Are Heat Warnings Effective? Mitigating Heat-Related Mortality Through Adaptation

Linsenmeier[1], Savazzi[2], Wenz[3]

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Abstract:

This study investigates the mitigative effects of issuing a heat warning on the well-established heat-mortality relationship. To this end, exploiting the errors in weather forecasts, we manage to compare days with similar meteorological conditions but different heat warning statuses. Employing a fixed-effects model applied to the German states, we find that within each temperature range, the impact of rising temperatures on mortality rates is moderated by the presence of a heat warning. The contribution of our results is twofold. First, we reveal the crucial role of meteorological alerts in enhancing people's adaptive capacity to climate change. Second, we underscore the importance of accurate weather forecasts for public safety.

[1] *Princeton University*

[2] *Univ. D'Evry, Université Paris Saclay*

[3] *Potsdam Institute for Climate Impact Research*

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1. Introduction

We live in a world that is destinated to heat up rapidly in the next decades and that is already 1.5 degrees hotter than in the preindustrial time. The severe effects of exposure to heat on human health have been documented for long (Deschênes & Greenstone (2011); Rupa & Samet (2002); Bosello et al. (2006)) and have often pointed out to an exacerbation of existing inequalities (Cruz (2024); Zhang, et al., (2024)). Despite some evidence that in developed countries the extreme heat is becoming less fatal over time (Barreca, et al., 2016), recent papers using daily data proof that heat caused mortality has been largely underestimated in the past (Huber, et al., 2024) even when accounting for adaptation (Carleton, et al., 2022). In Europe alone in the summer 2022 more than 61'600 people died because of heat stress (Ballester, et al., 2023).

The unavoidability of more frequent extreme heat hazards poses serious questions on how we can reduce the risk for human health making our communities resilient to the new climate. Since the late '90s, in the US at first, and in Europe later, early warning systems for heat stress have been put in place with the intent to reduce the exposure to heat, particularly of vulnerable people. Recently, in Europe operational, open-access, continental heat-cold-health early warning system has been implemented (Quijal-Zamorano, et al., (2024) Ballester, et al., (2024)). This advanced system not only uses weather forecast to issue warning, but it also considers the vulnerability and exposure of people and manages to produce gender and age group specific warnings both for heat and cold waves. At the same time however, despite the WMO great efforts to implement a global early warning system, today still 63% of the countries do not have an early warning system and most of them are developing and low-income countries (UN-WMO, 2024).

Despite a political consensus on the importance of informing people of the upcoming hazards, the academic literature has found mixed effects of the implementation of early warning systems on mortality and human health in general. Studies that have focused on the case of single North American cities found that early warning systems have reduced heat related mortality in cities like Toronto, Montreal, Philadelphia and New York (Smoyer-Tomic & Rainham, (2001); Benmarhnia et al., (2016); Ebi et al, (2004); Benmarhnia et al., (2019)). Likewise, papers that have looked at Asian cities lead to similar conclusions (Chau et al., (2009); Heo, et al., (2019)). On the contrary, Weinberger, et al., (2021) finds no effects on mortality of warning when looking at the entire US.

Each early warning system has its own particularities and characteristics. For this reason, the external validity of the cited studies is not to be taken for granted. As no study has so far looked at any European country we focus our research on the case of Germany. Germany offers a particularly interesting case study for several reasons. First, its warning system is very advanced and uses not only temperature but a much more comprehensive indicator of perceived temperature as well as night temperature and other weather factors that influence people's risk for heath. Second, Germany has significant climatic variability, with regions experiencing extremely high summer temperatures and others maintaining more temperate conditions. Third, in Germany there is high socioeconomic heterogeneity across states, which makes a comparison of the effects of alerts under heterogeneous climatic and economic conditions possible.

In our study, we aim to analyse the impact of heat alerts on the relationship between temperature and mortality in Germany. Using a fixed effects model applied to state data, we exploit discrepancies in weather forecasts to compare days with similar weather conditions but different alert states.

To the best of our knowledge, except for Weinberger, et al., (2021) we are the first to cover a long time period and an entire country. Although Weinberger, et al., (2021) represents a fundamental reference in the literature, in our work we manage to go in more details as we do not only look at the impact of maximum temperature and vapor pressure on mortality, but we also consider other climatic factors of the day, notably night temperature and the temperature of the previous days. Wang et al., (2024) shows that night temperatures have fatal effects on humans and are at the same time often used in the decision process of warning issuing, even in the US. It is therefore fundamental to account for it in the model as we do below. Finally, we bring novelty in the fact that we look at the heterogeneity of the effectiveness of warnings across temperatures and we explore the role of the fatigue to warnings. Our findings indicate that heat alerts systems are important to help people reducing their risk of dying due do heat. Moreover, we find that warnings are more effective at lower, but still hot, temperatures compared to extremely high ones, and that the first day of a series of warning days is the one in which most lives are saved.

The effectiveness of the warning system is strictly linked to the accuracy of weather forecasting. With our work, we therefore contribute to another stream of literature that advocate for more precise weather forecasting (Song, (2024); Downey et al., (2023)). Our results are in line with those of Shrader et al., (2023) that estimates the cost in terms of mortality of errors in weather forecast in the US. Finally, our findings have some implications for effectively implementing early warning systems in low-income countries. Indeed, these countries suffer from a largely inadequate weather forecast precision (Linsenmeier & Shrader, 2023) that makes the efforts in implementing early warning systems (UN-WMO, 2024) less effective.

In the next sections we proceed as follows: In Section 2 we present the data and in Section 3 the methodologies. Section 4 presents the results of the baseline model, while Section 5 explores the heterogeneity and the robustness of our results. Finally, we conclude with Section 6.

2. Data

To estimate the efficacy of heat warnings in reducing heat related mortality we have merged meteorological data and early heat warnings from the Deutscher Wetterdienst (Section 2.1) with data on mortality and population from the German Statistical Office (Section 2.2). Moreover, using the “suncalc” R package we obtain the daylight time of the geographical centre of each state in each day, and we have matched the dataset with the official German holiday calendar.

2.1. Meteorological and Warning Data

We obtained the weather station records of hourly observations for temperature, humidity and cumulative precipitations for each weather station within the German territory over the period 2005 - 2023 from the Deutscher Wetterdienst (DWD). These data are publicly available on the DWD opendata website[1]. The distribution of the stations in Germany is reported in Figure 1. Missing observations are imputed by iteratively training a Lasso model with cross-validated sparsity parameter for every station on all other stations. We then aggregated the 3 variables (temperature, humidity and precipitations) at district[2] and hour level by assigning a weighted average of the 3 stations closest to the centroid of each district using as weights the inverse distance from the centroid. The DWD uses forecasts for 12 UTC noon to inform the decision process of warning issuing. Therefore, we used temperature, humidity and precipitation at noon for each day and district. Moreover, we obtain night temperature and night humidity as the average of the temperatures and humidities respectively

[1] https://opendata.dwd.de/climate_environment/CDC/observations_germany/climate/hourly/

[2] In Germany there are 401 districts and 16 States.

registered between 10pm on day -1 and 6am of the current day. Furthermore, using the DWD model illustrated in Matzarakis et al., (2020), we computed the physically equivalent temperature (PET) for each day and district combination. We ran the DWD model with the temperature and humidity at noon obtained as described above. The remaining variables needed to compute PET are taken from the same DWD source when available and from the ERA5 dataset otherwise[3].

In the decision process of the DWD to issue a warning the variables that are taken into account are perceived temperature (PT), night temperature and humidity, and the temperature of the previous 30 days (Matzarakis, Laschewski, & Muthers, 2020). In our model we use physically equivalent temperature (PET) instead of PT because the model provided by the DWD to compute PT introduces many gaps and accumulation points in the frequency distribution. The temperature of the previous 30 days is important to be able to account for body adaptation to high temperature over time. We have constructed our previous 30 days PET variable by taking the average of PET in the previous 30 days and assigning lower weights to days further in time (from 1/30 for day -30, to 30/30 for day -1). Finally, the heat warning records are obtained from the DWD opendata historical database[4]. This database contains a list of the days for which a heat warning was issued at district level. We generate a dummy variable that takes value 1 if a warning was issued for that day and district and 0 otherwise.

As we will see in the next section, daily mortality data are only available at the state level. For this reason, we must aggregate all our meteorological variables from the district to the state level. To do so, for each of the variables described above, except for the heat warning dummy, we take the average across all districts within each state weighting by the population of the district in the corresponding trimester. As for warnings we aggregate the dummy variable in several manners across which we test the robustness of our results (Section 5.6). The main model uses a dummy variable that takes value 1 if all the districts within the state were under warning and 0 otherwise. We then also produce other version of the state level warning variable by assigning value 1 if at least 25% of the population within the state was under warning, and we do the same putting 50% and 75% as thresholds.

In Figure 2 we show the relationship between temperature at noon and PET at noon. We aggregate observations every 0.1C° for temperature and distinguish between observations with a relative humidity above average in red and below average in blue within each 0.1C° temperature aggregation. We observe that in general PET increases with temperature but for low temperatures PET is lower when humidity is high, while this relationship is almost reverted for high temperatures. The fact that the difference in the two means of humidity is shrinking with temperature (light colours), is part of the explanation of the convergence of the two dark lines.

In Figure 3 we show the distribution of PET distinguishing by heat warning days and non-warning days. in the left part of the figure we show the entre distribution, in the right one we zoom in to the upper tail of the distribution where we find both observations with and without warning for a same PET value. We observe that for values of PET above 25 degrees there are already observations with warning and observations without. The number of days with warning follows a surprisingly normal

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[3] Air temperature, vapor pressure (as a measure of humidity), surface air pressure, wind speed, and mean radiant temperature (as a measure of solar radiation) are the other variables needed to compute PET. All of these except for mean radiant temperature are also from the DWD station data and processed the same way as described for temperature and humidity. For wind speed we assume a logarithmic wind profile to map from wind speed at 10 m to wind speed at 2 meters (this is a standard assumption; we assume a "roughness length" of 0.1 m). The DWD does not provide mean radiant temperature (MRT) so we took it from ERA5. MRT is also extracted for 12 UTC and the aggregation from grid points to districts is done the same way as for the DWD station data.

[4] https://opendata.dwd.de/climate_environment/health/historical_alerts/heat_warnings/

distribution centred at 31.5C° PET. Finally, there are no more observations without warning for PET>35. The range between 25C° and 35C° is what allows us to compare days similar in PET but with different warning status.

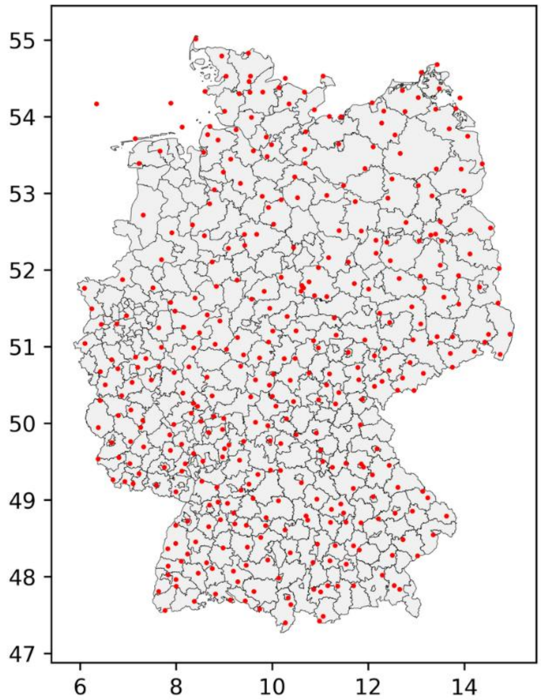

Figure 1: Distribution of weather stations in Germany

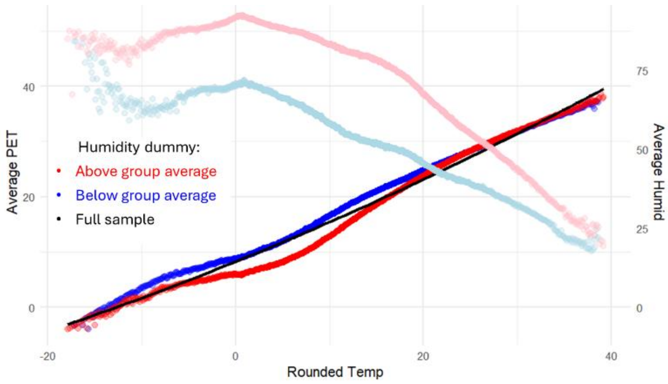

Figure 2: Scatterplot of rounded temperature and PET by humidity above and below average
Notes: in dark colours PET, in light colours humidity

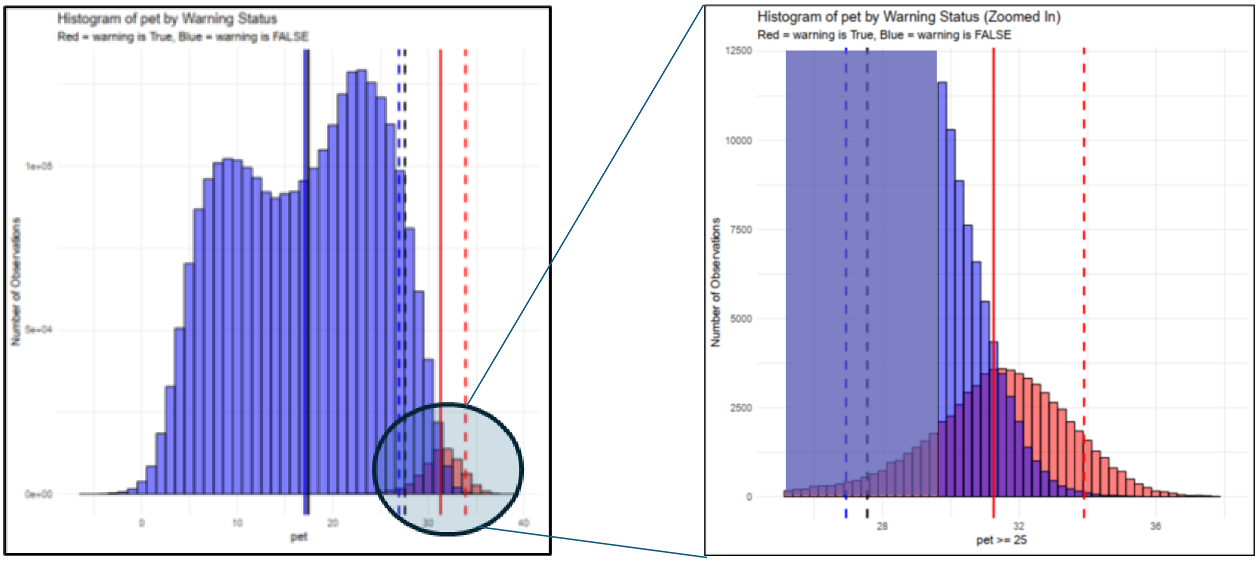

Figure 3: Frequency distribution of PET distinguishing by warning days in red and non-warning days in blue. On the right a zoom in to high temperature.

2.2. Mortality and Population Data

We obtained the mortality data from the German Statistical Office (DESTATIS)[5]. Daily number of deaths for each German state are publicly available from 2000 to 2024. From DESTATIS we obtained also data on the number of inhabitants per state at the trimester level[6]. Dividing the number of deaths in a day by the corresponding number of inhabitants and multiplying by 100 thousand, we obtain a mortality rate every 100th inhabitants at daily level for all the 16 German states. The average daily mortality rate all year round is 3.17 deaths every 100’000 inhabitants[7]. Finally, from the same data source we compute the share of people over 75 years old over the total population, obtaining an estimate at a trimestral frequency for each state.

In Figure 4 we show the relationship between PET and mortality distinguishing by warning and non-warning days. In this figure we have aggregated observations every 0.5C° PET. From this figure we can observe that the relationship between PET and mortality is positive for temperatures above 20C°. The difference in mortality within each PET bin between warning and non-warning days is unclear. However, an explanation for this is that, because of how the warning issuing process is made by the DWD, even if we are comparing observations with similar PET days with warning have a higher probability of having higher night temperatures and lower temperatures in the previous 30 days, which in turns increase mortality. For this reason, it is fundamental to account for all the factors that affect the probability of issuing a warning and to look at the impact of warning through PET as we do below.

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[5] https://www.destatis.de/DE/Themen/Gesellschaft-Umwelt/Bevoelkerung/Sterbefaelle-Lebenserwartung/_inhalt.html#_c6uskug3s

[6] https://www-genesis.destatis.de/genesis//online?operation=table&code=12411-0012&bypass=true&levelindex=0&levelid=1725974287379#abreadcrumb

[7] Considering only the subset of days used in our model as explained later in Section 3, the mortality rate is lowered to 3.07, indicating that in summer there is generally a lower risk of dying.

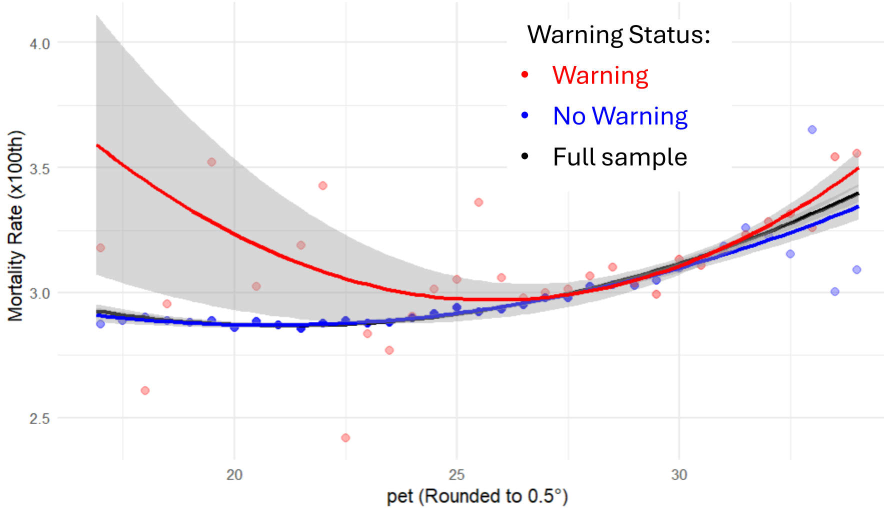

Figure 4: Scatterplot of rounded PET and mortality rate with quadratic fits distinguishing by warning and non-warning days.

3. Methods

After having merged all the dataset described above, we obtain a panel with, for each of the 16 German states, one observation for each day between 2005 and 2023. The heat warning system is only active in the hot months from May to September included. For this reason, we subset our sample to this period of the year. Moreover, in order to compare days with warning with days without warning that are as similar as possible based on the climatic conditions, but keeping enough observation within each group of comparison, we further subset the sample by restricting to observations within certain boundaries of PET. These limits are chosen as follows: we start from the highest registered PET and we create bins of PET every 0.5C°. Then we only include observations that are in those bins for which there are at least 10 observations with warning and 10 without warning. In this way we remove the highest values of PET (PET > 34.5) because there are not enough non warning observations and, similarly we exclude low PET values (PET <= 27) because there are not enough warning observations.

We then define a fixed effects (FE) liner model to identify the difference in mortality related to PET between warning and non-warning days within each state, year and 0.5C° PET bin, controlling for the other climatic and sociodemographic variables.

$$(1)\ mortality_{s,d} = \alpha_{s,y} + \beta_1 PET_{s,d} + \beta_2 warning_{s,d} + \beta_3 (warning\colon PET)_{s,d} + \gamma J + \delta_y + \theta_s + \sigma_m + \omega_b + \varepsilon_{s,d}$$

Where:

- $mortality_{s,d}$ is the mortality rate every 100’000 inhabitants in sate s on day d as defined in Section 2.2
- $PET_{s,d}$ is the population weighted average of the districts’ physically equivalent temperature in sate s on day d as described in Section 2.1
- $warning_{s,d}$ is a dummy variable = 1 if all the districts within the state s are under heat warning on day d
- δ_y is a set of dummies for each year y
- θ_s is a set of dummies for each of the 16 states s

- σ_m is a set of dummies for each of the 5 months-of-the-year m considered (from May to September)
- ω_b is a set of dummies for each PET 0.5C° bin b
- $\varepsilon_{s,d}$ is the overall error term for each sate s on day d
- J is a Nxj matrix of control variables with j being the number of control variables and N the number of observations ($N = S * D$)
- γ is a vector of j coefficients

The J control variables are the following as described in Section 2:

- $Previous\ 30d\ PET_{s,d}$ is the weighted average of the PET variable observed in the previous 30 days weighted by the distance from the current day
- $Night\ Humid_{s,d}$ is the average humidity during the night hours
- $Night\ Temp_{s,d}$ is the average temperature during the night hours
- $Precip_{s,d}$ is the cumulative precipitation at noon
- $Share\ of\ over\ 75_{s,t}$ is the share of residents over 75 years old in each state and each trimester
- $Population_{s,t}$ is the total population in each state and each trimester
- $Daylight_{s,d}$ is the difference in time between sunset and sunrise
- $Holiday\ or\ Weekend_{s,d}$ is a dummy variable equal 1 if the state is on holiday or if it is weekend, 0 otherwise
- $City_s$ is a dummy variable equal 1 if the state contains a municipality with more than 100 thousand inhabitants and 0 otherwise. This variable is interacted with $Night\ Temp_{s,d}$ and $Night\ Humid_{s,d}$ to capture urban heat island effects

The state effects capture the specificities of each state that do not vary over time, while the year effects capture everything that is common across states within each year. This is of extreme importance as the DWD decision process of issuing heat warnings has changed over time. To make sure we are comparing days within groups of similar risk of death we also control for the month of the year and for PET bins of 0.5C° size FEs. All the other control variables also serve to avoid omitted variable bias of those variables that simultaneously affects risk of dying and the probability of issuing a warning or the probability that this warning is equally acknowledged by the population.

The fixed effects linear model (1) is estimated using heteroskedasticity robust standard errors. We intentionally decided not to use clustered standard errors following Angrist & Jörn-Steffen, (2009) that sets 40-50 clusters as a rule of thumb for the minimum number of clusters. However, the Breusch-Pagan test still detects heteroskedasticity. We therefore use heteroskedasticity robust standard errors.

Our main coefficient of interest is β_3 that identifies how, within each FE group, the impact of a marginal increase of PET on the mortality rate differs in cases when there is a warning and when there is not. Indeed, excluding the interaction term to analyse the direct impact of warning on mortality would probably capture other factors that simultaneously affect the choice of issuing a warning and mortality. Although in our model we control for all the variables that the DWD uses to make a decision, we cannot know how exactly these variables are used and which weights are given to them in the process. However, looking at the indirect effect of warning through PET and within each PET 0.5C° bin, allows us to concentrate on one component at the time and properly infer the effects of warning on mortality through PET rather than an overall effect of warning.

4. Results

The results of the estimation of Model (1) are presented in Table 1. We can observe that the coefficient for the interaction term (β_3 = -0.0202) is negative and significant, which means that the presence of a warning reduces the impact of PET on mortality. Specifically, it suggests that when a warning is in place, a unit increase in PET (within each PET 0.5°C bin) results in 0.0202 fewer deaths per 100,000 inhabitants per day than it would without the warning. 0.0202 is equal to 0.66% of the average daily mortality rate in our sample. Moreover, we can interpret the coefficient of the warning variable as the total effect of warning on mortality when PET = 0. Being β_3 negative, we know that the overall effect of warning on mortality becomes smaller when PET increases. To estimate the value of PET for which the total effect of warning on mortality becomes negative we need to solve:

$$0 = \beta_2 + \beta_3 * PET$$

that leads to:

$$PET = \frac{0.6875}{0.0202} = 34.05 \text{ C}^\circ$$

This indicates that when PET = 34.05C° also the overall effects of warning on mortality becomes negative.

Table 1: The mitigative effects of warning on heat related mortality

	Dep. var: Mortality_rate_x100th Baseline (1)
PET	0.0042
	(0.0248)
Warning	0.6875**
	(0.3079)
PET × Warning	-0.0202**
	(0.0099)
Previous 30d PET	-0.0042**
	(0.0017)
Night Humid	7.27×10^{-5}
	(0.0006)
Night Temp	0.0437***
	(0.0023)
Precip	0.0251
	(0.0583)
Share of over 75	12.29***
	(0.9468)
Population	-2.25×10^{-7}***
	(3.36×10^{-8})
Holiday or Weekend	-0.0471***
	(0.0081)
Daylight	-0.0131
	(0.0097)
Night Humid × City	-6.12×10^{-5}
	(4.04×10^{-5})
Night Temp × City	0.0003
	(0.0002)
Standard-Errors	Hetero.-robust
Observations	11,470
R^2	0.56927
Within R^2	0.10088
State fixed effects	✓
Year fixed effects	✓
Temperature_bin_0.5deg_PET fixed effects	✓
month_of_year fixed effects	✓

Notes: Significance codes: '***' 0.01 '**' 0.05 '*' 0.1

The remaining variables have an intuitive coefficient's sign. As assumed by Matzarakis et al., (2020) the previous 30 days temperature plays an adaptation role. Night temperatures are associated with higher mortality and especially, even if not significantly, in cities. A higher share of elderly people increases the mortality rate and more inhabited states, probably due to better services, register lower mortality. Moreover, mortality is significantly lower during holiday and weekends. In the Appendix we also show the same results of Model (1) including the coefficients of the 0.5C° PET bins. As expected, higher PET bins are associated with higher mortality rates, and they capture most of the variation making β_1 non-significant.

5. Robustness and Additional Results

In this section we test for different specifications of Model (1). We look at other indirect effects of warning on mortality and at what happens when we increase the PET bin size within which we observe the effects of warning. We test if after the first day of warning within a row of warning days the mitigative effects on mortality are different and we explore the heterogeneity across PET groups.

5.1. Changing PET Bin Size

In this section we estimate what happens when we gradually increase the size of the bins of PET in the fixed effects. Making the range wider, we allow for more observations within each bin, but we are simultaneously allowing observations within each bin to be less similar and therefore comparable. For a clear comparison, we prefer, in this case, to maintain the same sample in all the models. The choice is between keeping the same sample in which we use PET bins of size 0.5C° to determine if there are et least 10 observations per group, or instead using different bin sizes not only as FE controls but also for the exclusion of observations with not enough counterfactuals.

Table 2 presents the results. We observe that increasing the size of the bins makes the effects of PET within the bins more significant while it reduces the significance of the mitigative effects of warnings. This result is in line with the expectations, warning is now just capturing the observations that within each bin have higher PET and in turn higher mortality.

Table 2: Warning effects with different PET bin FE size

	Dep. var: Mortality Rate x100th				
	Baseline	PET Bin 1 C°	PET Bin 2 C°	PET Bin 3 C°	PET Bin 5 C°
	(1)	(2)	(3)	(4)	(5)
PET	0.0042	0.0322**	0.0346***	0.0210***	0.0176***
	(0.0248)	(0.0126)	(0.0066)	(0.0056)	(0.0034)
Warning	0.6875**	0.6797**	0.5251*	0.3304	0.3476
	(0.3079)	(0.3024)	(0.2880)	(0.2683)	(0.2833)
PET × Warning	-0.0202**	-0.0200**	-0.0149	-0.0085	-0.0090
	(0.0099)	(0.0097)	(0.0092)	(0.0086)	(0.0091)
Previous 30d PET	-0.0042**	-0.0042**	-0.0042**	-0.0041**	-0.0042**
	(0.0017)	(0.0017)	(0.0017)	(0.0017)	(0.0017)
Night Humid	7.27×10^{-5}	7.91×10^{-5}	6.98×10^{-5}	2.88×10^{-5}	5.79×10^{-5}
	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)
Night Temp	0.0437***	0.0438***	0.0438***	0.0438***	0.0438***
	(0.0023)	(0.0023)	(0.0023)	(0.0023)	(0.0023)
Precipitations	0.0251	0.0255	0.0269	0.0269	0.0252
	(0.0583)	(0.0583)	(0.0583)	(0.0585)	(0.0583)
Share of over 75	12.29***	12.30***	12.31***	12.31***	12.35***
	(0.9468)	(0.9461)	(0.9457)	(0.9467)	(0.9471)
Population	$-2.25 \times 10^{-7***}$	$-2.25 \times 10^{-7***}$	$-2.25 \times 10^{-7***}$	$-2.26 \times 10^{-7***}$	$-2.23 \times 10^{-7***}$
	(3.36×10^{-8})	(3.36×10^{-8})	(3.35×10^{-8})	(3.36×10^{-8})	(3.36×10^{-8})
Holiday or Weekend	-0.0471***	-0.0469***	-0.0469***	-0.0461***	-0.0462***
	(0.0081)	(0.0081)	(0.0081)	(0.0081)	(0.0081)
Daylight	-0.0131	-0.0131	-0.0130	-0.0132	-0.0132
	(0.0097)	(0.0097)	(0.0097)	(0.0097)	(0.0097)
Night Humid × City	-6.12×10^{-5}	-6.03×10^{-5}	-6.31×10^{-5}	-6.12×10^{-5}	-6.43×10^{-5}
	(4.04×10^{-5})	(4.03×10^{-5})	(4.04×10^{-5})	(4.04×10^{-5})	(4.03×10^{-5})
Night Temp × City	0.0003	0.0002	0.0003	0.0003	0.0003
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Standard-Errors	Heteroskedasticity-robust				
Observations	11,470	11,470	11,470	11,470	11,470
R^2	0.56927	0.56912	0.56879	0.56841	0.56824
Within R^2	0.10088	0.10261	0.10950	0.11145	0.12768
State fixed effects	✓	✓	✓	✓	✓
Year fixed effects	✓	✓	✓	✓	✓
Month of the year fixed effects	✓	✓	✓	✓	✓
PET Bin FE	0.5 C°	1 C°	2 C°	3 C°	5 C°

Notes: Significance codes: '***' 0.01 '**' 0.05 '*' 0.1

5.2. Warning Effects through other Climate Variables

In this section we show that the indirect effects of warning on mortality reduction are not only visible through the physically equivalent temperature, but also through temperature itself. However, the effects through the night temperatures are not significant. In this case, as indicated by the different number of observations in the models, we also change the sample from one model to the other. Indeed, in each model we control for fixed effects relative to the variable that we want to analyse. For instance, when we look at the impacts of warning on mortality through temperature, we control for 0.5C° bins for temperature instead of PET. For this reason, we need to guarantee that within each temperature bin there are more than 10 observations both for warning and no warning cases. The same thing applies to the night temperature model. The results are in Table 3.

Table 3: Warning effects on mortality through different weather variables

	Dep. var: Mortality Rate x100th		
	Baseline	Via Temp	Via Night Temp
	(1)	(2)	(3)
PET	0.0042	0.0149***	0.0178***
	(0.0248)	(0.0052)	(0.0012)
Warning	0.6875**	0.3853**	-0.1396
	(0.3079)	(0.1862)	(0.1259)
Previous 30d PET	-0.0042**	-0.0030*	-0.0061***
	(0.0017)	(0.0017)	(0.0014)
Night Humid	7.27×10^{-5}	0.0008	0.0013***
	(0.0006)	(0.0006)	(0.0005)
Night Temp	0.0437***	0.0457***	0.0837***
	(0.0023)	(0.0025)	(0.0209)
Precipitations	0.0251	0.0431	0.0661***
	(0.0583)	(0.0593)	(0.0191)
Share of over 75	12.29***	11.99***	11.99***
	(0.9468)	(0.9776)	(0.7784)
Population	$-2.25 \times 10^{-7***}$	$-2.49 \times 10^{-7***}$	$-2.44 \times 10^{-7***}$
	(3.36×10^{-8})	(3.52×10^{-8})	(2.88×10^{-8})
Holiday or Weekend	-0.0471***	-0.0474***	-0.0561***
	(0.0081)	(0.0084)	(0.0067)
Daylight	-0.0131	-0.0173*	-0.0087
	(0.0097)	(0.0102)	(0.0077)
Night Humid × City	-6.12×10^{-5}	$-9.93 \times 10^{-5**}$	$-8.15 \times 10^{-5***}$
	(4.04×10^{-5})	(4.41×10^{-5})	(2.99×10^{-5})
Night Temp × City	0.0003	0.0004*	
	(0.0002)	(0.0002)	
Temperature		0.1006***	
		(0.0266)	
PET × Warning	-0.0202**		
	(0.0099)		
Temperature × Warning		-0.0120*	
		(0.0065)	
Night Temp × Warning			0.0108
			(0.0068)
Standard-Errors		Heteroskedasticity-robust	
Observations	11,470	10,254	16,874
R^2	0.56927	0.57490	0.56044
Within R^2	0.10088	0.10700	0.06185
State fixed effects	✓	✓	✓
Year fixed effects	✓	✓	✓
Month of the year fixed effects	✓	✓	✓
PET bin 0.5 CFE	✓		
Temperature bin 0.5 CFE		✓	
Night Temp bin 0.5 CFE			✓

Notes: Significance codes: '***' 0.01 '**' 0.05 '*' 0.1

5.3. Warning Fatigue

To test if people can maintain their adaptive behaviour for multiple days, we divide the warning variable in 5 groups. As in the baseline model, warning = 0 if not all the districts within the state are under warning. However, in Model (2) of Table 4, warning is = 1 if the entre state is under warning and it is the first day to be so (namely, on day -1 warning was 0). Warning is = 2 if it is the second day of warning for the entire state and so on up to warning = 4 that indicates if the entire state is in its 4th or later day of warning. By factorising this new warning variable, we compare the reference value of warning (warning = 0) with each of the other warning values. To make observations even more comparable we further control for the lag of the original warning variable that takes value 1 if the previous day was a warning day and 0 otherwise. From the results in Table 4 we observe that the effects of warning are only significant for the first day of warning suggesting that after a day, people get some level of warning fatigue. In model 3 we reproduce the baseline model adding only the lag of the warning dummy. The results remain unchanged.

Table 4: Warning effects on mortality distinguishing by the duration of the warning

	Dep. var: Mortality Rate x100th		
	Baseline	Factor Warning and Lag	Control for Lag
	(1)	(2)	(3)
PET	0.0042	0.0046	0.0054
	(0.0248)	(0.0246)	(0.0247)
Warning dummy	0.6875**		0.6243**
	(0.3079)		(0.3097)
Previous 30d PET	-0.0042**	-0.0063***	-0.0056***
	(0.0017)	(0.0017)	(0.0017)
Night Humid	7.27×10^{-5}	-2.07×10^{-5}	-1.69×10^{-5}
	(0.0006)	(0.0006)	(0.0006)
Night Temp	0.0437***	0.0377***	0.0381***
	(0.0023)	(0.0024)	(0.0023)
Precipitations	0.0251	0.0320	0.0300
	(0.0583)	(0.0579)	(0.0578)
Share of over 75	12.29***	12.26***	12.32***
	(0.9468)	(0.9433)	(0.9437)
Population	$-2.25 \times 10^{-7***}$	$-2.18 \times 10^{-7***}$	$-2.19 \times 10^{-7***}$
	(3.36×10^{-8})	(3.34×10^{-8})	(3.34×10^{-8})
Holiday or Weekend	-0.0471***	-0.0475***	-0.0474***
	(0.0081)	(0.0080)	(0.0080)
Daylight	-0.0131	-0.0091	-0.0093
	(0.0097)	(0.0097)	(0.0097)
PET × Warning	-0.0202**		-0.0206**
	(0.0099)		(0.0100)
Night Humid × City	-6.12×10^{-5}	$-6.5 \times 10^{-5*}$	-5.96×10^{-5}
	(4.04×10^{-5})	(3.9×10^{-5})	(3.91×10^{-5})
Night Temp × City	0.0003	0.0003*	0.0003*
	(0.0002)	(0.0002)	(0.0002)
Warning Factor, Day 1, ref = 0		1.294***	
		(0.4171)	
Warning Factor, Day 2, ref = 0		0.1698	
		(0.5495)	
Warning Factor, Day 3, ref = 0		0.0165	
		(0.5676)	
Warning Factor, Day 4+, ref = 0		0.3197	
		(0.5359)	
PET × Warning Factor, Day 1, ref = 0		-0.0412***	
		(0.0133)	
PET × Warning Factor, Day 2, ref = 0		-0.0092	
		(0.0173)	
PET × Warning Factor, Day 3, ref = 0		-0.0024	
		(0.0180)	
PET × Warning Factor, Day 4+, ref = 0		-0.0101	
		(0.0171)	
Warning Lag 1 day		0.1966***	0.1626***
		(0.0242)	(0.0161)
Standard-Errors		Heteroskedasticity-robust	
Observations	11,470	11,470	11,470
R^2	0.56927	0.57456	0.57360
Within R^2	0.10088	0.11191	0.10991
State fixed effects	✓	✓	✓
Year fixed effects	✓	✓	✓
Month of year fixed effects	✓	✓	✓
PET bin 0.5 C° FE	✓	✓	✓

Notes: Significance codes: '***' 0.01 '**' 0.05 '*' 0.1

5.4. Heterogeneous Effects for Low and High PET

In this subsection we answer the following question: “Are heat warning more effective at high or low values of PET?”, namely are most lives saved when warning is issued for lower (but still dangerous) temperatures or for extremely high ones? The answer to this question is shown in Table 5, in which we divided PET into 3 ranges: 27-29.5 C°; 29.5-32 C°; 32-34.5 C°. The coefficients for PET alone and for PET x Warning refer to the reference PET group which here is the low range 27-29.5 C°. The coefficients for Mid and High PET are to be interpreted with respect to this reference PET coefficients. From the table we can infer that the effects of warning mitigate mortality for all PET ranges, but they do less so for the mid values and significantly less so for the high values of PET. This suggest that it is important to issue warnings starting from low values of PET.

Table 5: The heterogeneous effect of warning on mortality by PET value

	Dep. var: Mortality Rate x100th	
	Baseline	Heterogeneity over PET
	(1)	(2)
PET	0.0042	0.0109
	(0.0248)	(0.0251)
Warning	0.6875**	1.629**
	(0.3079)	(0.6594)
Previous 30d PET	-0.0042**	-0.0042**
	(0.0017)	(0.0017)
Night Humid	7.27×10^{-5}	8.31×10^{-5}
	(0.0006)	(0.0006)
Night Temp	0.0437***	0.0437***
	(0.0023)	(0.0023)
Precipitations	0.0251	0.0250
	(0.0583)	(0.0582)
Share of over 75	12.29***	12.30***
	(0.9468)	(0.9473)
Population	$-2.25 \times 10^{-7***}$	$-2.24 \times 10^{-7***}$
	(3.36×10^{-8})	(3.36×10^{-8})
Holiday or Weekend	-0.0471***	-0.0472***
	(0.0081)	(0.0081)
Daylight	-0.0131	-0.0132
	(0.0097)	(0.0097)
PET × Warning	-0.0202**	-0.0539**
	(0.0099)	(0.0229)
Night Humid × City	-6.12×10^{-5}	-6.27×10^{-5}
	(4.04×10^{-5})	(4.04×10^{-5})
Night Temp × City	0.0003	0.0003
	(0.0002)	(0.0002)
PET Mid		-0.0018
		(0.0022)
PET High		-0.0076**
		(0.0035)
PET Mid × Warning		0.0031
		(0.0020)
PET High × Warning		0.0054*
		(0.0031)
Standard-Errors	Heteroskedasticity-robust	
Observations	11,470	11,470
R^2	0.56927	0.56943
Within R^2	0.10088	0.10120
State fixed effects	✓	✓
Year fixed effects	✓	✓
Month of year fixed effects	✓	✓
PET bin 0.5 C° FE	✓	✓

Notes: Significance codes: '***' 0.01 '**' 0.05 '*' 0.1

5.5. Robustness to Control Variables

In this section we test for the stability of the interaction term coefficient (our main coefficient of interest of model (1)) while adding and removing control variables. In Table 6, we show that our results are robust to the variation of the control variables and that the mitigative effects of warning on mortality through PET are stable across models. However, using fixed effects is crucial for our estimation.

Table 6: Robustness of the effects of warning on mortality to different control variables

	Dep. var: Mortality Rate x100th			
	Baseline	Only Clim Contr	No Contr FE	No Contr OLS
	(1)	(2)	(3)	(4)
PET	0.0042	-0.0002	0.0271	0.0659***
	(0.0248)	(0.0253)	(0.0260)	(0.0041)
Warning	0.6875**	0.6650**	1.491***	-0.2395
	(0.3079)	(0.3131)	(0.3225)	(0.3441)
Previous 30d PET	-0.0042**	-0.0052***		
	(0.0017)	(0.0017)		
Night Humid	7.27×10^{-5}	-0.0001		
	(0.0006)	(0.0006)		
Night Temp	0.0437***	0.0439***		
	(0.0023)	(0.0023)		
Precipitations	0.0251	0.0164		
	(0.0583)	(0.0587)		
Share of over 75	12.29***			
	(0.9468)			
Population	-2.25×10^{-7}***			
	(3.36×10^{-8})			
Holiday or Weekend	-0.0471***			
	(0.0081)			
Daylight	-0.0131			
	(0.0097)			
PET × Warning	-0.0202**	-0.0193*	-0.0438***	0.0081
	(0.0099)	(0.0101)	(0.0104)	(0.0110)
Night Humid × City	-6.12×10^{-5}	-2.64×10^{-5}		
	(4.04×10^{-5})	(4.07×10^{-5})		
Night Temp × City	0.0003	0.0003*		
	(0.0002)	(0.0002)		
Constant				1.135***
				(0.1170)
Standard-Errors		Heteroskedasticity-robust		
Observations	11,470	11,470	11,470	11,470
R^2	0.56927	0.55196	0.52592	0.04152
Within R^2	0.10088	0.06474	0.01038	
State fixed effects	✓	✓	✓	
Year fixed effects	✓	✓	✓	
Month of the year FE	✓	✓	✓	
PET bin 0.5 C° FE	✓	✓	✓	

Notes: Significance codes: '***' 0.01 '**' 0.05 '*' 0.1

5.6. Different Aggregations of Warning

In our baseline model we aggregate the warning variable from the district to the state level giving value 1 if all the districts within the state are under warning. Here we explore what happens when we change the definition of warning at the state level. In Table 7, we change the threshold to assign value 1 to the dummy variable. In model 2 we impose value 1 if at least 25% of the population within the state is under warning, and 0 otherwise. In model 3 and 4 we do the same but increasing the threshold to 50% and 75% respectively. In Model 5 instead, we define the warning variable as the share of inhabitants of the state that are under warning. Therefore, in this case, the warning variable is continuous and not binary. Although the coefficient of the interaction term remains negative in all model specifications, its significance is only strong in the baseline model.

Table 7: Robustness of the effects of warning on mortality to different data aggregation methods

	Dep. var: Mortality Rate x100th				
	Baseline (1)	Warning 25% (2)	Warning 50% (3)	Warning 75% (4)	Warning Share (5)
PET	0.0042	-0.0011	0.0009	0.0018	-0.0004
	(0.0248)	(0.0248)	(0.0248)	(0.0248)	(0.0248)
Previous 30d PET	-0.0042**	-0.0041**	-0.0039**	-0.0040**	-0.0039**
	(0.0017)	(0.0017)	(0.0017)	(0.0017)	(0.0017)
Night Humid	7.27×10^{-5}	-0.0001	-0.0001	-1.98×10^{-6}	-0.0001
	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)
Night Temp	0.0437***	0.0424***	0.0425***	0.0432***	0.0421***
	(0.0023)	(0.0023)	(0.0023)	(0.0023)	(0.0023)
Precipitations	0.0251	0.0232	0.0207	0.0247	0.0192
	(0.0583)	(0.0587)	(0.0585)	(0.0585)	(0.0585)
Share of over 75	12.29***	12.08***	12.18***	12.16***	12.15***
	(0.9468)	(0.9460)	(0.9459)	(0.9462)	(0.9457)
Population_Total_Gend	-2.25×10^{-7}***	-2.19×10^{-7}***	-2.15×10^{-7}***	-2.17×10^{-7}***	-2.16×10^{-7}***
	(3.36×10^{-8})	(3.36×10^{-8})	(3.37×10^{-8})	(3.37×10^{-8})	(3.37×10^{-8})
Holiday or Weekend	-0.0471***	-0.0468***	-0.0466***	-0.0468***	-0.0466***
	(0.0081)	(0.0081)	(0.0081)	(0.0081)	(0.0081)
Daylight	-0.0131	-0.0108	-0.0118	-0.0123	-0.0109
	(0.0097)	(0.0097)	(0.0097)	(0.0097)	(0.0097)
Night Humid × City	-6.12×10^{-5}	-6.12×10^{-5}	-6.33×10^{-5}	-6.42×10^{-5}	-6.33×10^{-5}
	(4.04×10^{-5})	(4.03×10^{-5})	(4.02×10^{-5})	(4.03×10^{-5})	(4.02×10^{-5})
Night Temp × City	0.0003	0.0002	0.0002	0.0002	0.0002
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Warning dy 100%	0.6875**				
	(0.3079)				
PET × Warning dy 100%	-0.0202**				
	(0.0099)				
Warning dy 25%		0.1058			
		(0.2615)			
PET × Warning dy 25%		-0.0007			
		(0.0087)			
Warning dy 50%			0.3986		
			(0.2866)		
pet × Warning dy 50%			-0.0103		
			(0.0094)		
Warning dy 75%				0.3275	
				(0.2990)	
pet × Warning dy 75%				-0.0081	
				(0.0097)	
Warning Population Share					0.3132
					(0.3164)
PET × Warning Population Share					-0.0070
					(0.0104)
Standard-Errors	Heteroskedasticity-robust				
Observations	11,470	11,470	11,470	11,470	11,470
R^2	0.56927	0.57006	0.57006	0.56966	0.57017
Within R^2	0.10088	0.10252	0.10253	0.10168	0.10274
State fixed effects	✓	✓	✓	✓	✓
Year fixed effects	✓	✓	✓	✓	✓
Month of the year FE	✓	✓	✓	✓	✓
PET bin 0.5 C° FE	✓	✓	✓	✓	✓

Notes: Significance codes: '***' 0.01 '**' 0.05 '*' 0.1

6. Conclusions

In conclusion, this study offers valuable insights into the efficacy of early heat warning systems. The findings reveal that heat related mortality is significantly reduced thanks to heat warnings. These results are robust to most specifications and evident also through other types of climate variables.

Interestingly, we find that the positive effect of issuing a heat warning is largely concentrated on the first day of a series of days under warning. This suggest the importance of issuing warnings in the right moment and that the warning fatigue must be taken into account in the warning issuing process.

Overall, the findings are of important guidance for policymakers and stakeholders involved in short term prevention of climate disasters. By understanding the factors that increase the efficacy of early warning systems, more targeted and effective strategies can be developed. Investing in weather forecast precision is fundamental to give people the time and the tools to take precautions in the short time preceding extreme weather events.

References

Angrist, J. D., & Jörn-Steffen, P. (2009). *Mostly harmless econometrics: An empiricist's companion.* Princeton university press.

Ballester, J., Beas-Moix, M., Beltrán-Barrón, N., Méndez Turrubiates, R., Peyrusse, F., & Quijal-Zamorano, M. (2024). Forecaster.Health. . *Available at https://forecaster.health/* .

Ballester, J., Quijal-Zamorano, M., Méndez Turrubiates, R. F., Pegenaute, F., Herrmann, F. R., Robine, M., . . . Achebak, H. (2023). Heat-related mortality in Europe during the summer of 2022. *Nature Medicine*, 1857–1866.

Barreca, A., Clay, K., Deschenes, O., Greenstone, M., Shapiro, J. S., & al., e. (2016). Adapting to Climate Change: The Remarkable Decline in the US Temperature-Mortality Relationship over the Twentieth Century. *Journal of Political Economy*.

Benmarhnia, T., Bailey, Z., Kaiser, D., Auger, N., King, N., & Kaufman, J. S. (2016). A Difference-in-Differences Approach to Assess the Effect of a Heat Action Plan on Heat-Related Mortality, and Differences in Effectiveness According to Sex, Age, and Socioeconomic Status (Montreal, Quebec). *Environmental Health Perspectives*.

Benmarhnia, T., Schwarz, L., Nori-Sarma, A., & Bell, M. L. (2019). Quantifying the impact of changing the threshold of New York City heat emergency plan in reducing heat-related illnesses. *Environ. Res. Lett.*

Bosello, F., Roson, R., & Tol, R. (2006). Economy-Wide Estimates of the. *Ecological Economics*, 579–91.

Carleton, T., Jin, A., Delgad, M., Greenston, M., Hous, T., Hsiang, S., . . . Zhang, A. T. (2022). Valuing the Global Mortality Consequences of Climate Change Accounting for Adaptation Costs and Benefits. *The Quarterly Journal of Economics, 137*(4), 2037–2105.

Chau, P. H., Chan, K. C., & Woo, J. (2009). Hot weather warning might help to reduce elderly mortality in Hong Kong. *International Journal of Biometeorology*, 461–468.

Cruz, J.-L. (2024). The Economic Geography of Global Warming. *Review of Economic Studies, 91*, , 899–939.

Deschênes , O., & Greenstone, M. (2011). Climate Change, Mortality, and Adaptation: Evidence from Annual Fluctuations in Weather in the US. *American Economic Journal: Applied Economics* , 152-185.

Downey, M., Lind, N., & Shrader, J. G. (2023). Adjusting to Rain Before It Falls. *Management Science*, 7399-7422.

Ebi, K. L., Teisberg, T. J., Kalkstein, L. S., Robinson, L., & Weiher, R. F. (2004). Heat Watch/Warning Systems Save Lives: Estimated Costs and Benefits for Philadelphia 1995–98. *Bulletin of the American Meteorological Society*.

Heo, S., Nori-Sarma, A., Lee, K., Benmarhnia, T., Dominici, F., & Bell, M. L. (2019). The Use of a Quasi-Experimental Study on the Mortality Effect of a Heat Wave Warning System in Korea. *International Journal of Environmental Research and Public Health*.

Huber, V., Breitner-Busch, S., He, C., Matthies-Wiesler, F., Peters, A., & Schneider, A. (2024). Heat-Related Mortality in the Extreme Summer of 2022: An Analysis Based on Daily Data. *Deutsches Ärzteblatt International*, 79-95.

Linsenmeier, M., & Shrader, J. (2023). Global inequalities in weather forecasts. *Working Paper*.

Matzarakis, A., Laschewski, G., & Muthers, S. (2020). The Heat Health Warning System in Germany—Application and Warnings for 2005 to 2019. *Atmosphere*.

Quijal-Zamorano, M., Petrova, D., Martínez-Solanas, È., Herrmann, F. R., Rodó, X., Robine, J.-M., . . . Ballester, J. (2024). Forecast skill assessment of an operational continental heat-cold-health forecasting system: New avenues for health early warning systems. *Science Advances* .

Rupa, B., & Samet, J. M. (2002). Relation Between Elevated Ambient Temperature and Mortality: A Review of the Epidemiologic Evidence. *Epidemiologic Reviews*, 190-202.

Shrader, J. G., Bakkensen, L., & Lemoine, D. (2023). Fatal Errors: The Mortality Value of Accurate Weather Forecasts. *Working Paper - NATIONAL BUREAU OF ECONOMIC RESEARCH*.

Smoyer-Tomic, K. E., & Rainham, D. G. (2001). Beating the Heat: Development and Evaluation of a Canadian Hot Weather Health-Response Plan. *Environ Health Perspective*.

Song, Y. (2024). The value of weather forecasts: Evidence from labor responses to accurate versus inaccurate temperature forecasts in China. *Journal of Environmental Economics and Management*.

UN-WMO. (2024). *Global Status of Multi-Hazard Early Warning Systems.* Geneva, Switzerland: United Nations Office for Disaster Risk Reduction and World Meteorological Organization.

Wang, J., Nikolaou, N., Heiden, M. a., & Irrgang, C. (2024). High-resolution modeling and projection of heat-related mortality in Germany under climate change. *Commun Med*.

Weinberger, K. R., Wu, X., Sun, S., Spangler, K. R., Nori-Sarma, A., Schwartz, J., . . . Wellenius, G. A. (2021). Heat warnings, mortality, and hospital admissions among older adults in the United States. *Environment International*.

Zhang, S., Breitner, S., Donato, F. d., Stafoggia, M., Nikolaou, N., Aunan, K., . . . Schneider, A. (2024). Heat and cause-specific cardiopulmonary mortality in Germany: a case-crossover study using small-area assessment. *The Lancet Regional Health - Europe*.

Appendix

Herein we report the additional tables and figures.

Table A. 1: Results of Model (1) including PET bins as factors

	Dep. var: Mortality_rate_x100th Baseline (1)
PET	0.0042
	(0.0248)
Warning	0.6875**
	(0.3079)
PET × Warning	-0.0202**
	(0.0099)
Previous 30d PET	-0.0042**
	(0.0017)
Night Humid	7.27×10^{-5}
	(0.0006)
Night Temp	0.0437***
	(0.0023)
Precip	0.0251
	(0.0583)
Share of over 75	12.29***
	(0.9468)
Population	$-2.25 \times 10^{-7***}$
	(3.36×10^{-8})
Holiday or Weekend	-0.0471***
	(0.0081)
Daylight	-0.0131
	(0.0097)
Night Humid × City	-6.12×10^{-5}
	(4.04×10^{-5})
Night Temp × City	0.0003
	(0.0002)
factor(Temperature_bin_0.5deg_PET)[27.5,28)	0.0162
	(0.0180)
factor(Temperature_bin_0.5deg_PET)[28,28.5)	0.0119
	(0.0280)
factor(Temperature_bin_0.5deg_PET)[28.5,29)	0.0379
	(0.0397)
factor(Temperature_bin_0.5deg_PET)[29,29.5)	-0.0053
	(0.0518)
factor(Temperature_bin_0.5deg_PET)[29.5,30)	0.0132
	(0.0634)
factor(Temperature_bin_0.5deg_PET)[30,30.5)	0.0459
	(0.0760)
factor(Temperature_bin_0.5deg_PET)[30.5,31)	0.0486
	(0.0887)
factor(Temperature_bin_0.5deg_PET)[31,31.5)	0.0634
	(0.1008)
factor(Temperature_bin_0.5deg_PET)[31.5,32)	0.0846
	(0.1131)
factor(Temperature_bin_0.5deg_PET)[32,32.5)	0.1244
	(0.1251)
factor(Temperature_bin_0.5deg_PET)[32.5,33)	0.1329
	(0.1384)
factor(Temperature_bin_0.5deg_PET)[33,33.5)	0.1506
	(0.1510)
factor(Temperature_bin_0.5deg_PET)[33.5,34)	0.2149
	(0.1653)
factor(Temperature_bin_0.5deg_PET)[34,34.5)	0.3050*
Standard-Errors	Hetero.-robust
Observations	11,470
R^2	0.56927
Within R^2	0.10088
State fixed effects	✓
Year fixed effects	✓
month__of_year fixed effects	✓

Notes: Significance codes: '***' 0.01 '**' 0.05 '*' 0.1