of the year-specific distribution of the per capita local government social expenditure lagged by 1 year. Then we estimate Equation (2) separately for the first, the central (second to fourth), and the fifth quintiles using our preferred specification with temperature deviation bins. The results are reported in Table 4. The table shows evidence of a gradient in the effect of interest related to the level of expenditure. The estimated adverse effect of extreme weather conditions is particularly large in the lowest expenditure quintile. This effect is above the average effect reported in Figure 3 and (except for mortality) in the central expenditure quintiles group. Conversely, point estimates are very close to zero and not statically significant in the highest spending quintile except for respiratory admissions during hot days. We also test the difference across quantile groups. While the difference

TABLE 3 Regression results of mortality and hospital admission rates by age group

	(1) 0–4 years	(2) 5–24 years	(3) 25–44 years	(4) 45–64 years	(5) Over 65 years
Mortality					
Cold	0.0170	−0.0172	−0.000498	0.00543*	0.00742***
	(0.0140)	(0.0107)	(0.00763)	(0.00262)	(0.00142)
Hot	−0.00568	0.00890	0.0321***	0.0102**	0.0166***
	(0.0182)	(0.0178)	(0.00778)	(0.00385)	(0.00207)
Hospital admissions for cardiovascular diseases					
Cold	−0.00795	−0.00797	−0.00382	0.00122	0.00408**
	(0.0212)	(0.00829)	(0.00320)	(0.00253)	(0.00145)
Hot	0.0393	−0.00252	0.00742	0.00189	0.00619**
	(0.0205)	(0.00938)	(0.00649)	(0.00306)	(0.00217)
Hospital admissions for respiratory diseases					
Cold	0.0103*	0.00000286	−0.00294	0.0106**	0.00864***
	(0.00453)	(0.00547)	(0.00428)	(0.00341)	(0.00203)
Hot	0.00870	0.00159	0.00484	0.00411	0.00813***
	(0.00500)	(0.00524)	(0.00704)	(0.00342)	(0.00193)

Note: The table summarizes regression results of mortality and hospital admission rates by age group. *Cold* and *Hot* measure the number of days per month with average temperature falling below −2 SDs or above 2 SDs, respectively, relative to the municipality-specific (or province-specific) mean temperature for the period 2001–2015. The coefficients and standard errors are normalized by the mean of the dependent variable. All models control for month × year fixed effects, province-specific time trends, monthly precipitation and population age structure. Models of hospital admission rates further control for municipality × month fixed effects, and models of mortality rates further control for province × month fixed effects. Standard errors (in parenthesis) are robust and clustered by province. All regressions are weighted by the age-group specific population.

Significance levels: ***$p < 0.001$, **$p < 0.01$, *$p < 0.05$.

between the first and the last quintile is always statistically significant, the difference between the first and the central quintile group is not at conventional levels.

Since social expenditure mostly targets the elderly and the children (see Section 2.2), we further investigate whether there are heterogeneous mitigating effects on adverse health outcomes by age groups when extreme weather events occur (Table A.2). As expected, the mitigating effect of social expenditure on health outcomes estimated in Table 4 is driven entirely by the elderly group (65+). Although social expenditure also targets children, we are not surprised to find unclear evidence of a gradient for this age group. The services provided to this age group, mainly expenditure and subsidies for childcare services, should not affect children exposure to weather shocks.

4.4 | Robustness checks

As anticipated in Section 3.4 we run a large set of robustness checks. First, we re-estimate Equation (2) using alternative measures of temperature based on deviations from municipality- and season-specific mean temperatures. In particular, we generate 0.5 SD bins and consider positive deviations during Spring/Summer months (April–September) and negative deviations during Autumn/Winter months (October–March). Using seasonal means as a reference for temperature deviations differs from our baseline temperature deviation approach since it takes into account that municipalities having the same average temperature may differ in the yearly temperature variations between hot and cold months.[21] For both mortality and hospital admission rates, we find that the results using this alternative temperature measure are very similar to our preferred results from the temperature deviation approach (see Figure A.5 in the Appendix). This is likely due to the fact that the models in Equation (2) control for *province × month* fixed effects, which account for fixed heterogeneity in yearly cycles in temperatures across provinces.

Second, we run a placebo test where we estimate Equation (2) using the elective hospital admission rate per 10,000 individuals as the dependent variable. The results do not show significant coefficients, except for the positive effect of the 1–1.5 SDs bin and the negative effect of the above 2 SDs bin on respiratory diseases (see Figure A.6).[22] We also run an alternative

TABLE 4 Regression results of mortality and hospital admission rates by quintiles of per capita social expenditure

	(1)	(2)	(3)
	Mortality		
	Q1	**Q2–Q4**	**Q5**
Cold	0.00727	0.00764***	0.00134
	(0.00460)	(0.00159)	(0.00528)
Hot	0.0111**	0.0170***	0.00488
	(0.00424)	(0.00249)	(0.00430)
	Hospital admissions—Cardiovascular		
	Q1	**Q2–Q4**	**Q5**
Cold	0.00412	0.00352**	0.0000236
	(0.00325)	(0.00136)	(0.00255)
Hot	0.00867*	0.00477*	0.000694
	(0.00410)	(0.00222)	(0.00307)
	Hospital admissions—Respiratory		
	Q1	**Q2–Q4**	**Q5**
Cold	0.0115*	0.00824***	0.00282
	(0.00525)	(0.00249)	(0.00290)
Hot	0.0117***	0.00513*	0.00721*
	(0.00347)	(0.00242)	(0.00289)

Note: The table summarizes the results of separate regressions by quintiles of per capita local government social expenditure. *Cold* and *Hot* measure the number of days per month with average temperature falling below −2 SDs or above 2 SDs, respectively, relative to the municipality-specific (or province-specific) mean temperature for the period 2001–2015. The coefficients and standard errors are normalized by the mean of the dependent variable. All models control for month × year fixed effects, province-specific time trends, monthly precipitation and population age structure. Models of hospital admission rates further control for municipality × month fixed effects, and models of mortality rates further control for province × month fixed effects. Standard errors (in parenthesis) are robust and clustered by province. Significance levels: ***$p < 0.001$, **$p < 0.01$, *$p < 0.05$.

placebo test estimating the effect of current temperature shocks on future mortality and hospitalizations. Since extreme temperatures tend to be correlated over time, we still find some lag effects on following months (Figure A.9 reports 1-month lag), but these effects rapidly disappear as we increase the time distance (Figure A.10). The results of these placebo tests provide strong support for our identification strategy since they confirm that the effect of extreme temperatures on emergency hospital admissions is causal and not determined by other unobserved factors correlated with temperatures.

Third, we account for the harvesting effect following the approach used by Barreca (2012) and express temperature bins as 2-month moving averages.[23] The results are very similar to our baseline estimates, which suggest that temporal displacement is a minor issue in our identification strategy (see Figure A.7).

We also test the robustness of our results to the exclusion of municipalities where the distance between the centroid and the closest weather station exceeds 40 km (20% of the sample). We find that coefficients of temperature deviation bins are very similar to our baseline estimates both in magnitude and significance (see Figure A.8). Therefore, we argue that temperature measurement for municipalities far away from weather stations has a negligible effect on our estimates.

Finally, to improve the strategy used to identify the mitigating effect of social expenditure on health outcomes, we run a placebo test where we classify municipalities based on quintiles of the year-specific distribution of the per capita local government expenditure for the general administration, which is not expected to affect health outcomes, and re-estimate Equation (2) separately for each quintile. Differently from the analysis based on social expenditure groups, the results do not show a clear pattern that relates health outcomes to expenditure for the general administration (see Figure A.11 in the Appendix). This result is expected since services provided by the general administration are not related to the provision of health and social care, and suggests that the mitigating effect of social expenditure is not confounded by unobserved factors, even though a causal evidence cannot be claimed.

4.5 | Net benefits of social care: A back-of-the-envelope calculation

We perform a back-of-the envelope calculation to monetize the health costs for the 65+ population generated by temperature shocks beyond |2| SD or |1.5| from municipality-specific average temperature. Then, we compare the benefits from higher social expenditure for 65+ (moving from municipalities in the first quintile to municipalities in the fifth quintile of social expenditure) with the costs associated to temperature shocks. Our calculation considers the cost for hospitalizations—direct health care costs plus costs due to days lost—and the cost due to life losses because of death. In Table 5, we report the summary of our calculation, while further details regarding the formulas applied are provided in the Appendix section *Back-of-the envelope calculation* and in Tables A.3 and A.4.

4.5.1 | Direct health care cost per capita

We multiply per capita hospital admissions per year in hot/cold days by the cost per case (column 1 in Table 5). The case rate is derived from the average of all Diagnosis Related Group tariffs applied to the universe of admissions in hot and cold days for cardiovascular and respiratory diseases for 65+ between 2001 and 2015 in our dataset, and is equal to €2700.

4.5.2 | Cost for quality-adjusted days lost

This is calculated using per capita hospital admissions per year in hot/cold days as above × the average hospital stay per case × the yearly value of a statistical life (VSLY) × 1 ÷ 365 (column 2 in Table 5). The average hospital stay in Italy for age 80–84 corresponds to 11 days and is derived from Eurostat tables (Eurostat, 2020). We assume full quality of life for older adults, therefore, each day spent in hospital has a value equal to 1 ÷ 365 in terms of quality-adjusted life years. As for the cost of a statistical life per year (VSLY), we consider the Italian-specific value of a statistical life calculated by Viscusi and Masterman (2017) divided by the average life expectancy in Italy (83 years): VSLY = €62396 (1€ ≈ 1.09$ at the end of 2015).[24]

4.5.3 | Cost of life losses

This represents the most substantial component of our calculation. We first consider the remaining life expectancy of 65+ individuals conditional on being alive at the age of 80–84: 9.12 years. This figure is derived from tables prepared by the Italian

TABLE 5 Back-of-the-envelope calculation: summary of costs and savings

Temperature variation	Health care costs (€ per capita) (1)	Costs for quality-adjusted days lost (€ per capita) (2)	Value of life losses (€ per capita) (3)	Total costs (€ per capita) (4)
T > |2| SD	0.58	0.41	140.83	141.82
T > |1.5| SD	1.38	0.96	881.74	884.08
Cost savings from higher social expenditure: Δ(Q5–Q1)				
T > |2| SD	0.64	0.44	80.84	81.92
T > |1.5| SD	3.16	2.20	149.61	154.97

Note: In the upper part of the table, we summarize the costs per capita in the 65+ population generated by temperature variation beyond |2| SD and |1.5| SD from municipality-specific average temperature. In the lower part of the table, we report potential savings generated by social expenditure for older adults and the disabled that mitigates the effects of temperature variation, looking at the difference (Δ) between municipalities in the first (Q1) and the fifth (Q5) quintile of social expenditure. We apply a value for a statistical life (VSLY) equal to €62396. We report costs/savings associated to hospitalizations, separately for the two categories of direct health care costs (column 1) and the costs (quality-adjusted) due to days lost for hospital stay (column 2), and costs due to life losses because of extreme temperature variation (column 3). Figures for the three cost categories are summed up in column 4. Details on calculations are provided in Tables A.3 and A.4 in the Appendix. See also the Appendix section *Back-of-the envelope calculation* for further details about the procedure and formulas applied.

National Institute of Statistics (Istat, 2020). Then, we multiply deaths in hot/cold days by the remaining life-years × VSLY (see column 3 in Table 5).

The total cost per capita of temperature shocks is the sum of the three cost categories above (column 4 in Table 5). For our reference value of a statistical life, this cost amounts to €141.82 per capita, but substantially increases (€884.08) if we widen the range of temperature shocks to $T > |1.5|$ SD.

Karlsson and Ziebarth (2018) perform a similar exercise for the assessment of health costs generated by temperature shocks in Germany, but a direct comparison with their results is complicated because the two exercises are quite different.[25] While the estimated cost of hospital admissions is not so different, the contrast is extremely large for mortality. Depending on the specification used in Karlsson and Ziebarth (2018), we calculate that our estimated yearly cost per capita can be even 50 times larger. Even though part of this difference is due to divergent assumptions on the remaining life expectancy, the rest comes from substantial dissimilarity in the estimated effects of hot and cold days. This difference might be partly due to the estimation method but also to geographical aspects.

To assess the costs and benefits of social expenditure, we then calculate the cost figures described above, separately for municipalities in the first (Q1) and the fifth (Q5) quintiles of social expenditure. For each cost figure, we report the difference between Q1 and Q5 in the lower part of Table 5, which represents savings from higher social expenditure. Total cost savings per capita lay between €81.92 and €154.97, respectively, for temperature shocks $T > |2|$ SD and $T > |1.5|$ SD. Since social expenditure per capita is €24.13 and €289.37, respectively, for municipalities in the first (Q1) and the fifth (Q5) quintiles, the difference is €265.24. Approximately 44.3% of this expenditure (€117.5) is allocated to older adults and disabled (Istat, 2017). Consequently, all additional social expenditure for the 65+ is compensated by benefits arising from the lower impact of temperature shocks above |1.5| SD (net benefits are approximately €40 per capita). Even in the most conservative case of temperature shocks above $T > |2|$ SD, gross benefits are significant since they represent almost 70% of the additional social expenditure.

5 | CONCLUSIONS

We estimate the causal impact of local extreme temperature shocks on health outcomes using monthly mortality data from Italian provinces and hospital discharge data for cardiovascular and respiratory diseases aggregated by municipality and month for the period 2001–2015. We merge these data with temperatures measured at weather stations across the Italian territory. Our identification strategy allows for non-linear temperature effects and accounts for province-specific time trends and municipality or province, *month × year* and *province × month* fixed effects. We also analyze the mitigating effect of local social expenditure on the adverse effects of temperature shocks using balance sheet data at municipal level.

Consistent with recent evidence by Heutel et al. (2021), our results confirm the importance of accounting for regional heterogeneity in the effects of temperature shocks to consider local resilience driven by offsetting behavior and adaptation. We find that the two approaches based on temperature levels and deviations from local mean temperatures may differ in capturing the effects of temperature shocks. The former approach could be less precise when it does not account for regional heterogeneity. Although the recent literature has extended this approach to allow for differential effects across climate regions, the application to our setting is more complicated because it is very demanding in terms of data requirements.

Our preferred model based on deviations from municipality-specific mean temperatures shows that one additional extremely cold (below −2 SDs from the mean) and hot day (above 2 SDs from the mean) in a month increases mortality rates by 0.79% and 1.67%, respectively. Hot and cold days increase also hospital admissions for cardiovascular and respiratory diseases, though the estimated effects are lower in magnitude. These effects are driven by the most vulnerable part of the population, namely the oldest age group and partially young children, although also the working-age group faces heat-related surges in mortality due to outdoor working (Dillender, 2019).

In line with Bradley et al. (2011) and Costa-Font et al. (2018), we show that municipalities in the lowest social expenditure group face higher mortality and emergency hospital admission rates as compared to municipalities with higher per capita expenditure on social services. Again, the results are mainly driven by the effect of social expenditure on the elderly who benefit most from easier access to home and community care. Indeed, social expenditure may allow to mitigate the effect of extreme temperatures because access to dedicated social care units, such as recreation centers, or subsidies for home care services are effective in preventing or postponing the need for hospital care (Bradley et al., 2011; Vavken et al., 2012).

Our back-of-the envelope calculation suggests that the additional social expenditure of municipalities in the top quintile, relative to municipalities in the lowest quintile, could be offset by the health benefits generated by the reduced impact of temperature shocks. Despite this expenditure is not specifically meant to mitigate the effects of temperature shocks, we testify that important spillovers may arise from resources allocated to social care.

Since we are not exploiting any clear exogenous variation in local social expenditure we cannot make any clear causal statement about its mediating role. Still, our overall results allow to exclude many important potential confounders, providing support for social expenditure as a tool to improve health outcomes and reduce costly hospital care utilization. Future research could try to quantify the degree of substitution between health and social care services, and investigate the efficient allocation of public resources to health and social care services with the aim to maximize health outcomes and minimize costs.

CONFLICT OF INTEREST
Authors declare they have no conflict of interest.

DATA AVAILABILITY STATEMENT
The hospital data that support the findings of this study are available from the Italian Ministry of Health (Ministero della Salute—Direzione Generale della Programmazione sanitaria—banca dati SDO). Restrictions apply to the availability of these data, which were used under license for this study. These data are available upon request from the authors in aggregate form only. All the other data and programming code are available from the corresponding author upon request.

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ENDNOTES

[1] See Dell et al. (2014) for a review of studies and applied methodologies on the impact of climate shocks on economic aspects.

[2] See also Karlsson and Ziebarth (2018) for a comprehensive review and comparison of the economic and epidemiological approach.

[3] Besides prevention, other mechanisms of the effect of social care can arise from a shelter function and financial support to people with strong disability and elderly people with limited autonomy. Moreover, social care expenditure might allocate elderly people without caregivers at home to nursing homes and care units, were rooms and common spaces are safer, personal care is better monitored, and heating/cooling measures are improved.

[4] This holds particularly when data at hand are not as rich as in Heutel et al. (2021) who use daily observations on mortality and temperature at the US ZIP code level for 22 years, that is about 250 million observations.

[5] Some regions, such as Trentino Alto Adige and Lombardia, adopt a co-payment system (*ticket*) for non-urgent illnesses as a deterrent for over-utilization of emergency wards.

[6] Art. 118 of the Italian Constitution. An exception is the special-statute region of Valle d'Aosta where social care is provided by the province.

[7] Law 328/2000.

[8] Since the number of provinces changed from 103 to 110 between 2001 and 2015, we replicate the 2015 structure of provinces and allocate deaths based on the age-group-specific population of municipalities that changed province.

[9] Since a small number of municipalities merged over the period 2001–2015 and some variables are available only for the 2016 municipality structure, we replicate the 2016 municipality structure to construct a balanced panel.

[10] Generally, sub-categories do not reflect the actual services provided by the municipality. Indeed, a comparison between social expenditure reported in balance sheet sub-categories and expenditure reported in the surveys on local government social expenditure performed by ISTAT since 2013 highlights that balance sheet spending categories are not sufficiently detailed to allow an assessment of expenditure by type of service provided.

[11] We test the robustness of our results to the inclusion/exclusion of these municipalities in the later Section 4.

[12] We exclude from the sample 151 small mountain municipalities located in the North-West regions of Valle d'Aosta and Piedmont with absolute temperature in the extreme bin (above 2SD) below 59°F. Such low temperatures are the result of a number of weather stations located close to the top of a mountain. However, their inclusion in the sample does not change our results.

[13] Note that all statistics presented in Table 2 are weighted by the population.

[14] Since the data-generation process has a count nature, count data models may be preferable to OLS models. However, count data models rely on maximum likelihood estimation (MLE) and, since the size of the dataset is very large and we need to control for a very large set of fixed effects for

a valid identification of the effect of temperatures on health, the computational time is extremely high (e.g., 160 iterations in 1 week) and the MLE hardly converges.

[15] We avoid the last two controls in the main specification because temperature could affect economic activity and pollution levels (i.e., "bad controls"). In the Appendix (Figure A.4), we show that our results are robust to their inclusion.

[16] In a preliminary analysis, we also included the second-order terms of province-specific time trends. However, we did not find different results from those presented later in the paper.

[17] We prefer to run separate regressions for each sub-sample rather than running a single regression with interaction terms between temperature bins and social expenditure quintile dummies, because the latter approach requires more parameter restrictions and would complicate the interpretation of our findings due to the large set of temperature bins.

[18] Per capita social expenditure at provincial level is measured as the population-weighted sum of per capita social expenditure of municipal governments belonging to the province.

[19] We avoid the log-transformation because of the substantial number of observations with zero hospitalizations, especially in the age-group analysis.

[20] These differences may be due to heterogeneity in the degree of diffusion of air conditioning systems, local climatic conditions or time periods under investigation.

[21] It may be the case that two municipalities (or provinces) have the same average temperature, but one municipality (or province) has hotter Summers and colder Winters as compared to the other.

[22] Note that, if we use temperature level bins instead of temperature deviation bins, none of the coefficients would be significant.

[23] We also try to use the approach proposed by Barreca et al. (2016) and to control for both current and lagged temperature bins. The results are very similar to those presented here.

[24] In the Appendix, we also consider an upper-bound value about 50% higher than our reference value, that is VSLY = €100000 (also adopted by Karlsson & Ziebarth, 2018), and a conservative lower-bound value about 30% lower than our reference value, that is VSLY = €50000.

[25] The main reasons are the following: (i) we focus on the elderly population; (ii) we estimate the total effect of hot and cold days rather than hot days only; (iii) the definition of hot days is different and our estimated effects are almost 5 times larger; (iv) Karlsson and Ziebarth (2018) assume only 1 year of survival while we use the conditional life expectancy of people aged 80–84 which is 9 years; (v) Karlsson and Ziebarth (2018) base their calculation on the estimated additional hospital days, while we use the estimated number of additional hospitalizations and then calculate the cost using the average cost per case (DRG or Diagnosis Related Group tariff).

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