Mortality, Temperature, and Public Adaptation Policy: Evidence from Italy*

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Abstract

In 2004, Italy introduced a national program to address heat-related health risks through public awareness campaigns, heatwave warning systems, and hospital protocols. Leveraging administrative mortality data, temperature variations, and the plausibly exogenous timing of the policy's rollout, this paper shows that the program mitigated the mortality impact of extreme heat (days at or above 30 °C) by more than 57%. Exploring the mechanisms, we find that the staggered implementation of the heat wave warning systems contributed to reducing excess mortality on days exceeding 30 °C in treated provinces. We further show that enhancing access to information is essential to achieving these mitigating effects. Our findings underscore the critical role of public adaptation policies that leverage information disclosure on the health risks associated with heat stress.

JEL Classification: Q54, Q58, H510

Keywords: Temperature, mortality, adaptation, information, warning systems

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1 Introduction

Climate change, recognized as one of the most significant health threats of the coming decades (Lancet, 2009), increases mortality risk through more frequent, intense, and prolonged temperature shocks. A growing body of evidence highlights the crucial role of private adaptation, such as the widespread adoption of air conditioning (AC), in mitigating the adverse impacts of extreme temperatures, with a particular relevance for health outcomes (Barreca et al., 2016). While private adaptation can be highly effective, its potential is often constrained by market failures and behavioral frictions, such as imperfect information or inaccurate beliefs (Carleton et al., 2024). In this context, information and awareness interventions (e.g., weather forecasts) have emerged as cost-effective tools to reduce the health burden of environmental exposure (Zivin and Neidell, 2009; Barwick et al., 2024; Molina and Rudik, 2024). These interventions operate under the premise that individuals adjust their behavior in response to new information, thereby minimizing their health damages.

However, the effectiveness of such programs crucially depends on the accuracy and quality of the information provided (Rosenzweig and Udry, 2014; Shrader et al., 2023). Because information can act as a friction to private adaptation, constitutes a public good, and critically shapes behavioral responses, these features together provide a clear rationale for public intervention to ensure access to timely and reliable information and to facilitate effective adaptation (Carleton et al., 2024). Yet, despite its policy relevance, the effectiveness of public adaptation strategies—and in particular the potential role of information disclosure to mitigate climate-related health risks—remains largely understudied.

This paper evaluates the effectiveness of Italy's national heat adaptation plan, introduced in 2004 to reduce heat-related mortality. The program combines measures aimed at improving the responses of the healthcare system and enhancing public awareness. Key components include a national mortality surveillance system, specialized training for healthcare services, emergency protocols in medical centers, heat health watch warning systems (HHWWS) in 27 major cities, public information campaigns, targeted interventions for vulnerable groups, and a nationwide helpline for informing about health risks during heat waves. Our empirical analysis proceeds in three stages.

First, we estimate the causal effect of temperature, leveraging reasonably exogenous random weather shocks. Using mortality data from the Italian National Institute of Statistics

(ISTAT) at the province-month level from 1992 to 2019, we exploit extensive spatial and temporal variation to analyze changes in the temperature-mortality relationship over nearly three decades. Our findings reveal that an additional day with a temperature at or exceeding 30 °C increases deaths by 0.0187 per 1,000 inhabitants compared to a day with a reference temperature between 10 and 15 °C. Over time, however, the total excess mortality attributable to heat exposure has declined. Notably, the mortality impact of more extreme heat days halved in the period 2004–2019 compared to the pre-policy period of 1992–2002, suggesting an increase in adaptive capacity.

Second, we link this exogenous temperature variation with the implementation of the national program against heat waves, to investigate the policy effectiveness in reducing heat-related excess mortality. We rely on a Difference-in-Differences-in-Temperature (DiDiT) approach to identify how the adoption of this plan modified the temperature-mortality relationship. Specifically, we combine temporal variation before and after the policy with plausibly exogenous fluctuations in daily average temperature, while keeping constant potential confounding factors at the month and province level that are correlated with the policy and might have modified the temperature-mortality relationship. We find that the reduced effect of extreme heat on mortality can be largely attributed to the successful national adaptation plan against heat. On average, the policy is associated with a reduction in the adverse impact of hot temperatures (days at or above 30 °C) by approximately 57% compared to the pre-policy period. Moreover, the effectiveness of the plan persists and even slightly increases over time, with the reduction in heat-related mortality rising from 38% in the initial phase (2004-2010) to 46% during the full implementation period (2011-2019) compared to the pre-policy year.

Third, we explore the mechanisms behind the effectiveness of the heat adaptation plan delving into the set of measures implemented within the policy. We start examining the role of behavioural responses prompted by the adaptation plan, to which the implementation of the HHWWS has likely made a significant contribution. This system, deployed in 27 major Italian cities, provides daily risk-level information from May to September and plays a crucial role in raising public awareness. To assess the impact of these warnings on reducing excess mortality caused by extreme heat, we employ a staggered Difference-in-Differences-in-Temperature (DiDiT) strategy. This approach leverages the gradual inclusion of cities in the system, comparing treated provinces to those not yet treated and those never treated. This variation is then again combined with quasi-exogenous shocks in daily average temperature while allowing for time-invariant differences in the temperature-mortality relationship across provinces, and unit-invariant differences in the temperature-mortality relationship over years. We thus account for any unobserved changes in the temperature-mortality relationship due to confounders correlated with the policy at the province and yearly level. Our results suggest that treated provinces are associated with approximately a 22% reduction in the adverse effects of extreme temperatures, compared to those not yet treated or never treated, relative to the pre-implementation period. To further explore this finding, we perform auxiliary regressions using province-level daily data on mobility patterns. We find that heatwave warnings significantly increase the share of people staying at home and reduce long-distance travel. These identified behavioral adjustments likely contribute to the observed effectiveness of these adaptation measures.

Next, we examine the role of improved access to information on heat-related risks through mass media, focusing on newspapers. We construct a pre-intervention measure of newspaper diffusion (excluding sports newspapers) at the provincial level and interact it with temperature and the post-policy indicator in a triple-difference specification. This measure of newspaper readership proxies for the intensity of policy compliance across areas (Durante et al., 2025). Our estimates indicate that the policy's impact is significantly stronger in provinces with higher newspaper readership, where individuals are more likely to engage with and act upon the information and recommendations received—thereby amplifying the effectiveness of information-disclosure efforts.

Finally, using a similar triple-interaction design, we examine whether the initial quality and operational efficiency of the healthcare sector influenced the program's effectiveness. Our analysis does not reveal systematic effects for any of the operational efficiency indicators. This result is informative: unlike the information and awareness components, whose impact clearly emerges from our estimates, improvements in healthcare system efficiency do not appear to have been a primary driver of the program's effectiveness.

Our paper makes several significant contributions to the study of the impacts of extreme temperatures. First, it directly speaks to the literature on temperature and mortality, providing new causal estimates of heat damage in Italy. While most of the studies show evidence for the United States (Deschenes and Moretti, 2009; Deschênes and Greenstone, 2011; Barreca, 2012; Barreca et al., 2015, 2016; Heutel et al., 2021; Mullins and White, 2020), only a few focused on developing countries (Burgess et al., 2014; Cohen and Dechezleprêtre, 2022; Yu et al., 2019) and Europe (Adélaïde et al., 2022; Masiero et al., 2022). Moreover, Italy faces both a rapidly ageing population and significant exposure to climate change, making it a particularly compelling case study at the intersection of these two challenges.

Second, by analysing the effectiveness of the national heat action plan, we are able to assess the potential of public adaptation in mitigating the impact of extreme temperatures. This represents a substantial novelty. Despite its study has been acknowledged as a priority for the global research agenda for this century (Organization et al., 2009), the role of adaptation in the temperature-mortality relationship remains underexplored in the literature, with only a limited number of studies addressing it (Deschenes, 2014). Some attempts focused on the regional differences in adaptation, exploiting cross-sectional variation (Heutel et al., 2021; Barreca et al., 2015). The most significant contributions relates to residential energy consumption (Deschênes and Greenstone, 2011; Barreca, 2012) and air conditioning adoption (Barreca et al., 2016). Additionally, a few studies have investigated the role of changes in health care access, provision and organization (Barreca et al., 2016; Mullins and White, 2020; Cohen and Dechezleprêtre, 2022). Finally, geographical mobility (Deschenes and Moretti, 2009) and the allocation of time (Graff Zivin and Neidell, 2014) have been examined as adaptive responses to extreme temperature exposure. To the best of our knowledge, no studies have examined the impact of a national adaptation plan against extreme heat. This presents a remarkable opportunity to gain insights into the role of public adaptation in mitigating mortality from extreme temperatures.

Third, our study demonstrates that information on environmental risks is a critical determinant of avoidance behavior and an effective strategy for mitigating the dose-response relationship between environmental exposure and mortality. Our findings shed light on the impact of early warning systems, evaluating their capacity to induce behavioural changes among individuals. Previous work has investigated their role in preventing exposure to pollution (Zivin and Neidell, 2009; Barwick et al., 2024), and recently few studies focused on the warnings related to heat risk (Rabassa et al., 2021). These studies found a tangible impact in modifying individuals' behaviours, leading to avoidance of outdoor exposure or activities and increased spending on protective products. Our study makes a step forward in this direction by evaluating the benefits of reduced heat-related mortality attributable to these behavioral changes. Additionally, we provide evidence that enhancing access to this information is essential for achieving such mitigating effects.

Finally, we contribute to the literature on the role of the policy environment in mediating or emphasising climate impacts on socio-economic outcomes (Mullins and White, 2020; Cohen and Dechezleprêtre, 2022; Colmer and Doleac, 2023; Pavanello and Zappalà, 2024). In line with this literature, we employ a methodology combining exogenous variation in daily temperatures and a Difference-in-Difference design of a policy intervention. However, differently from these studies, we focus on a policy that directly targets temperature exposure.

The remainder of the paper is organized as follows. Section 2 provides background on the policy. Section 3 presents the data. Section 4 outlines the empirical strategy and presents the results on the mortality-temperature relationship. Section 5 discusses the empirical approach used to assess the policy's impact and reports the main findings. Section 6.1 explores the potential mechanisms, including the implementation of the HHWWS, the role of access to information, and the operational efficiency of the healthcare system. Finally, Section 7 concludes with a summary of the main results and an outline of the next steps for the further development of this paper.

2 Background

The Mediterranean area is highly vulnerable to heat waves (Michelozzi et al., 2007) due to a combination of population susceptibility and extreme weather events. During the recent heat wave hitting Europe in the summer of 2022, Italy recorded the highest heat-related mortality rates, with approximately 18,010 deaths (Ballester et al., 2023). In particular, it reported the highest number of deaths among European countries for individuals aged 65–79 and those 80 years and older.

This evidence intersects with the demographic trend that Italy experienced in the last decades, characterised by a substantial ageing process. In Italy, people aged 65 and over were approximately 8% of the total population in 1951. However, in recent years, despite the large mortality caused by COVID-19, this share has more than tripled, reaching approximately 24% by 2023 and pushing the average population age to 46.4 years (Tomassini and Lamura, 2009; ISTAT, 2023). Demographic projections forecast a 35% increase in the proportion of elderly above 80 in the next two decades, raising the total amount to 6 million individuals. Italy is not alone in experiencing this sharp increase in its elderly population; similar trends are observed in other Southern European countries such as Portugal, Spain, and Greece.

Overall, the demographic shift raises many concerns about the increase in health expenditure in these countries and poses a substantial challenge to the sustainability of the national health system (Lopreite and Mauro, 2017). The increased exposure due to climate change, combined with the heightened susceptibility of the population from demographic shifts, will raise overall vulnerability.

2.1 The national plan for preventing the health effects of heat

As a response to the dramatic consequences of the heat wave in 2003, the Department of Civil Protection and the Ministry of Health adopted in 2004 a national plan aimed to prevent the health effects of heat. The plan is organised into multiple actions aimed at reducing excess mortality caused by heat (De'Donato et al., 2018). These measures can be summarised into three main categories: preventive actions, monitoring actions, and response actions.

First, the **preventive actions** encompass a comprehensive set of initiatives designed to inform the population about heat risk and recommend actions to prevent health consequences, thereby raising general awareness. Disseminating advice on heat stress risks and protective behaviours is pursued through the promotion of information campaigns. At a national level, campaigns act via the main mass media, while at the local level through direct communications on local authorities' websites and informative flyers to elderly care centres, public spaces, local pharmacies, health centres, and General Practitioners (GPs). Moreover, a dedicated heat helpline can be reached to receive information on preventive measures and the availability of local services. Some adaptation measures were also implemented, including increased adoption of air conditioning in health and social centres. Access to these facilities has been extended during heatwaves to provide a refuge from the heat. One key preventive initiative was the realization of the Heat Health Watch Warning System (HH-

WWS), which issues daily risk levels for major Italian cities during the summer months. This system helps inform the public and local authorities about heatwave occurrences and alerts the healthcare system to put in place prompt response actions.

Then, **monitoring actions** were arranged to collect information on the mortality trend and identify the most susceptible individuals and their distribution on the territory. This is possible, first, via the health information providing details on hospitalisation records, drug prescriptions and socio-economic conditions. Then, GPs or social workers are entitled to carry out questionnaires to spot further risky conditions. Trained caregivers operate in the network of community services to monitor the more vulnerable individuals. To this, it adds the action of volunteers and social workers in performing telemonitoring, carrying out phone calls to elderly patients recorded as frail. Finally, GPs raised their surveillance through phone calls and home visits addressed to the most vulnerable patients. This involvement is voluntary and reaches approximately 30% of the GPs. Overall, while the socio-demographic and health characteristics used to classify vulnerable individuals are consistent across Italy, the above-discussed practices vary by region, leading to some degree of heterogeneity in the registries of susceptible individuals.

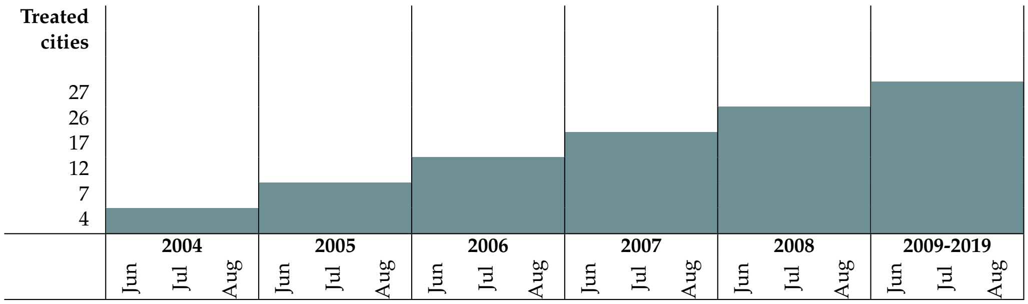
Finally, **emergency response actions** were designed to strengthen the healthcare system's capacity to deal with prolonged and extreme heat. These measures, activated when the warning signals level 2 or 3, aim to enhance the operational efficiency in hospitals, nursing homes and social structures, through a better organisation of the resources available during heat waves. Key actions include increasing staff in the emergency department or critical wards (intensive care units, geriatrics, etc.), redistributing available beds, rescheduling non-urgent admissions and surgeries, and revising the discharge planning. Additionally, there is an increased supply of medication and water, and at-risk patients are moved to air-conditioned areas. Public places with cooling facilities remain open to protect during peak heat periods. In addition, prior to the state of emergency, educational activities (seminars/workshops, dissemination of thematic guidelines, meetings, etc.) were organised to improve social and health workers' abilities related to heat wave emergencies.

2.2 Heat Health Watch Warning System (HHWWS)

Among the main actions implemented, the National Plan for Preventing the Health Effects of Heat established the launch of the Heat Health Watch Warning System (HHWWS) managed by the Lazio Region Department of Epidemiology. This system introduced daily warnings for the largest Italian cities between May and September. Each city is assigned a daily risk level ranging from 0 to 3, where 0 indicates no risk for the population, 1 indicates conditions that may precede the occurrence of a heatwave, 2 indicates the presence of a risk mainly for highly vulnerable individuals, and 3 indicates a prolonged risk situation for the entire population lasting more than two days. Italy was one of the pioneering countries in Europe to adopt HHWWS following the 2003 heatwave. Unlike other countries relying on fixed temperature thresholds, Italy's city-specific HHWWS incorporates local climate characteristics, adaptation levels and population vulnerabilities. This is achieved through an assignment of the bulletin based on a retrospective analysis of the relationship between mortality and weather conditions (air temperature, dew point temperature, atmospheric pressure, wind speed, and direction) to identify circumstances associated with a significant increase in mortality rates (for more details on the methodology, see Michelozzi et al. (2010)). Moreover, centralized coordination and a robust information network are crucial in the effective spreading of warning bulletins, enhancing heat health prevention strategies (Michelozzi et al., 2010). The daily bulletins are published on the Italian Department of Civil Protection and the Ministry of Health websites. Moreover, local centres are promptly informed of the daily risk level and are responsible for taking action and disseminating information within the territory are expressly notified of the daily risk level.

The inclusion of cities in the HHWWS and the daily mortality surveillance system follows specific criteria, targeting large cities (>500,000 inhabitants), medium-large cities (200,000-500,000 inhabitants) and regional capitals with populations under 200,000 inhabitants. In total, 34 cities are covered, encompassing 21.3% of the Italian population aged 65 or older. Among these, 7 cities are exclusively part of the daily mortality surveillance system. These include 5 regional capitals (Aosta, Catanzaro, L'Aquila, Potenza, and Trento) and 2 cities with populations exceeding 200,000 (Padua and Taranto). The remaining 27 cities are also covered by the HHWWS. Notably, the implementation of the warning system was carried out gradually across the cities involved. Table 1 provides a detailed overview of the cities

Table 1: Timeline of the implementation of the Heat Health Watch Warning System (HH-WWS) in italian cities



New Cities Covered by the HHWWS:

2004: Rome, Milan, Turin, Bologna;
2005: Brescia, Genoa, Palermo;
2006: Bari, Catania, Florence, Naples, Venice;
2007: Cagliari, Campobasso, Pescara, Trieste, Verona;
2008: Bolzano, Perugia, Viterbo, Rieti, Civitavecchia, Frosinone, Latina, Reggio Calabria, Messina.
2009: Ancona.

under the HHWWS and their respective entry years into the program.

3 Data

In this section, we first provide an overview of the data employed in this study and their sources. To conduct our analysis, we combine administrative data on the number of deaths at the province-level with high-quality weather information. We also obtain data on age shares, air conditioning ownership and GDP per capita. We conclude with key descriptive analyses that offer relevant insights into the main characteristics of our data.

3.1 Mortality rates

Data on deaths are supplied by ISTAT, providing nearly 30 years of monthly data at the provincial level. This includes the number of deaths reported to the civil registry offices in the municipality where the event occurred. Additionally, complementary information is available, such as the gender of the deceased individuals and the cause of death. Our main dependent variable is the mortality rate per 1000 people. Mortality rates are computed at the province-monthly level using annual resident population data for the provinces, also sourced from ISTAT. In cases where provinces underwent administrative changes, we aggregate the information at the broader administrative area affected by the variation.

3.2 Weather

We process weather data from the ERA5-Land reanalysis product Muñoz Sabater et al. (2019), which provides hourly temperature and precipitation from 1950 to present at a 0.1° spatial resolution (about 11km). We combine weather data with 15 arc-seconds population CIESIN (2018) to compute the province-level population-weighted daily average temperature and total precipitation.

3.3 Additional data

We complement the core data set with further information collected from various sources.

Age-specific population shares. Using population data from ISTAT we also construct province-level population shares for four age groups (0-1, 2-24, 25-64, and ≥ 65) for the years 1992-2019.

Ownership of air conditioning. We obtain annual information on residential air conditioning ownership for the period 1997-2019 at the NUTS1 level from ISTAT.[1] This data are obtained aggregating at the most granular level available household information from the Italian Household Budget Survey (HBS).

Income. We gather annual NUTS3[2] data on GDP at costant prices from the ARDECO database of the EUROSTAT for the years 1992-2019. GDP is measured in Million EUR2015. We then divide by population to obtain province-level GDP per capita.

Newspapers' diffusion. We construct province level exposure to information through data on newspapers circulation from Accertamenti Diffusione Stampa (ADS).[3] We download data on sales of non-sport newsapapers at province-level for the year 2003—this is the only year available before the policy. We then divide these data by population to obtain this measure of readership in per capita terms.

[1] NUTS1 divides Italy in five macro-regions: North-West, North-East, Center, South, and Isles

[2] For Italy NUTS3 corresponds to provinces.

[3] Data can be accessed here.

Healthcare system. We obtain variables related to the operational efficiency of the healthcare system from the platform "Health for All".[4] Specifically, we download annual data for each province on the number of beds, total hospital stay days, and the average length of hospital stays for the period 1996–2003. We also construct two additional efficiency indicators: the utilization rate and the turnover rate. Finally, we average all these variables across the pre-policy period (1996–2003) for each province.

Movement distribution. Finally, we obtain daily data on people's movement from Meta's Movement Distribution Maps, which provide an overview of how far people in different regions travel from home on a given day.[5] These maps identify a *home tile* for each user, defined as their location during nighttime hours (8 PM to 6 AM), based on location data from the Facebook app for users who have enabled Location Services on their devices. A randomly selected location update logged during the day, referred to as the *visit tile*, is then used to calculate the distance traveled from the home tile. Distances are aggregated by mapping each home tile to an administrative-level polygon and classifying travel into four distance categories: 0 km, 0–10 km, 10–100 km, and 100 km or more. For our analysis, we utilize daily mobility data for all Italian provinces in 2023.

3.4 Descriptive statistics

After data collection and processing, the final dataset includes 104,040 observations across 106 provinces. As shown in Table 2, the average mortality rate in the full sample is 0.826 per 1,000 individuals, with a slight increase observed between the pre-policy and post-policy periods. Similarly, the average temperature rose from 13.70 °C before 2003 to 13.96 °C in the following period. This increase in temperature might be one of the drivers of the rise in mortality, along with the growing proportion of older individuals in the population, particularly those aged 25-64 and 65 and older. Conversely, the population among younger age groups experienced a decreasing trend.

Table 2 also provides descriptive statistics for other key control variables, such as GDP per capita and air conditioning penetration. Note that data on air conditioning are only

[4]Data can be accessed here.

[5]Data can be accessed here.

available from 1997 onward, resulting in fewer observations. The average GDP per capita is 60,258.91 (EUR2015 PPP), while the average air conditioning penetration rate is 0.267. Both variables show an upward trend over time, with air conditioning penetration experiencing a particularly sharp increase, nearly tripling between the two periods.

Table 2: Descriptive statistics

	Full Sample			Pre-policy Sample			Post-policy Sample		
	Obs.	Mean	SD	Obs.	Mean	SD	Obs.	Mean	SD
Outcome Variable									
Mortality rate	104040	0.826	0.175	43632	0.813	0.193	60408	0.835	0.160
Climate Variables									
Daily Avg. Temperature	104040	13.653	7.145	43632	13.489	7.089	60408	13.771	7.182
Days Avg. Temp $\geq$ 30 °C	104040	0.0355	0.377	43632	0.028	0.329	60408	0.0408	0.397
Daily Avg. Precipitation	104040	0.686	1.250	43632	1.069	1.321	60408	0.412	1.119
Control Variables									
% Pop. (age: 0-1)	104040	0.903	0.158	43632	0.937	0.189	60408	0.879	0.127
% Pop. (age: 2-24)	104040	24.678	4.591	43632	27.978	4.294	60408	22.316	3.098
% Pop. (age: 25-64)	104040	53.280	2.401	43632	51.995	2.569	60408	54.199	1.773
% Pop. (age: $\geq$ 65)	104040	21.138	3.654	43632	19.090	3.333	60408	22.605	3.132
GDP per capita	104040	60258.910	56547.070	43632	50216.050	47402.170	60408	67447.380	61271.310
air conditioning	86364	0.267	0.143	25956	0.100	0.058	60408	0.337	0.105

Notes: Mortality rates are calculated per 1,000 individuals, with all statistics weighted by population size.

4 The temperature-mortality relationship in Italy

4.1 Empirical framework

We start identifying the causal effect of temperature on mortality by leveraging plausibly exogenous weather shocks at the provincial level, specifically daily fluctuations in temperature relative to the underlying local climate. To achieve this, we define and estimate the baseline relationship between temperature and mortality as follows:

$$Y_{imy} = \alpha + \beta f(T)_{imy} + \gamma g(P)_{imy} + \mathbf{X}_{imy}\boldsymbol{\lambda} + \mu_{im} + \theta_{r(i)y} + \delta_{my} + \varepsilon_{imy} \tag{1}$$

where Y_{imy} is the all-age mortality rate in 1,000s of province i in month m and year y; $\mathbf{X}_{imy}$ is a vector of annual province-level shares of population in three age group (0-1, 2-24, and $\geq$ 65) interacted with month dummies;[6] μ_{im}, $\theta_{r(i)y}$, δ_{my} are respectively province-month,

[6]The excluded age group is 25-64.

region-year and month-year fixed-effects; ε_{imy} is the error term. Standard errors are two-way clustered at the province and month-year level.

In Equation 1, $f(T)_{imy}$ and $g(P)_{imy}$ are some function of daily average temperature and total precipitation in a province i in month m and year y. In our baseline specification we model temperature non-parametrically using ten 5-degree temperature bins, obtained counting the number of days in a month in each temperature interval. The omitted bin is the interval 10-15 °C.[7] As for precipitation, we model it by the means of a second-order polynomial in all our specification. All regressions are weighted by the average population for the period 1992-2003.

4.2 Results: Declining impact of temperature on mortality over time

Main results. In this section, we present the results based on the baseline specification defined in Equation 1. We estimate the mortality-temperature relationship for three samples: the full, the pre-policy and the post-policy ones. Figure 1 represents the results along the distribution of the bins. Detailed estimates are presented in the related Tables A1 and A2 in Appendix A.

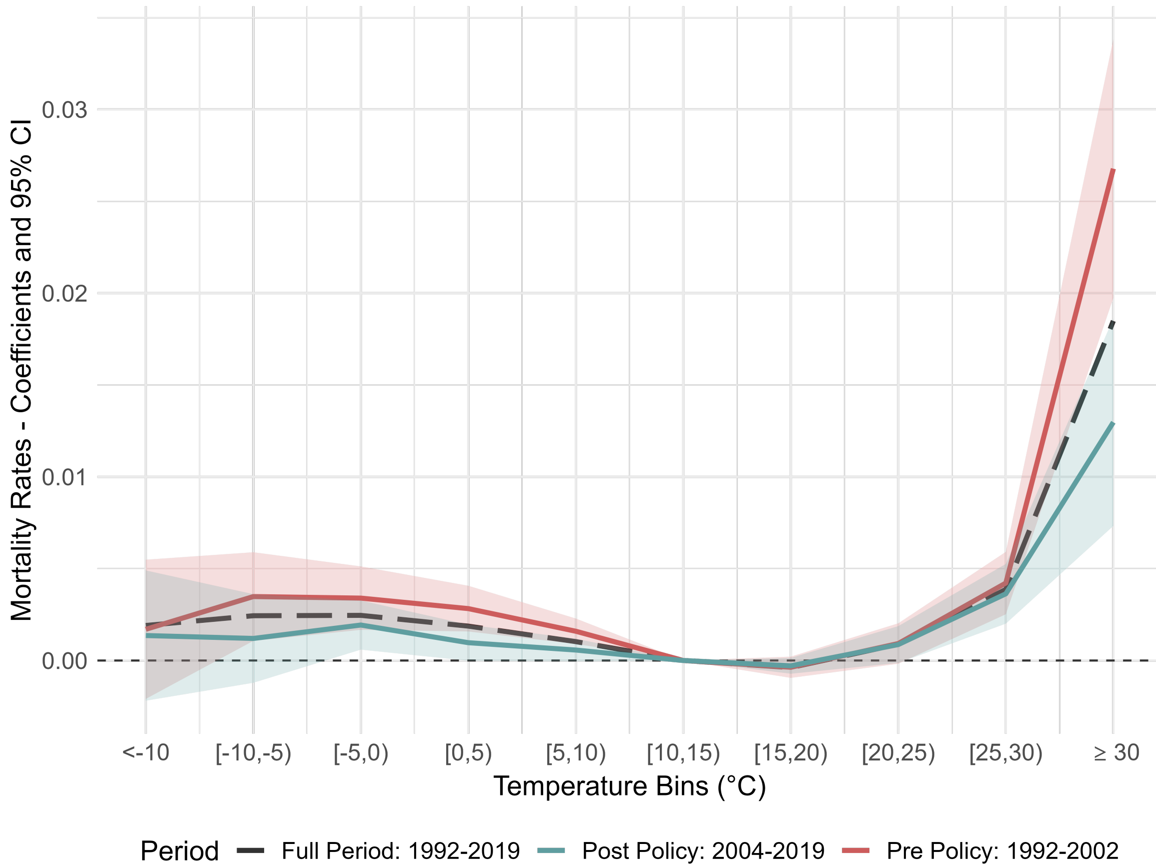
We observe the well-documented U-shaped relationship between temperature and mortality. However, the impact of high temperatures is more consistently robust across specifications and exhibits a larger magnitude compared to that of cold temperatures. Specifically, temperatures exceeding 25 °C have a positive and significant effect on mortality. For each additional day with an average temperature above 30 °C, the mortality rate increases by 0.0189 deaths per 1,000 individuals, which corresponds to an approximate 2% increase. This result remains robust across different specifications.

Table A3 contextualizes the results by comparing the estimates with previous studies on both developed and developing countries. We find that the overall effect for Italy is substantially larger than the estimates reported by Barreca et al. (2016) for the United States and Burgess et al. (2017) for India. Although Italy has higher air conditioning (AC) penetration rates compared to India, its older population likely drives the higher estimated impact.

The red and blue lines in Figure 1 represent estimates for the pre-policy and post-policy

[7] We also estimate models (i) including only the extreme cold and hot bins, < -10 °C and ≥ 30 °C,[8], (ii) including only the warmer bins ($20-24$°C, $25-29$°C, and ≥ 30 °C), (iii) using polynomials up to the third degree, (iv) using maximum daily temperature, and (v) using relative measures of temperature.

Figure 1: Temperature-mortality estimates for the pre- and post-policy periods

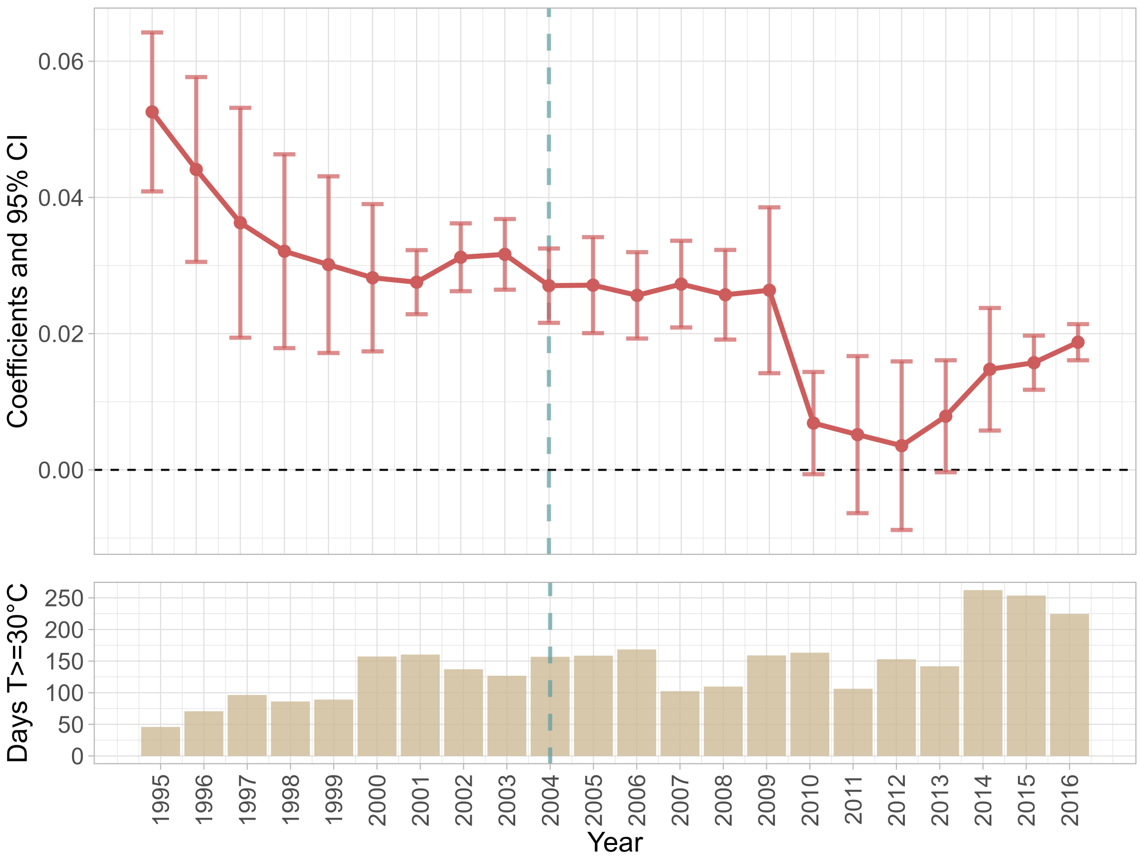


Notes: The figure plots the response function between monthly mortality rate and daily average temperature bins (Equation 1) for the years: 1992-2019, 2004-2019, and 1992-2002. The response function is normalised with the 10-15 °C category set equal to zero so that each estimate corresponds to the estimated impact of an additional day in bin j on the annual mortality rate relative to the mortality rate associated with a day on which the temperature is between 10 C and 15 °C. Full regression results are presented in Table A1 and Table A2. All regressions are weighted by province population. Standard errors are clustered at the district level.

periods, respectively. The results reveal a considerable difference starting at temperatures above 25°C, with the gap widening at temperatures exceeding 30 °C. This indicates a substantial reduction in the impact of high temperatures in the period following 2004.

The temporal evolution depicted in Figure 2 provides a clearer perspective on the trends observed. The red line and corresponding points illustrate the estimates and their 95% confidence intervals for a rolling 7-year window centred on each indicated year. The relationship between temperature and mortality diminishes over time, with a notable decline occurring particularly after the policy implementation. On the bottom part of the same Figure, the vertical bars (light beige) represent the 7-year rolling average of the yearly total number of days with temperatures exceeding 30 °C. A comparison of these two trends reveals that the observed reduction in the relationship between temperature and mortality cannot be attributed to a decrease in exposure to high temperatures.

Figure 2: Trends in heat-related mortality across 7-year rolling samples



Notes: The figure plots the effect of an additional day at or above 30 °C, relative to a day between 10 and 15 °C across a sample limited to a 7-year period centered around the indicated year (above), and the average number of days at or above 30 °C in the 7-year period. The teal dashed line indicates the year when the national program started. All regressions are weighted by province population. Standard errors are clustered at the district level.

Robustness checks. To ensure the validity of our baseline results, we conduct several robustness checks by testing the specification with alternative temperature measures. Specifically, Table B1 in Appendix B presents the results for both the full sample and the split sample, using average temperature percentiles as regressors. In addition, Table B2 shows the results for the analogous specification testing for maximum temperature bins. Results are consistent with the baseline specification using absolute average temperature thresholds.

5 The implementation of the national adaptation plan against heat stress

5.1 Empirical framework

Equation 1 establishes the baseline relationship between temperature and mortality, suggesting that temperature's effect on mortality decreased after 2004. Building on this, we now estimate the mitigation effect of the 2004 policy on this adverse effect of temperature.

Conceptually, our empirical approach is to estimate a Difference-in-Differences (DiD) design for the effect of the national program on the temperature-mortality relationship. Since the policy was implemented nationally, our estimates are derived by identifying changes in the temperature-mortality relationship before and after the program's introduction.

The first approach is to estimate a simple interaction model, also defined as Difference-in-Temperature (DiT) (Colmer and Doleac, 2023). That is, we modify Equation 1 as it follows:

$$\begin{aligned} Y_{imy} = \alpha + \beta f(T)_{imy} + \pi f(T)_{imy} \times D_t + \gamma g(P)_{imy} + \mathbf{X}_{imy}\boldsymbol{\lambda} + \\ \mu_{im} + \theta_{r(i)y} + \delta_{my} + \varepsilon_{imy} \end{aligned} \tag{2}$$

where D_t is a binary indicator equal to 1 after 2004.[9] At this stage, we focus on the upper tail of the temperature distribution. Specifically, we estimate a more parsimonious model that includes only the three highest temperature bins as regressors, as these are most directly affected by the policy introduction. The results remain robust when the full temperature distribution is included.

To make π the causal mitigation effect of the policy the key assumption is that no other unobserved policies or time-invariant and time-varying local factors, which are correlated with the policy itself, also moderate the temperature-mortality relationship. However, it is unlikely that this assumption holds in the DiT setting, as other policies, such as shock to public health expenditure, might have influenced the effect of temperature on mortality.

[9]Notice that the coefficient related to the uninteracted term of D_t would be omitted because of the collinearity with the fixed effects. For this reason, we do not include it in Equation 2

To solve the identification problem in the DiT specification, we rely on a Difference-in-Differences-in-Temperature (DiDiT) specification (Colmer and Doleac, 2023; Pavanello and Zappalà, 2024; Mullins and White, 2020). This introduces flexible modelling of temperature over time and space, ensuring that the potential confounders are kept fixed over time. To illustrate it, we modify Equation 2 as follows:

$$\begin{aligned} Y_{imy} = \pi f(T)_{imy} \times D_t + \gamma g(P)_{imy} + \mathbf{X}_{imy}\boldsymbol{\lambda} + \\ \eta_i f(T)_{imy} + \phi_m f(T)_{imy} + \mu_{im} + \theta_{r(i)y} + \delta_{my} + \varepsilon_{imy} \end{aligned} \tag{3}$$

where $\eta_i f(T)_{imy}$ and $\phi_m f(T)_{imy}$ indicate that we allow temperature to vary across provinces and month.[10] In this way, we can isolate the effect of the policy, while controlling for other potential unobservables that change the temperature-mortality relationship. In additional regressions, we also let the temperature-mortality relationship vary before and after the summer 2003 heatwave to account for potential changes in the public perception of health risks related to heat stress.

Finally, an important drawback of this analysis is that at this stage we are not controlling for regional air conditioning penetration. The policy included informative campaign measures that aimed at making the population more aware of the risks related to heat stress. This implies that air conditioning is a bad control in our regression, as the policy itself likely induced an increase its adoption. For this reason, we are going to interpret our coefficient as a gross effect of the policy, which however does not distinguish the role of private adaptation. Besides, to control for potential better adaptation opportunities, such as air conditioning, we include in the vector of covariates $\mathbf{X}$ province-level annual GDP per capita interacted with month indicators.

The identifying assumption underlying our analysis is that, in the absence of treatment, trends in the temperature-mortality relationship would have not changed. We provide indirect tests of this assumption by estimating binned event studies. Furthermore, since the national plan to address the health impacts of heat waves was introduced in 2004, with a more stringent phase starting in 2011, the binned event study enables to assess the dynamic effects of the policy over time.

[10] We also test for allowing temperature effect varying across summers rather than month.

5.2 Results: policy effectiveness in reducing heat-related mortality

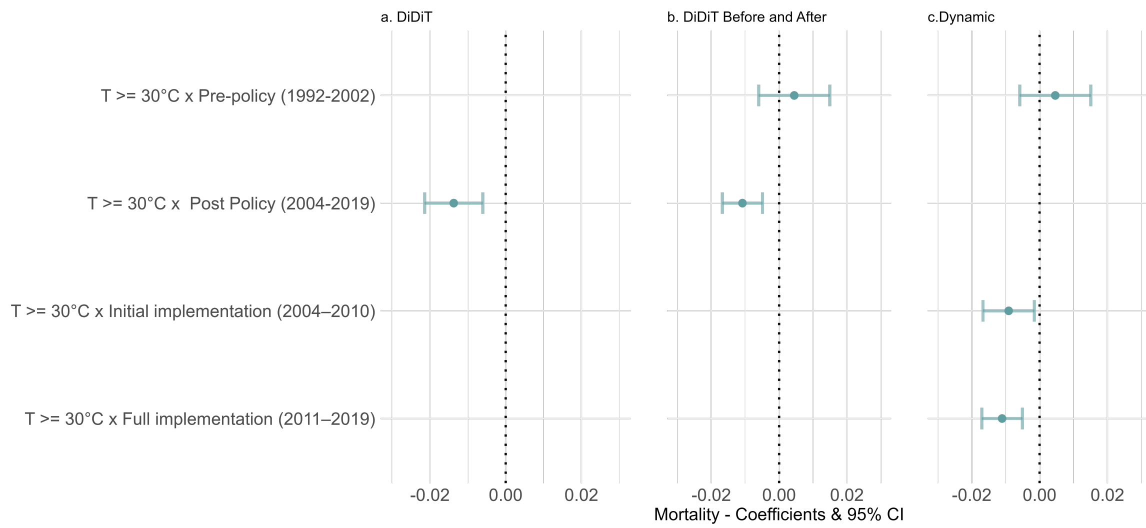
Initial results. Our results are displayed in Figure 3, and exact point estimates are summarized in Table C1 and Table C2 in Appendix C. In panel (a), we observe the results of the DiDiT estimation. The policy successfully decreases by -0.0137 the deaths per 1,000 individuals, mitigating the 57% of the adverse effects of temperatures exceeding 30 °C compared to the pre-policy period. As shown in Table C1, it also effectively reduced the impact of temperatures between 20-25°C and 25-30 °C by 43% and 39%, respectively.

Dynamic effects. Panels (b) and (c) of Figure 3 present the results of the binned event study, accounting for dynamic effects. Panel (b) compares the pre- and post-policy periods with the year prior to implementation, while panel (c) distinguishes between two post-implementation phases: the initial phase in 2004 and the full implementation phase from 2011 to 2019, estimating their effects separately. Results are detailed in Table C2 in Appendix C.

A key observation from both specifications is the absence of any pre-trend for the hottest temperature bin (T $\geq$ 30 °C), while the policy's contribution is evident in significantly reducing the temperature's impact. Furthermore, when examining the policy's effectiveness across the two phases of implementation, we observe a stronger impact during the second phase, which aligns with expectations given the more stringent measures introduced during this period. Specifically, we find that the policy resulted in a 38% reduction in the negative impacts of exposure to temperatures above 30 °C, with this mitigating effect increasing to 46% after 2011.

Robustness checks. We explore alternative model specifications by using temperature bins based on percentiles and maximum temperatures. The results using average temperature percentiles as regressors are presented in Appendix D, Table D1, while those using maximum temperature bins are found in Table D2. These robustness checks confirm the consistency and reliability of the policy impact findings across different temperature measures.

Figure 3: The dynamic impact of the 2004 national plan



Notes: The figure plots the coefficients from the interaction term between the hottest temperature bin (T $\geq$ 30 °C), and in panel (a) an indicator variable that takes value of one after the policy implementation, in panel (b) indicator variables for pre- and post-intervention, and in panel (c) indicator variables for pre-, short-run post-, and long-run post-intervention. The regression also controls for: the interaction between temperature bins and province and month fixed effects, second-degree polynomial of precipitation, annual province-level shares of population in three age group (0-1, 2-24, and $\geq$ 65) interacted with month dummies, and province-month, month-year and region-year fixed effects. Bins represent the 95% confidence intervals with standard errors clustered at the province-level.

6 Exploring the mechanisms

The previous section shows that the 2004 policy against extreme heat was effective at reducing heat-related mortality. The next step is to identify the channels through which the policy achieved this attenuation of temperature's impact. To this aim, we examine the set of measures included in the policy.

6.1 The role of the Heat Health Watch Warning Systems

First, we estimate the mitigation effect of the staggered introduction of heat wave warning systems in 27 major Italian cities.

Empirical framework. We begin by restricting our sample to provinces where at least one city is part of the program.[11] These cities have been indeed specifically selected for the program based on population figures and weather conditions. To identify the effect of the introduction of the heatwave warning systems, we exploit the staggered roll-out of this measure across province capitals. Our baseline specification is a Difference-in-Differences-Temperature regression (DiDiT) that looks as follows:

$$\begin{aligned} Y_{imy} = {} & \beta f(T)_{imy} + \pi f(T)_{imy} \times H_{iy} + \psi H_{iy} + \gamma g(P)_{imy} + \mathbf{X}_{imy}\boldsymbol{\lambda} + \\ & \eta_i f(T)_{imy} + \phi_y f(T)_{imy} + \mathrm{AC}_{ny} \times f(T)_{imy} + \\ & \mu_{im} + \theta_{r(i)y} + \delta_{my} + \varepsilon_{imy} \end{aligned} \tag{4}$$

where our coefficient of interest is π, and H_{iy} is a binary indicator equal to 1 when in province i and year y a heatwave warning system is fully operational. The remaining of the equation is identical to 3. Equation 4 then allows to identify the effect of the policy comparing treated units with not yet treated units. To make π causal, we allow for fixed differences in the effect of temperature across the provinces and years. In addition, we control for the interaction between temperature and NUTS1-level air conditioning penetration, $\mathrm{AC}_{ny} \times f(T)_{imy}$. In this way, we aim to isolate the effect of the introduction of the heatwave warning systems from private adaptation (i.e. AC). Air conditioning (AC) ownership represents a significant investment due to its relatively high cost and the time required for installation, making it a long-term decision rather than a short-term reaction. This suggests that AC adoption is more likely influenced by broader efforts to raise awareness and educate the public — key components of the overall policy — rather than the immediate response triggered by the heat warning systems. The warnings are, indeed, expected to prompt short-term behavioural changes, such as modifying time spent outdoors and adopting precautionary measures. However, we cannot entirely dismiss the possibility that the introduction of the early warning system indirectly contributed to the rise in AC ownership, a factor that could confound our analysis (often referred to as a "bad control"). It is important to note that when we control for air conditioning the time span is reduced, and it covers

[11] Data at the province level are not available for Civitavecchia since it is not a province but a municipality (comune). However, Civitavecchia is part of the province of Rome, and so it is indirectly included in the analysis. We consider Civitavecchia treated at the same time of Rome.

the period 1997-2019.

After having included all these controls, the identifying assumption in Equation 4 is that in the absence of treatment, trends in the temperature-mortality relationship would have been similar in provinces where HHWWS were implemented in different years. We again provide indirect tests of this assumption, estimating binned event studies. This also allows to evaluate the dynamic effects of the HHWWS implementation.

Finally, we provide robustness checks where we include both treated and not treated units. With respect to Equation 4 we substitute the interaction between temperature and province indicators with the interaction between temperature and a treated unit indicator, $\eta_t \times f(T)_{imy}$. This resembles the approach used by Mullins and White (2020). In this case, the identifying assumption is less restricted: in the absence of the treatment, trends in the temperature-mortality relationship would have been similar in counties where HHWWS were implemented in different years or not at all.

Although HHWWS is implemented at the city level, we adopt the province level for treatment assignment due to the spatial disaggregation constraints in our data. This approach also addresses potential spatial spillovers across different areas. To accurately estimate the causal effect of HHWWS, the Stable Unit Treatment Value Assumption (SUTVA) must hold. SUTVA assumes that the treatment has no impact on non-treated units, meaning that the outcomes for non-treated areas are not influenced by the treatment assigned to treated areas. Given the likelihood of heat alerts spreading beyond city boundaries—due to similar weather conditions, population mobility within provinces and sources of information—we cannot fully rule out such spillovers. Therefore, defining treatment at the provincial level helps to mitigate these potential cross-boundary influences.

Initial results. Panel (a) of Figure 4 highlights the key findings on the impact of Heat Health Warning Systems (HHWWS) implementation by comparing provinces that have received the treatment with those that have not yet been treated (but will be in the future). Detailed results are presented in Table E1 in Appendix E. Each column in the table reports estimates from the Difference-in-Differences-in-Temperature (DiDiT) model, which accounts for variations in the temperature-mortality relationship across different years and provinces.

In Panel (a) of Figure 4, we observe no significant effect of HHWWS in reducing mortality from temperatures exceeding 30 °C in treated cities, compared to those not yet treated. However, as indicated in columns (1) and (2) of Table E1, we do detect a significant effect of HHWWS at lower temperature ranges, specifically between 20–25 °C and 25–30 °C.

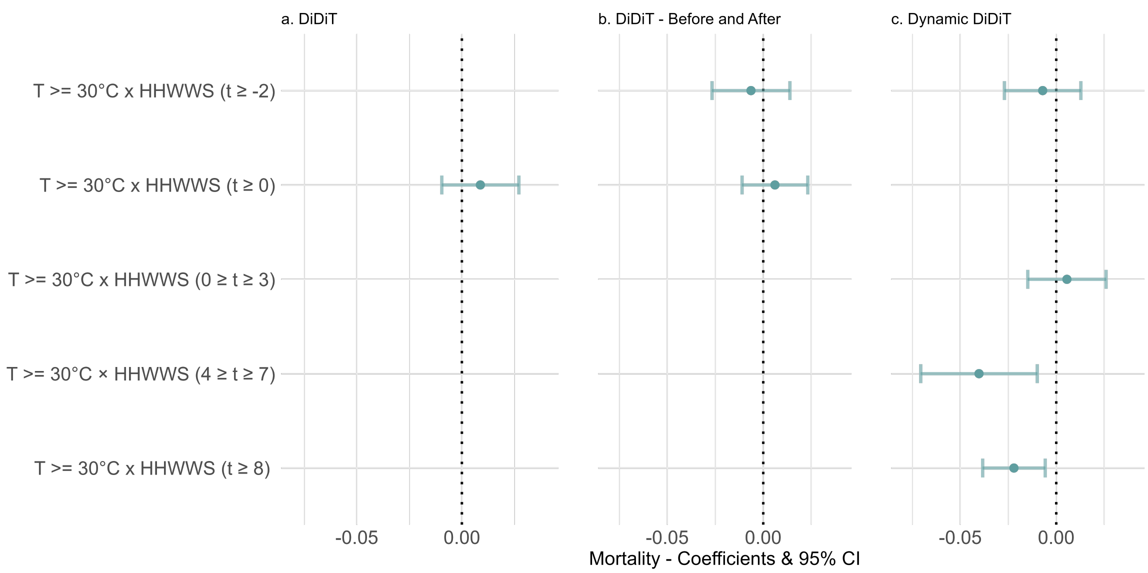
It is important to emphasise that these results reflect average effects and do not capture potential variations in the policy's impact over time. The subsequent analysis will explore the dynamic nature of the policy's effectiveness, offering a more detailed understanding of its evolving impact.

Dynamic effects. The dynamic effects of HHWWS (Heat Health Warning Systems) implementation are illustrated in Panels (b) and (c) of Figure 4, with detailed results provided in columns (3) to (6) of Table E1 in Appendix E. Panel (b) compares the year immediately preceding the implementation of HHWWS to both the pre-implementation and post-implementation periods. In this comparison, while no statistically significant effects of HHWWS are observed in reducing the adverse impact of temperatures above 30 °C, we do observe a mediating effect for temperatures in the range of 25–30 °C.

In Panel (c), we extend the analysis by comparing the year before HHWWS implementation to the pre-implementation period, this time using a binned post-implementation period divided into three intervals: $0 \leq t \leq 3$, $4 \leq t \leq 7$, and $t \geq 8$ years. When analyzing the evolution of HHWWS implementation, we find a statistically significant reduction in mortality rates associated with temperatures above 30 °C. Notably, this effect emerges only after a delay, becoming significant from the third year after implementation. Specifically, between the 4th and 7th years post-implementation, HHWWS reduces mortality from exposure to temperatures above 30 °C by approximately 104% compared to the pre-implementation period. This effect remains significant in the long term, corresponding to a 57% mediating effect.

Including non-treated cities. Up to this point, we have assessed the impact of Heat Health Warning Systems (HHWWS) by comparing provinces that have been treated with those that have not yet implemented the system. To further strengthen the validity of our results, we conduct a robustness check that includes both not-yet-treated and never-treated provinces. This expanded approach allows us to compare treated provinces against both these groups. The results are derived from estimates of the Difference-in-Differences-in-Temperature (DiDiT) model, which accounts for variations in the temperature-mortality

Figure 4: The dynamic impact of the HHWWS (Treated vs not-yet treated provinces)



Notes: The figure plots the coefficients from the interaction term between the hottest temperature bin (T $\geq$ 30 °C), and in panel (a) a treatment indicator that takes value of one after the warning system implementation in the treated province, in panel (b) indicator variables for pre- and post-intervention, and in panel (c) indicator variables for pre-, short-run post-, and long-run post-intervention. The sample is restricted to treated provinces. The regression also controls for: the interaction between temperature bins and province and month fixed effects, the interaction between temperature bins and NUTS-1 level penetration of air conditioning, second-degree polynomial of precipitation, annual province-level shares of population in three age group (0-1, 2-24, and $\geq$ 65) interacted with month dummies, and province-month, month-year and region-year fixed effects. Bins represent the 95% confidence intervals with standard errors clustered at the province-level.

relationship across different years, as well as differences between treated and untreated provinces.

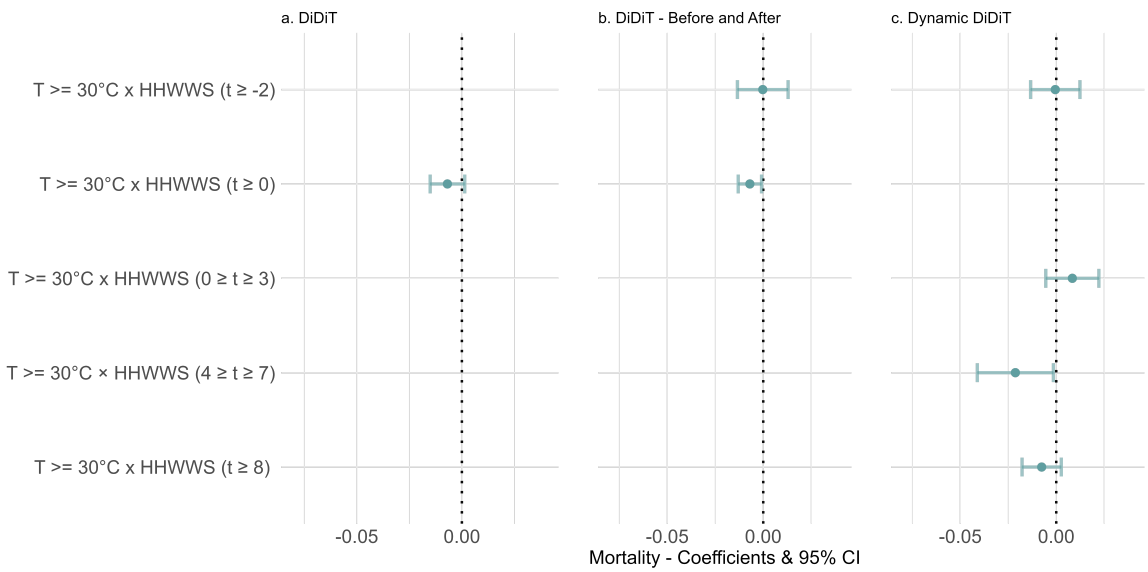
Figure 5 illustrates these findings, which are detailed in Table E2 in Appendix E. As in previous analyses, panel (a) shows the comparison between the pre and post-treatment periods. In this case, we observe a significant effect of the HHWWS in mitigating the negative impact of temperatures exceeding 30 °C in treated provinces, compared to those that were not yet or never treated. This translates to an approximate 22% reduction in the adverse effects relative to the period before the warning system was implemented. Additionally, the HHWWS shows a significant mediating effect on temperatures in the 20-25 °C, confirming the findings from the comparison with the not-yet-treated provinces.

The dynamic model results, presented in columns (3) to (4) of Table E2, compare the pre and post-early warning system implementation with the year before its introduction. These results highlight the effectiveness of the HHWWS in mitigating the adverse effects of temperatures across all temperature bins above 20 °C. As shown in Figure 5 panel (c), the full dynamics reveal that the system's impact becomes significant after the third year of implementation, achieving a 70% reduction in the effect of temperatures exceeding 30 °C compared to the pre-treatment period. Although this effect decreases to a 24% reduction in later years, it remains persistent. These findings confirm that similar to the comparison with not-yet-treated provinces, the impact of the warning system materializes with a certain delay. Overall, we find that the effectiveness of the HHWWS remains robust when comparing treated units not only with those yet to be treated but also with never-treated units. In fact, this comparison allows for an even clearer identification of the early warning system's impact.

6.2 Warnings and avoidance behaviour

Why do heatwave warnings reduce heat-related mortality? To compound previous analysis, we investigate whether heatwave warnings influence individuals' movement patterns, using Meta's daily data on population mobility in Italian provinces in 2023. Specifically, we test whether warnings encourage people to spend more time at home, which could mitigate health risks if dwellings are equipped with air conditioning.

Figure 5: The dynamic impact of the HHWWS (Treated vs not-yet and never-treated provinces)



Notes: The figure plots the coefficients from the interaction term between the hottest temperature bin ($T \geq 30$ °C), and in panel (a) a treatment indicator that takes value of one after the policy implementation in the treated province, in panel (b) indicator variables for pre- and post-intervention, and in panel (c) indicator variables for pre-, short-run post-, and long-run post-intervention. The sample includes both treated and never treated provinces. The regression also controls for: the interaction between temperature bins and province and month fixed effects, the interaction between temperature bins and NUTS-1 level penetration of air conditioning, second-degree polynomial of precipitation, annual province-level shares of population in three age group (0-1, 2-24, and ≥ 65) interacted with month dummies, and province-month, month-year and region-year fixed effects. Bins represent the 95% confidence intervals with standard errors clustered at the province-level.

Empirical framework. To do so, we use the following specification:

$$S_{jidwm} = \beta W_{jidwm} + X_{jidwm}\boldsymbol{\lambda} + \mu_{jidw} + \delta_{jim} + \varepsilon_{jidwm} \tag{5}$$

where S_{jidwmy} indicates the share of province i's population at the j distance [0, 0-10, 10-100, +100] in day d, week w, and month m; W_{jidwm} is an indicator equal to 1 if in that province a heatwave warning of level two or above has been issued; X_{jidwm} is a set of controls including daily maximum temperature, total precipitation, and wind speed. Both W and X are interacted with a categorical variable for the distance from home. We also control for distance-province-day-of-the-week μ_{jidw} and distance-province-month fixed effects δ_{jim}. Standard errors are clustered at the province level, and we weight our regression using province population.

Results. Table 3 summarizes the results. Heatwave warnings significantly increase the share of individuals staying at home on the same day, with an increase of 0.3 percentage points, or 0.8% relative to the mean (a 0.6 standard deviation increase). Simultaneously, the share of individuals traveling decreases. Warnings reduce the share at 0–10 km, 10–100 km, and >100 km from home by 0.4, 0.5, and 0.3 percentage points, respectively—corresponding to reductions of 0.7%, 8.2%, and 22% relative to their respective means.

These findings provide evidence that individuals adopt avoidance behaviors in response to heatwave warnings. Coupled with rising air conditioning adoption in Italy, these behavioral changes help explain the mitigating effect of heatwave warning systems on heat-related mortality.

6.3 Information access: newspapers readership

We then examine whether the policy's effectiveness is enhanced in areas where the dissemination of information on heat-related risks and the communication of heat warning days likely reached a larger number of individuals.

Empirical framework. To test the role of information access, we modify Equation 3 interacting temperature bins with the post policy dummy and our pre-intervention measure of

Table 3: Heatwave warnings and people's movements

	Share at distance j from home	
	(1)	(2)
Warning $\times$ 0 km	0.00306***	0.00256***
	(0.001)	(0.001)
Warning $\times$ 0-10 km	-0.00414***	-0.00384***
	(0.001)	(0.001)
Warning $\times$ 10-100 km	-0.00528**	-0.00435***
	(0.002)	(0.001)
Warning $\times$ +100 km	-0.00281**	-0.00202***
	(0.001)	(0.001)
Weather controls	Yes	Yes
Distance-Province-Day-of-the-Week FE	Yes	Yes
Distance-Month FE	Yes	No
Distance-Province-Month FE	No	Yes
Mean Outcome (0 km)	0.377	0.377
Mean Outcome (0-10 km)	0.552	0.552
Mean Outcome (10-100 km)	0.061	0.061
Mean Outcome (+100 km)	0.009	0.009
Observations	33700	33700

Notes: The dependent variable is the share of people at distance j. The estimated period is 2023. Standard errors are clustered at the province level. * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$). All regressions are weighted by province population.

newspapers readership. Our specification is declined as follows:

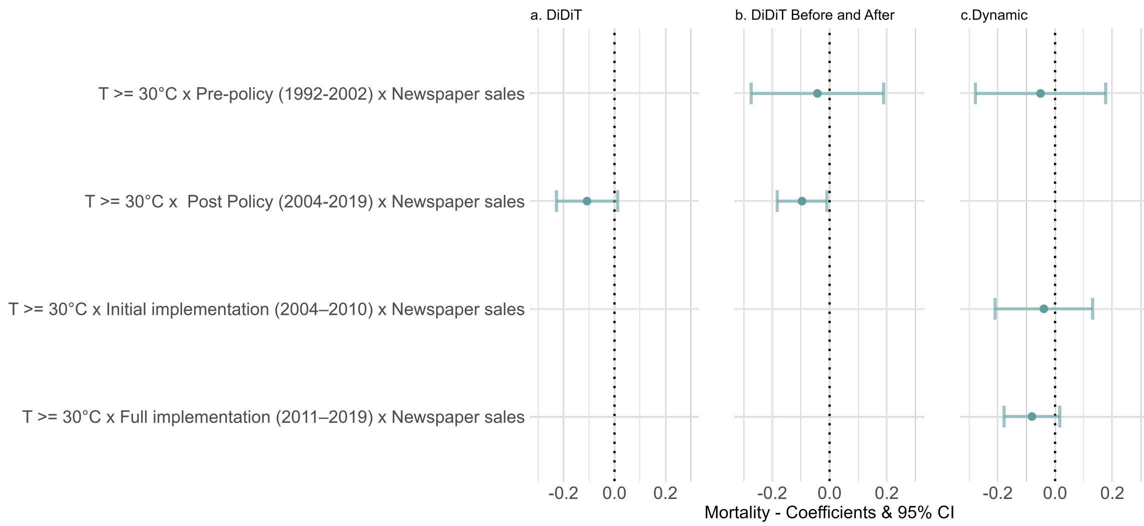
$$\begin{aligned} Y_{imy} = \pi f(T)_{imy} \times D_t \times N_i + \gamma g(P)_{imy} + \mathbf{X}_{imy}\boldsymbol{\lambda} + \\ \eta_y f(T)_{imy} + \mu_{im} + \theta_{r(i)y} + \delta_{my} + \varepsilon_{imy} \end{aligned} \tag{6}$$

where N_i indicates the number of non-sport newspapers' sales per capita in province i in 2003. Our strategy identifies differences in the temperature-mortality relationship between provinces with higher and lower pre-policy newspaper readership before and after 2004.

A threat to our identification is the existence of other policies that might be correlated with newspaper readership and the temperature-mortality relationship simultaneously. For this reason, we allow the temperature-mortality gradient to vary across years, $\eta_y f(T)_{imy}$, keeping common unobservables fixed over time.[12] In addition, by using a pre-intervention

[12]Notice that we do not allow the relationship between temperature and mortality to vary across provinces anymore. An interaction between temperature and province fixed-effects would indeed perfectly correlate with the readership measure.

Figure 6: The dynamic impact of the 2004 national plan (DiDiT), triple interaction with newspapers sales



Notes: The figure plots the coefficients from the triple interaction term between the hottest temperature bin (T $\geq$ 30 °C), pre-intervention level of newspaper readership as the province-level number of non-sport newspaper sales per capita, and in panel (a) a treatment indicator that takes after value of one the policy implementation in the treated province, in panel (b) indicator variables for pre- and post-intervention, and in panel (c) indicator variables for pre-, short-run post-, and long-run post-intervention. The sample includes both treated and never treated provinces. The regression also controls for: the interaction between temperature bins and province and month fixed effects, the interaction between temperature bins and NUTS-1 level penetration of air conditioning, second-degree polynomial of precipitation, annual province-level shares of population in three age group (0-1, 2-24, and $\geq$ 65) interacted with month dummies, and province-month, month-year and region-year fixed effects. Bins represent the 95% confidence intervals with standard errors clustered at the province-level.

measure we avoid that policy might have also influenced information access.

Results. Figure 6 reports our estimates for the latest bin (T $\geq$ 30 °C), and Table E3 and Table E4 present all the coefficients.

The triple interaction coefficients indicate that the joint effect of heat waves, policy, and readership is negative and statistically significant for the highest temperature intervals, though at a weak level of significance. For instance, our results suggest that at average newspaper readership (0.8), the policy is associated with 0.11 less deaths per 1,000s people due to an additional day at or above 30 °C. This is about a 40% reduction in the total effect of an additional day at or above 30 °C before the policy. Importantly, the impact of temperature on mortality does not change over readership level before 2004, but only after the policy intervention.

Looking at the dynamics, once we control for potential pre-trends—which are all highly non-significant—the estimates for the extreme bin become strongly significant, and the coefficient size remains quite the same. There is also suggestive evidence the triple interaction coefficient is larger after the full policy implementation. However, point estimates are not statistically different from each other.

6.4 Strengthening the healthcare system

Finally, we consider that the policy aimed to improve the operational efficiency of emergency departments and hospitals during periods of extreme heat. Although the lack of monthly or daily hospitalization data prevents us from directly assessing the policy's impact on hospital outcomes, we can evaluate whether the operational efficiency of emergency departments and hospitals serves as a key factor in the policy's effectiveness.

Empirical framework. Specifically, we estimate the same specification used in Equation 6, substituting the pre-intervention cross-sectional term in the triple interaction. The regression looks as follows:

$$\begin{aligned} Y_{imy} = \pi\, f(T)_{imy} \times D_t \times H_i + \gamma g(P)_{imy} + \mathbf{X}_{imy}\boldsymbol{\lambda} + \\ \eta_y\, f(T)_{imy} + \mu_{im} + \theta_{r(i)y} + \delta_{my} + \varepsilon_{imy} \end{aligned} \tag{7}$$

where H_i indicates one of three pre-policy operational efficiency indicators of the healthcare systems in province i. This specification identifies differences in the temperature-mortality relationship between provinces with higher and lower pre-policy operational efficiency before and after 2004. In this way, we can assess whether the policy's success in mitigating heat-related mortality was contingent on pre-existing healthcare capacity. For example, one of the healthcare responses activated during heat waves involves redistributing available beds and staff across wards. The effectiveness of this action is plausibly influenced by the overall availability of resources. This approach intends to indirectly infer the role of emergency response efficiency in the policy's effectiveness. If provinces with higher initial operational efficiency show a stronger reduction in heat-related mortality, it suggests that the policy's impact was amplified by better baseline healthcare infrastructure. Conversely, if no difference is observed, it may indicate that operational efficiency did not condition the policy's success.

Results. Table E5 presents our estimates. The results do not offer clear or consistent evidence that healthcare efficiency played a significant role across the indicators we examine. This suggests that the primary driver of the policy's effectiveness was the behavioral responses it triggered, rather than improvements in healthcare system operations during heatwave periods.

7 Discussion and conclusions

This paper evaluates the effectiveness of Italy's national heat prevention plan, implemented in 2004, in reducing heat-related mortality. By investigating the mechanisms driving the policy's success, it identifies the critical role of the heat warning system and the dissemination of heat risk information in mitigating the adverse health effects of extreme heat. Using provincial-level administrative data spanning from 1992 to 2019 with monthly frequency, we leverage random temperature variations and the exogenous policy's implementation to estimate the mitigation impact of the program on the temperature-mortality relationship.

Our baseline analysis reveals that temperature has a significant impact on mortality, and the effect is not negligible compared to other developed and developing countries. This substantial effect can largely be attributed to Italy's ageing population, a key factor contributing to the country's vulnerability to climate change. To address these health risks, a national heat adaptation plan was introduced in 2004. Our findings indicate that the plan successfully reduced excess mortality caused by temperatures over 30 °C by more than 57% and its effect has been persistent over time.

To investigate the mechanisms driving this reduction, we first focus on the role of the Heat Health Watch Warning System (HHWWS), which was phased in across 27 Italian cities to encourage avoidance behaviour during heatwaves and trigger the emergency response of the health care system by implementing ad hoc protocols. Our results show that provinces with HHWWS experienced a significant and lasting reduction in the mortality impact of temperatures above 30°C, with treated provinces showing, on average, a 22 percent decrease in the adverse effects of high temperatures relative to not-yet and never-treated provinces. In addition, we show this reduction can be partially attributed to changes in mobility patterns during the day. Second, using pre-policy data on newspaper circulation as a proxy for information access, we find that higher readership levels increase policy's effectiveness. Since the policy aimed at disseminating heat risk information, access to this information proved to be a crucial channel driving the policy's success in ensuring individuals' adoption of protective behaviours. Third, we examine whether the pre-existing quality of the healthcare sector influenced the policy's effectiveness. Our findings do not support this hypothesis, indicating that the program's success was driven primarily by its information dissemination and public awareness components rather than by enhancements in healthcare system efficiency.

This paper makes a novel contribution by demonstrating how public programs targeting heat adaptation can substantially mitigate the health impacts of climate change, thereby enhancing societal well-being. Our analysis highlights the potential of providing heat risk information as a cost-effective strategy for future adaptation policies. For example, the operational cost of running a warning system is estimated at approximately $17,000 (USD, 2024) per day (Ebi et al., 2004), which is significantly lower than the value of saving an additional life, with the average value of a statistical life (VSL) in EU-27 countries estimated at $5.62 million (USD, 2024) (OECD, 2012).

Nonetheless, our analysis has some limitations. Notably, we lack data to explore whether the policy influenced avoidance behaviors, such as the purchase of air-conditioning systems or changes in energy consumption. Additionally, the absence of data on public perceptions prevents us from fully assessing whether the policy affected individuals' awareness of climate change and associated health risks. These limitations suggest promising directions for future research to further investigate the behavioral and perceptual dimensions of public adaptation policies aimed at mitigating heat stress.

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Appendices

A Additional results — Baseline

Table A1: The baseline temperature and mortality relationship

	Mortality rate (in 1,000s)				
	(1)	(2)	(3)	(4)	(5)
$T_{AVG} < -10$ °C	0.00742*	0.00955**	0.00230	0.00198	0.00191
	(0.004)	(0.004)	(0.002)	(0.002)	(0.002)
$T_{AVG} \in [-10, -5)$ °C	0.00824***	0.0104***	0.00258***	0.00244***	0.00244***
	(0.003)	(0.003)	(0.001)	(0.001)	(0.001)
$T_{AVG} \in [-5, 0)$ °C	0.00619***	0.00803***	0.00271***	0.00262***	0.00246***
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
$T_{AVG} \in [0, 5)$ °C	0.00404***	0.00537***	0.00201***	0.00190***	0.00187***
	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)
$T_{AVG} \in [5, 10)$ °C	0.00176***	0.00253***	0.00102***	0.00106***	0.00103***
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
$T_{AVG} \in [15, 20)$ °C	-0.000964**	-0.000954***	-0.000339**	-0.000430***	-0.000382**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$T_{AVG} \in [20, 25)$ °C	0.000297	-0.000449	0.000944***	0.000838**	0.000888**
	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)
$T_{AVG} \in [25, 30)$ °C	0.00668***	0.00458***	0.00387***	0.00374***	0.00387***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$T_{AVG} \geq 30$ °C	0.0247***	0.0196***	0.0190***	0.0188***	0.0185***
	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)
Precipitation controls	Yes	Yes	Yes	Yes	Yes
Province-Month FE	Yes	Yes	Yes	Yes	Yes
Region-Year FE	No	Yes	Yes	Yes	Yes
Month-Year FE	No	No	Yes	Yes	Yes
Pop. share × Month	No	No	No	Yes	Yes
Log income × Month	No	No	No	No	Yes
Mean Outcome	0.827	0.827	0.827	0.827	0.827
Observations	34680	34680	34680	34680	34680

Notes: The dependent variable is the number of deaths per 1,000 people (mortality rate). The estimated period is 1992-2019. The reference category for temperature is bin 10-15 °C. Standard errors are two-way clustered at the province and month-year level. * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$). All regressions are weighted by province population.

Table A2: The baseline temperature and mortality relationship

	Mortality rate (in 1,000s)							
	Pre-Policy: 1992-2002				Post-Policy: 2004-2019			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$T_{AVG} < -10$ °C	0.00753*	0.00851*	0.00179	0.00170	0.00726	0.00982*	0.00136	0.00136
	(0.004)	(0.004)	(0.002)	(0.002)	(0.005)	(0.005)	(0.002)	(0.002)
$T_{AVG} \in [-10, -5)$ °C	0.00972***	0.0113***	0.00310**	0.00348***	0.00737*	0.00974**	0.00145	0.00120
	(0.003)	(0.003)	(0.001)	(0.001)	(0.004)	(0.004)	(0.001)	(0.001)
$T_{AVG} \in [-5, 0)$ °C	0.00804***	0.00893***	0.00333***	0.00340***	0.00558*	0.00773***	0.00206***	0.00193***
	(0.002)	(0.002)	(0.001)	(0.001)	(0.003)	(0.003)	(0.001)	(0.001)
$T_{AVG} \in [0, 5)$ °C	0.00600***	0.00643***	0.00288***	0.00283***	0.00297**	0.00458***	0.00113**	0.000970*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$T_{AVG} \in [5, 10)$ °C	0.00296***	0.00322***	0.00157***	0.00159***	0.00121*	0.00200***	0.000552	0.000570*
	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)
$T_{AVG} \in [15, 20)$ °C	-0.00145***	-0.00148**	-0.000341	-0.000367	-0.000395	-0.000691*	-0.000254	-0.000288
	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)
$T_{AVG} \in [20, 25)$ °C	-0.000181	-0.000667	0.000919	0.000925	0.00136*	-0.000434	0.000991*	0.000869*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$T_{AVG} \in [25, 30)$ °C	0.00751***	0.00647***	0.00456***	0.00422***	0.00647***	0.00338***	0.00364***	0.00363***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$T_{AVG} \geq 30$ °C	0.0335***	0.0301***	0.0302***	0.0268***	0.0205***	0.0147***	0.0131***	0.0130***
	(0.006)	(0.002)	(0.002)	(0.004)	(0.003)	(0.002)	(0.003)	(0.003)
Precipitation controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province-Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region-Year FE	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Month-Year FE	No	No	Yes	Yes	No	No	Yes	Yes
Covariates × Month	No	No	No	Yes	No	No	No	Yes
Mean Outcome	0.814	0.814	0.814	0.814	0.837	0.837	0.837	0.837
Observations	14544	14544	14544	14544	20136	20136	20136	20136

Notes: The dependent variable is the number of deaths per 1,000 people (mortality rate). The estimated period is 1992-2019. The reference category for temperature is bin 10-15 °C. Covariates include the share of population by age groups interacted with the month indicator. Standard errors are two-way clustered at the province and month-year level. * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$). All regressions are weighted by province population.

Table A3: Comparison of the mortality-temperature relationship estimates

Country	Period	Temp. Bin (°C)	Estimates	Life Expect.	AC Penetr.
United States (Barreca et al., 2016)	1960–2004	T > 32.2	0.0034	70-77	12-87%
India (Burgess et al., 2017)	1957-2000	T > 35	0.0074	45-63	0-7%
Italy (our study)	1992-2019	T > 30	0.021	81-83	10-40%

Notes: Estimates refer to the logarithmic transformation of mortality rates

B Robustness — Baseline

Table B1 presents the results of estimating Equation 1 using average temperature percentiles as regressors. This table offers a robustness check of our main findings by exploiting relative temperature measures, with percentiles calculated based on the local (province-specific) temperature distribution. Table B2 presents the results for an additional robustness check by testing the baseline specification with the average maximum temperature bins as regressors.

Table B1: The baseline temperature and mortality relationship — Temperature percentiles

	Mortality rate (in 1,000s)					
	Pre-Policy: 1992-2002			Post-Policy: 2004-2019		
	(1)	(2)	(3)	(4)	(5)	(6)
$T_{AVG} < 5^{th}$ perc	0.00340***	0.00313***	0.00471***	0.00462***	0.00222***	0.00220***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$T_{AVG} \in 5^{th} - 10^{th}$ perc	0.00238***	0.00231***	0.00273***	0.00273***	0.00161***	0.00162***
	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)
$T_{AVG} \in 10^{th} - 15^{th}$ perc	0.00150***	0.00123**	0.00254***	0.00235***	0.000396	0.000369
	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)
$T_{AVG} \in 15^{th} - 20^{th}$ perc	0.00163***	0.00143***	0.00153**	0.00127**	0.00174***	0.00169***
	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)
$T_{AVG} \in 25^{th} - 30^{th}$ perc	0.000579	0.000610*	0.000851	0.000902	0.000574	0.000549
	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
$T_{AVG} \in 30^{th} - 35^{th}$ perc	-0.0000860	-0.000209	0.000536	0.000493	-0.000364	-0.000348
	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)
$T_{AVG} \in 70^{th} - 75^{th}$ perc	-0.000102	-0.000207	-0.000336	-0.000625*	0.000571	0.000591*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$T_{AVG} \in 75^{th} - 80^{th}$ perc	-0.000292	-0.000239	0.000148	0.000312	-0.000325	-0.000301
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$T_{AVG} \in 80^{th} - 85^{th}$ perc	0.0000973	0.0000222	-0.0000950	-0.000450	0.000538	0.000491
	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)
$T_{AVG} \in 85^{th} - 90^{th}$ perc	0.000554	0.000745*	0.000783	0.000953*	0.00109**	0.00111**
	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
$T_{AVG} \in 90^{th} - 95^{th}$ perc	0.00141***	0.00137***	0.00246***	0.00243***	0.00140**	0.00135**
	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
$T_{AVG} \geq 95^{th}$ perc	0.00600***	0.00602***	0.00737***	0.00727***	0.00547***	0.00543***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Precipitation controls	Yes	Yes	Yes	Yes	Yes	Yes
Province-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Region-Year FE	No	Yes	Yes	Yes	Yes	Yes
Month-Year FE	No	No	Yes	Yes	Yes	Yes
Pop. share × Month	Yes	Yes	Yes	Yes	Yes	Yes
Log Income × Month	No	Yes	No	Yes	No	Yes
Mean Outcome	0.814	0.814	0.814	0.837	0.837	0.837
Observations	34680	34680	14544	14544	20136	20136

Notes: The dependent variable is the number of deaths per 1,000 people (mortality rate). The estimated period is 1992-2019 in columns 1-2, 1992-2002 in columns 3-4, and in 2004-2019 in columns 5-6. The reference category for temperature is bin 12-27 °C. Standard errors are two-way clustered at the province and month-year level. * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$). All regressions are weighted by province population.

Table B2: The baseline temperature and mortality relationship — Maximum temperature

	Mortality rate (in 1,000s)					
	Pre-Policy: 1992-2002			Post-Policy: 2004-2019		
	(1)	(2)	(3)	(4)	(5)	(6)
$T_{MAX} < 0$ °C	0.00294***	0.00304***	0.00312**	0.00274*	0.00245**	0.00254**
	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)
$T_{MAX} \in [0, 3)$ °C	0.00202***	0.00208***	0.00299***	0.00343***	0.00124	0.00122
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$T_{MAX} \in [3, 6)$ °C	0.00172***	0.00180***	0.00161*	0.00148	0.00167***	0.00169***
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)
$T_{MAX} \in [6, 9)$ °C	0.00140***	0.00148***	0.00214***	0.00221***	0.000717	0.000711
	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)
$T_{MAX} \in [9, 12)$ °C	0.000669**	0.000727**	0.000535	0.000605	0.000754**	0.000785**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$T_{MAX} \in [27, 30)$ °C	0.00159***	0.00150***	0.00215***	0.00211***	0.00128***	0.00126***
	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)
$T_{MAX} \in [30, 33)$ °C	0.00313***	0.00311***	0.00428***	0.00426***	0.00258***	0.00262***
	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)
$T_{MAX} \in [33, 36)$ °C	0.00591***	0.00580***	0.00669***	0.00679***	0.00533***	0.00535***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$T_{MAX} \in [36, 39)$ °C	0.0161***	0.0156***	0.0213***	0.0182***	0.0116***	0.0116***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
$T_{MAX} \geq 39$ °C	0.0280***	0.0282***	0.0329***	0.0384***	0.0275***	0.0269***
	(0.005)	(0.006)	(0.009)	(0.013)	(0.004)	(0.004)
Precipitation controls	Yes	Yes	Yes	Yes	Yes	Yes
Province-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Region-Year FE	No	Yes	Yes	Yes	Yes	Yes
Month-Year FE	No	No	Yes	Yes	Yes	Yes
Pop. share × Month	Yes	Yes	Yes	Yes	Yes	Yes
Log Income × Month	No	Yes	No	Yes	No	Yes
Mean Outcome	0.814	0.814	0.814	0.837	0.837	0.837
Observations	34680	34680	14544	14544	20136	20136

Notes: The dependent variable is the number of deaths per 1,000 people (mortality rate). The estimated period is 1992-2019 in columns 1-2, 1992-2002 in columns 3-4, and in 2004-2019 in columns 5-6. The reference category for temperature is bin 12-27 °C. Standard errors are two-way clustered at the province and month-year level. * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$). All regressions are weighted by province population.

C Additional results — Policy

Table C1: Mortality-temperature relationship and the impact of the 2004 national plan

	Mortality rate (in 1,000s)			
	Baseline	**Policy**		
		DiT	DiDiT	DiDiT
	(1)	(2)	(3)	(4)
$T_{AVG} \in [20, 25)$ °C	0.00135***	0.00175***		
	(0.000)	(0.000)		
$T_{AVG} \in [25, 30)$ °C	0.00437***	0.00555***		
	(0.001)	(0.001)		
$T_{AVG} \geq 30$ °C	0.0190***	0.0268***		
	(0.003)	(0.003)		
$T_{AVG} \in [20, 25)$ °C $\times$ Post (2004-2019)		-0.000737**	-0.000612*	-0.000620*
		(0.000)	(0.000)	(0.000)
$T_{AVG} \in [25, 30)$ °C $\times$ Post (2004-2019)		-0.00200***	-0.00191***	-0.00191***
		(0.001)	(0.001)	(0.001)
$T_{AVG} \geq 30$°C $\times$ Post (2004-2019)		-0.0123***	-0.0131***	-0.0137***
		(0.004)	(0.004)	(0.004)
Precipitation controls	Yes	Yes	Yes	Yes
Province-Month FE	Yes	Yes	Yes	Yes
Region-Year FE	Yes	Yes	Yes	Yes
Month-Year FE	Yes	Yes	Yes	Yes
Covariates $\times$ Month	Yes	Yes	Yes	Yes
Bins $\times$ Summer	No	No	Yes	No
Bins $\times$ Month	No	No	No	Yes
Bins $\times$ Province	No	No	Yes	Yes
Mean Outcome	0.827	0.827	0.827	0.827
Observations	34680	34680	34680	34680

Notes: The dependent variable is the number of deaths per 1,000 people (mortality rate). The estimated period is 1992-2019. The reference category for temperature is bin < 20 °C. Covariates include the share of population by age groups and province-level GDP per capita interacted with the month indicator. Standard errors are two-way clustered at the province and month-year level. * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$). All regressions are weighted by province population.

Table C2: Mortality-temperature relationship and the impact of the 2004 national plan — Binned event study

	Mortality rate (in 1,000s)					
	DiT	DiDiT	DiDiT	DiT	DiDiT	DiDiT
	(1)	(2)	(3)	(4)	(5)	(6)
$T_{AVG} \in [25,30)$°C × Pre (1992-2002)	0.000471	0.00116**	0.00128**	0.000473	0.00117**	0.00129**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$T_{AVG} \in [20,25)$°C × Pre (1992-2002)	0.00208***	0.00104	0.00120*	0.00208***	0.00103	0.00118*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$T_{AVG} \geq 30$°C × Pre (1992-2002)	0.0101*	0.00533	0.00445	0.0101*	0.00567	0.00462
	(0.005)	(0.006)	(0.005)	(0.005)	(0.006)	(0.005)
$T_{AVG} \in [25,30)$°C × Post (2004-2019)	-0.000298	0.000450	0.000557			
	(0.001)	(0.001)	(0.001)			
$T_{AVG} \in [20,25)$°C × Post (2004-2019)	-0.000180	-0.000961	-0.000815			
	(0.001)	(0.001)	(0.001)			
$T_{AVG} \geq 30$°C × Post (2004-2019)	-0.00832***	-0.00982***	-0.0108***			
	(0.003)	(0.003)	(0.003)			
$T_{AVG} \in [25,30)$°C × Initial Implementation (2004-2010)				0.0000438	0.000754	0.000862
				(0.001)	(0.001)	(0.001)
$T_{AVG} \in [20,25)$°C × Initial Implementation (2004-2010)				-0.000204	-0.00112*	-0.000986
				(0.001)	(0.001)	(0.001)
$T_{AVG} \geq 30$°C × Initial Implementation (2004-2010)				-0.00207	-0.00672**	-0.00911**
				(0.004)	(0.003)	(0.004)
$T_{AVG} \in [25,30)$°C × Full Implementation (2011-2019)				-0.000557	0.000244	0.000352
				(0.001)	(0.001)	(0.001)
$T_{AVG} \in [20,25)$°C × Full Implementation (2011-2019)				-0.000271	-0.000907	-0.000741
				(0.001)	(0.001)	(0.001)
$T_{AVG} \geq 30$°C × Full Implementation (2011-2019)				-0.00981***	-0.0103***	-0.0110***
				(0.003)	(0.003)	(0.003)
Precipitation controls	Yes	Yes	Yes	Yes	Yes	Yes
Province-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Region-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Month-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Covariates × Month	Yes	Yes	Yes	Yes	Yes	Yes
Bins × Summer	No	Yes	No	No	Yes	No
Bins × Month	No	No	Yes	No	No	Yes
Bins × Province	No	Yes	Yes	No	Yes	Yes
Mean Outcome	0.827	0.827	0.827	0.827	0.827	0.827
Observations	34680	34680	34680	34680	34680	34680

Notes: The dependent variable is the number of deaths per 1,000 people (mortality rate). The estimated period is 1992-2019. The reference category for temperature is bin < 20 °C. Covariates include the share of population by age groups and province-level GDP per capita interacted with the month indicator. Standard errors are two-way clustered at the province and month-year level. * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$). All regressions are weighted by province population.

D Robustness — Policy

Table D1 provides a robustness check for the policy results, estimating Equations 2 and 3 using average temperature percentiles as regressors. This approach offers additional validation by incorporating relative temperature measures based on local (province-specific) distributions. Similarly, Table D2 presents analogous results, this time using maximum temperature bins as the temperature variables. In both cases, the findings remain robust.

Table D1: Mortality-temperature relationship and the impact of the 2004 national plan — Temperature percentiles

	Mortality rate (in 1,000s)				
	Baseline	**Policy**			
		DiT	DiDiT	Dynamic DiT	Dynamic DiDiT
$T_{AVG} \in 85^{th} - 90^{th}$ perc	0.000846***	0.000936***		0.00232	
	(0.000)	(0.000)		(0.002)	
$T_{AVG} \in 90^{th} - 95^{th}$ perc	0.00145***	0.00232***		0.000254	
	(0.000)	(0.001)		(0.006)	
$T_{AVG} \geq 95^{th}$ perc	0.00611***	0.00760***		0.00857***	
	(0.001)	(0.001)		(0.003)	
$T_{AVG} \in 85^{th} - 90^{th}$ perc × Pre (1992-2002)				-0.00152	0.00182
				(0.002)	(0.002)
$T_{AVG} \in 90^{th} - 95^{th}$ perc × Pre (1992-2002)				0.00221	0.000925
				(0.006)	(0.005)
$T_{AVG} \geq 95^{th}$ perc × Pre (1992-2002)				-0.00126	-0.00230
				(0.003)	(0.003)
$T_{AVG} \in 85^{th} - 90^{th}$ perc × Post Policy (2004-2019)		-0.000228	0.0000901		
		(0.000)	(0.000)		
$T_{AVG} \in 90^{th} - 95^{th}$ perc × Post Policy (2004-2019)		-0.00139*	-0.00100		
		(0.001)	(0.001)		
$T_{AVG} \geq 95^{th}$ perc × Post Policy (2004-2019)		-0.00236***	-0.00274***		
		(0.001)	(0.001)		
$T_{AVG} \in 85^{th} - 90^{th}$ perc × Initial Implementation (2004-2010)				-0.00121	0.00248
				(0.002)	(0.002)
$T_{AVG} \in 90^{th} - 95^{th}$ perc × Initial Implementation (2004-2010)				0.00152	0.00103
				(0.006)	(0.005)
$T_{AVG} \geq 95^{th}$ perc × Initial Implementation (2004-2010)				-0.00331	-0.00445*
				(0.003)	(0.002)
$T_{AVG} \in 85^{th} - 90^{th}$ perc × Full Implementation (2011-2019)				-0.00177	0.00159
				(0.002)	(0.002)
$T_{AVG} \in 90^{th} - 95^{th}$ perc × Full Implementation (2011-2019)				0.000249	-0.000774
				(0.006)	(0.005)
$T_{AVG} \geq 95^{th}$ perc × Full Implementation (2011-2019)				-0.00326	-0.00478*
				(0.003)	(0.003)
Precipitation controls	Yes	Yes	Yes	Yes	Yes
Province-Month FE	Yes	Yes	Yes	Yes	Yes
Region-Year FE	Yes	Yes	Yes	Yes	Yes
Month-Year FE	Yes	Yes	Yes	Yes	Yes
Covariates × Month	Yes	Yes	Yes	Yes	Yes
Bins × Month	No	No	Yes	No	Yes
Bins × Province	No	No	Yes	No	Yes
Mean Outcome	0.857	0.857	0.857	0.857	0.857
Observations	34320	34320	34320	34320	34320

Notes: The dependent variable is the number of deaths per 1,000 people (mortality rate). The estimated period is 1992-2019. The reference category for temperature is bin < 20 °C. Covariates include the share of population by age groups interacted with the month indicator. Standard errors are clustered at the province and month-year level. * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$). All regressions are weighted by province population.

Table D2: Mortality-temperature relationship and the impact of the 2004 national plan — Maximum temperatures

	Mortality rate (in 1,000s)				
	Baseline	**Policy**			
		DiT	DiDiT	Dynamic DiT	Dynamic DiDiT
$T_{MAX} \in [30,33)$ °C	0.00238***	0.00386***		0.00212**	
	(0.000)	(0.000)		(0.001)	
$T_{MAX} \in [33,36)$ °C	0.00448***	0.00474***		0.00210	
	(0.001)	(0.001)		(0.002)	
$T_{MAX} \geq 36$ °C	0.0146***	0.0194***		0.0195***	
	(0.002)	(0.002)		(0.002)	
$T_{MAX} \in [33,36)$°C × Pre (1992-2002)				0.00182	0.00143
				(0.001)	(0.001)
$T_{MAX} \in [30,33)$°C × Pre (1992-2002)				0.00409**	0.00164
				(0.002)	(0.001)
$T_{MAX} \geq 36$°C × Pre (1992-2002)				-0.000329	-0.00335
				(0.003)	(0.004)
$T_{MAX} \in [33,36)$°C × Post (2004-2019)		-0.00237***	-0.00232***		
		(0.001)	(0.001)		
$T_{MAX} \in [30,33)$°C × Post (2004-2019)		-0.000210	-0.000526		
		(0.001)	(0.001)		
$T_{MAX} \geq 36$°C × Post (2004-2019)		-0.00756***	-0.00671**		
		(0.002)	(0.003)		
$T_{MAX} \in [33,36)$°C × Initial Implementation (2004-2010)				-0.000410	-0.000851
				(0.001)	(0.001)
$T_{MAX} \in [30,33)$°C × Initial Implementation (2004-2010)				0.00229	0.000104
				(0.002)	(0.001)
$T_{MAX} \geq 36$°C × Initial Implementation (2004-2010)				-0.00742***	-0.0100***
				(0.002)	(0.003)
$T_{MAX} \in [33,36)$°C × Full Implementation (2011-2019)				-0.000734	-0.00103
				(0.001)	(0.001)
$T_{MAX} \in [30,33)$°C × Full Implementation (2011-2019)				0.00265	0.000813
				(0.002)	(0.001)
$T_{MAX} \geq 36$°C × Full Implementation (2011-2019)				-0.00749***	-0.00826**
				(0.002)	(0.004)
Precipitation controls	Yes	Yes	Yes	Yes	Yes
Province-Month FE	Yes	Yes	Yes	Yes	Yes
Region-Year FE	Yes	Yes	Yes	Yes	Yes
Month-Year FE	Yes	Yes	Yes	Yes	Yes
Pop. share × Month	Yes	Yes	Yes	Yes	Yes
Log Income × Month	Yes	Yes	Yes	Yes	Yes
Bins × Month	No	No	Yes	No	Yes
Bins × Province	No	No	Yes	No	Yes
Mean Outcome	0.857	0.857	0.857	0.857	0.857
Observations	34320	34320	34320	34320	34320

Notes: The dependent variable is the number of deaths per 1,000 people (mortality rate). The estimated period is 1992-2019. The reference category for temperature is bin < 20 °C. Covariates include the share of population by age groups interacted with the month indicator. Standard errors are clustered at the province and month-year level. * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$). All regressions are weighted by province population.

E Additional results — Mechanisms

Table E1: The mitigation effect of heat-wave warning systems — Not-yet Treated

	Mortality rate (in 1,000s)					
	Post		**Before and After**		**Dynamic**	
	DiDiT (1)	DiDiT (2)	DiDiT (3)	DiDiT (4)	DiDiT (5)	DiDiT (6)
$T_{AVG} \in [20, 25)$°C × HHWWS (t ≤ -2)			0.000122	0.0000431	0.000113	0.0000501
			(0.000)	(0.000)	(0.000)	(0.000)
$T_{AVG} \in [25, 30)$°C × HHWWS (t ≤ -2)			-0.000378	-0.000223	-0.000256	-0.000161
			(0.001)	(0.001)	(0.001)	(0.001)
$T_{AVG} \geq 30$°C × HHWWS (t ≥ -2)			-0.00335	-0.00639	-0.00426	-0.00707
			(0.010)	(0.010)	(0.009)	(0.010)
$T_{AVG} \in [20, 25)$°C × HHWWS (t ≥ 0)	-0.000695*	-0.000644*	-0.000633	-0.000615		
	(0.000)	(0.000)	(0.000)	(0.000)		
$T_{AVG} \in [25, 30)$°C × HHWWS (t ≥ 0)	-0.000831*	-0.00105**	-0.000946*	-0.00112**		
	(0.000)	(0.000)	(0.001)	(0.001)		
$T_{AVG} \geq 30$°C × HHWWS (t ≥ 0)	0.00681	0.00880	0.00476	0.00609		
	(0.009)	(0.009)	(0.008)	(0.008)		
$T_{AVG} \in [20, 25)$°C × HHWWS (0 ≥ t ≥ 3)					-0.000623	-0.000611
					(0.001)	(0.000)
$T_{AVG} \in [25, 30)$°C × HHWWS (0 ≥ t ≥ 3)					-0.00103**	-0.00118**
					(0.000)	(0.000)
$T_{AVG} \geq 30$°C × HHWWS (0 ≥ t ≥ 3)					0.00457	0.00556
					(0.009)	(0.010)
$T_{AVG} \in [20, 25)$°C × HHWWS (4 ≥ t ≥ 7)					-0.000738	-0.000850
					(0.001)	(0.001)
$T_{AVG} \in [25, 30)$°C × HHWWS (4 ≥ t ≥ 7)					-0.000959	-0.000685
					(0.001)	(0.001)
$T_{AVG} \geq 30$°C × HHWWS (4 ≥ t ≥ 7)					-0.0391***	-0.0402**
					(0.013)	(0.015)
$T_{AVG} \in [20, 25)$°C × HHWWS (t ≥ 8)					-0.000658	-0.000849
					(0.001)	(0.001)
$T_{AVG} \in [25, 30)$°C × HHWWS (t ≥ 8)					-0.00182**	-0.00133
					(0.001)	(0.001)
$T_{AVG} \geq 30$°C × HHWWS (t ≥ 8)					-0.0178**	-0.0220**
					(0.007)	(0.008)
Precipitation controls	Yes	Yes	Yes	Yes	Yes	Yes
Province-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Region-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Month-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Covariates × Month	Yes	Yes	Yes	Yes	Yes	Yes
Bins × Year	Yes	Yes	Yes	Yes	Yes	Yes
Bins × Province	Yes	Yes	Yes	Yes	Yes	Yes
Bins × AC	No	Yes	No	Yes	No	Yes
Mean Outcome	0.792	0.800	0.792	0.800	0.792	0.800
Observations	8736	7176	8736	7176	8736	7176

Notes: The dependent variable is the number of deaths per 1,000 people (mortality rate). The estimated period is 1992-2019. The reference category for temperature is bin < 20 °C. Covariates include the share of population by age groups and province-level GDP per capita interacted with the month indicator. Standard errors are two-way clustered at the province and month-year level. * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$). All regressions are weighted by province population.

Table E2: The mitigation effect of heat-wave warning systems — Not-yet and Never Treated

	Mortality rate (in 1,000s)					
	Post		**Before and After**		**Dynamic**	
	DiDiT (1)	DiDiT (2)	DiDiT (3)	DiDiT (4)	DiDiT (5)	DiDiT (6)
$T_{AVG} \in [20, 25)$°C × HHWWS (t ≤ -2)			-0.0000366	-0.000144	-0.0000343	-0.000136
			(0.000)	(0.000)	(0.000)	(0.000)
$T_{AVG} \in [25, 30)$°C × HHWWS (t ≤ -2)			-0.000474	-0.000446	-0.000562*	-0.000535
			(0.000)	(0.000)	(0.000)	(0.000)
$T_{AVG} \geq 30$°C × HHWWS (t ≥ -2)			-0.00577	-0.000250	-0.00556	-0.000504
			(0.008)	(0.007)	(0.008)	(0.006)
$T_{AVG} \in [20, 25)$°C × HHWWS (t ≥ 0)	-0.000723***	-0.000727***	-0.000751**	-0.000850***		
	(0.000)	(0.000)	(0.000)	(0.000)		
$T_{AVG} \in [25, 30)$°C × HHWWS (t ≥ 0)	-0.000771	-0.000457	-0.00118***	-0.000799**		
	(0.001)	(0.000)	(0.000)	(0.000)		
$T_{AVG} \geq 30$°C × HHWWS (t ≥ 0)	-0.0113***	-0.00688	-0.0135***	-0.00697**		
	(0.004)	(0.004)	(0.003)	(0.003)		
$T_{AVG} \in [20, 25)$°C × HHWWS (0 ≥ t ≥ 3)					-0.00109***	-0.00115***
					(0.000)	(0.000)
$T_{AVG} \in [25, 30)$°C × HHWWS (0 ≥ t ≥ 3)					-0.000222	0.0000763
					(0.001)	(0.001)
$T_{AVG} \geq 30$°C × HHWWS (0 ≥ t ≥ 3)					0.00232	0.00839
					(0.008)	(0.007)
$T_{AVG} \in [20, 25)$°C × HHWWS (4 ≥ t ≥ 7)					-0.000758*	-0.000841**
					(0.000)	(0.000)
$T_{AVG} \in [25, 30)$°C × HHWWS (4 ≥ t ≥ 7)					-0.00103*	-0.000662
					(0.001)	(0.000)
$T_{AVG} \geq 30$°C × HHWWS (4 ≥ t ≥ 7)					-0.0316***	-0.0213**
					(0.010)	(0.010)
$T_{AVG} \in [20, 25)$°C × HHWWS (t ≥ 8)					-0.000621	-0.000722*
					(0.000)	(0.000)
$T_{AVG} \in [25, 30)$°C × HHWWS (t ≥ 8)					-0.00174***	-0.00140***
					(0.000)	(0.000)
$T_{AVG} \geq 30$°C × HHWWS (t ≥ 8)					-0.0135***	-0.00760
					(0.004)	(0.005)
Precipitation controls	Yes	Yes	Yes	Yes	Yes	Yes
Province-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Region-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Month-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Covariates × Month	Yes	Yes	Yes	Yes	Yes	Yes
Bins × Year	Yes	Yes	Yes	Yes	Yes	Yes
Bins × Province	Yes	Yes	Yes	Yes	Yes	Yes
Bins × AC	No	Yes	No	Yes	No	Yes
Mean Outcome	0.827	0.831	0.827	0.831	0.827	0.831
Observations	34680	28788	34680	28788	34680	28788

Notes: The dependent variable is the number of deaths per 1,000 people (mortality rate). The estimated period is 1992-2019. The reference category for temperature is bin < 20 °C. Covariates include the share of population by age groups and province-level GDP per capita interacted with the month indicator. Standard errors are two-way clustered at the province and month-year level. * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$). All regressions are weighted by province population.

Table E3: The 2004 national plan and the access to information

	Mortality rate (in 1,000s)		
	DiT	DiDiT	
	(1)	(2)	(3)
$T_{AVG} \in [20, 25)$ °C	0.00152***		
	(0.000)		
$T_{AVG} \in [25, 30)$ °C	0.00456***		
	(0.001)		
$T_{AVG} \geq 30$ °C	0.0325***		
	(0.007)		
$T_{AVG} \in [20, 25)$ °C $\times$ Newspaper Sales	0.00237	0.000384	0.00220
	(0.005)	(0.004)	(0.005)
$T_{AVG} \in [25, 30)$ °C $\times$ Newspaper Sales	0.0111	0.00860	0.0111
	(0.012)	(0.012)	(0.012)
$T_{AVG} \geq 30$°C $\times$ Newspaper Sales	-0.0620	-0.0641	0.00789
	(0.048)	(0.046)	(0.052)
$T_{AVG} \in [20, 25)$ °C $\times$ Post (2004-2019)	-0.000294	-0.000296	
	(0.000)	(0.000)	
$T_{AVG} \in [25, 30)$ °C $\times$ Post (2004-2019)	-0.000692	-0.000604	
	(0.001)	(0.001)	
$T_{AVG} \geq 30$°C $\times$ Post (2004-2019)	-0.00961	-0.00922	
	(0.007)	(0.007)	
$T_{AVG} \in [20, 25)$ °C $\times$ Post (2004-2019) $\times$ Newspaper Sales	-0.00434	-0.00407	-0.00358
	(0.004)	(0.004)	(0.004)
$T_{AVG} \in [25, 30)$ °C $\times$ Post (2004-2019) $\times$ Newspaper Sales	-0.0136*	-0.0139*	-0.0134*
	(0.008)	(0.008)	(0.008)
$T_{AVG} \geq 30$°C $\times$ Post (2004-2019) $\times$ Newspaper Sales	-0.0638	-0.0657	-0.108*
	(0.048)	(0.049)	(0.061)
Precipitation controls	Yes	Yes	Yes
Province-Month FE	Yes	Yes	Yes
Region-Year FE	Yes	Yes	Yes
Month-Year FE	Yes	Yes	Yes
Covariates $\times$ Month	Yes	Yes	Yes
Bins $\times$ Summer	No	Yes	No
Bins $\times$ Year	No	No	Yes
Mean Outcome	0.827	0.827	0.827
Observations	34320	34320	34320

Notes: The dependent variable is the number of deaths per 1,000 people (mortality rate). The estimated period is 1992-2019. The reference category for temperature is bin <20 °C. Covariates include the share of population by age groups and province-level GDP per capita interacted with the month indicator. Standard errors are two-way clustered at the province and month-year level. * $(p < 0.10)$, ** $(p < 0.05)$, *** $(p < 0.01)$. All regressions are weighted by province population.

Table E4: The 2004 national plan and the access to information — Dynamic effects

	Mortality rate (in 1,000s)	
	Before and After	**Dynamic**
	DiDiT	DiDiT
	(1)	(2)
$T_{AVG} \in [25, 30)$°C × Pre × Newspaper Sales	-0.00535	-0.00439
	(0.009)	(0.009)
$T_{AVG} \in [20, 25)$°C × Pre × Newspaper Sales	-0.0108	-0.0103
	(0.015)	(0.015)
$T_{AVG} \geq 30$°C × Pre × Newspaper Sales	-0.0426	-0.0507
	(0.117)	(0.115)
$T_{AVG} \in [25, 30)$°C × Post × Newspaper Sales	-0.00901	
	(0.008)	
$T_{AVG} \in [20, 25)$°C × Post × Newspaper Sales	-0.0190	
	(0.013)	
$T_{AVG} \geq 30$°C × Post × Newspaper Sales	-0.0962**	
	(0.044)	
$T_{AVG} \in [25, 30)$°C × Initial Imp. × Newspaper Sales		-0.0102
		(0.009)
$T_{AVG} \in [20, 25)$°C × Initial Imp. × Newspaper Sales		-0.0165
		(0.014)
$T_{AVG} \geq 30$°C × Initial Imp. × Newspaper Sales		-0.0393
		(0.086)
$T_{AVG} \in [25, 30)$°C × Full Imp. × Newspaper Sales		-0.00704
		(0.008)
$T_{AVG} \in [20, 25)$°C × Full Imp. × Newspaper Sales		-0.0184
		(0.013)
$T_{AVG} \geq 30$°C × Full × Newspaper Sales		-0.0809
		(0.049)
Precipitation controls	Yes	Yes
Province-Month FE	Yes	Yes
Region-Year FE	Yes	Yes
Month-Year FE	Yes	Yes
Covariates × Month	Yes	Yes
Bins × Year	Yes	Yes
Mean Outcome	0.827	0.827
Observations	34320	34320

Notes: The dependent variable is the number of deaths per 1,000 people (mortality rate). The estimated period is 1992-2019. The reference category for temperature is bin <20 °C. Covariates include the share of population by age groups and province-level GDP per capita interacted with the month indicator. Standard errors are two-way clustered at the province and month-year level. * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$). All regressions are weighted by province population.

Table E5: The 2004 national plan and the healthcare efficiency

	Mortality rate (in 1,000s)		
	Avg. length stay	Utilization rate	Turnover rate
	DiDiT	DiDiT	DiDiT
	(1)	(2)	(3)
$T_{AVG} \in [20, 25)$ °C × Post (2004-2019) × Efficiency	-0.00000943		
	(0.000)		
$T_{AVG} \in [25, 30)$ °C × Post (2004-2019) × Efficiency	-0.000314***		
	(0.000)		
$T_{AVG} \geq 30$°C × Post (2004-2019) × Efficiency	-0.0000259		
	(0.003)		
$T_{AVG} \in [20, 25)$ °C × Post (2004-2019) × Efficiency		-0.00409**	
		(0.002)	
$T_{AVG} \in [25, 30)$ °C × Post (2004-2019) × Efficiency		-0.00619	
		(0.004)	
$T_{AVG} \geq 30$°C × Post (2004-2019) × Efficiency		-0.0658	
		(0.082)	
$T_{AVG} \in [20, 25)$ °C × Post (2004-2019) × Efficiency			0.00632
			(0.004)
$T_{AVG} \in [25, 30)$ °C × Post (2004-2019) × Efficiency			0.0185*
			(0.010)
$T_{AVG} \geq 30$°C × Post (2004-2019) × Efficiency			0.0151
			(0.213)
Precipitation controls	Yes	Yes	Yes
Province-Month FE	Yes	Yes	Yes
Region-Year FE	Yes	Yes	Yes
Month-Year FE	Yes	Yes	Yes
Covariates × Month	Yes	Yes	Yes
Bins × Year	Yes	Yes	Yes
Mean Outcome	0.827	0.827	0.827
Observations	34320	34320	34320

Notes: The dependent variable is the number of deaths per 1,000 people (mortality rate). The estimated period is 1992-2019. The reference category for temperature is bin < 20 °C. Covariates include the share of population by age groups and province-level GDP per capita interacted with the month indicator. Standard errors are two-way clustered at the province and month-year level. * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$). All regressions are weighted by province population.