Temperature variability and mortality*

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November 11, 2019

Abstract

While economists have focused on the effect of mean temperatures on mortality, the climate sciences have emphasized that global warming might not only lead to an increase in mean temperatures, but can potentially also affect the temperature variance. This is the first paper to estimate the causal effect of temperature variability on mortality. Using monthly state-level data for the US in the period 1969-2004, I offer three main results: (1) Increased monthly temperature variation causes increased mortality, (2) omitting the effect of temperature variation on mortality can severely bias our predictions on the number of temperature-induced fatalities caused by global warming, and (3) adaptation to increased temperature variation is more difficult than adaptation to increased mean temperatures.

Keywords: Global warming, mortality, temperature variation.

JEL Classification: I10, 118, Q51, Q54

*I thank David Archer, Fiona Burlig, Colin Green, Costanza Biavaschi, Amir Jina, Elisabeth Moyer, Ragnar Torvik, Kevin Schwarzwald, and seminar participants at the University of Chicago, University of Reading, the 4th Conference on "Econometric Models of Climate Change", and the 24th Annual Conference of EAERE for helpful comments and discussions. Parts of this research was conducted while visiting the University of Chicago Harris School of Public Policy.

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1 Introduction

Human-induced climate change, also known as global warming, is not only causing an increase in the frequency of extreme heat events, but heat waves in the 21st century will also become more intense and longer-lasting than before (Meehl and Tebaldi, 2004). For several US states, even at modest warming levels, almost all summers by mid-century will exceed the historically hottest one (Duffy and Tebaldi, 2012). The first event study of its kind found that human influences made the 2003 heat wave in Europe, which is believed to have led to more than 70 000 additional deaths (Robine et al., 2008), twice as likely (Stott et al., 2004). Yet, despite the increased likelihood, Stott et al. (2004) found the heatwave to be an extremely unlikely event, on average happening only once every millennium. Just ten years later, Christidis et al. (2015) found in an updated study that the same heat event was now to be expected once every century. Given this dramatic increase in the probability of extreme heat event, the question naturally arises: Will global warming only lead to a simple increase in mean temperatures, or will it also affect the variability of temperatures? While it has been established with a high degree of certainty that global warming will cause a shift in the temperature probability distribution towards a higher mean temperature (IPCC, 2014), there is less certainty regarding the effect of global warming on the temperature variation. This is, however, a question of increasing concern among climate scientists (Klavans et al., 2017).

This is the first paper to estimate the effect of temperature variability on mortality. By using a within-state identification strategy as in the influential paper on the temperature-mortality relationship by Barreca et al. (2016), I estimate the effect of temperature variability on mortality for the US in the period 1969-2004. I offer three main findings. First, over my sample period I find that a 1 °C increase in the monthly standard deviation of daily mean temperatures causes an additional 0.223 deaths per 100 000 people. The magnitude of this effect is comparable to that of experiencing an additional day during the month with the mean temperature above 31.5 °C. While the effect of low and high mean temperatures on human health has received a lot of attention, temperature variation also matters because higher variation in temperatures makes it more difficult to adapt to the current temperature. More variation means less time for physiological acclimatization to the new temperature, and it reduces the marginal effectiveness of implementing protective measures. Second, in a simple prediction exercise I show how omitting the effect of temperature variation from the temperature-mortality relationship can severely bias our predictions on the number of temperature-induced fatalities caused by global warming. Third, adaptation to increased temperature variation is more difficult than adaptation to an increase in mean temperatures. Although there are technologies that can mitigate the exposure to harmful temperatures, e.g. air-conditioning, these technologies can be costly, causing only limited adaptation to harmful temperatures, even in rich, developed countries (Barreca et al., 2015). Previous studies have shown how the harmful impact of exposure to extreme temperatures on mortality declines as a result of people becoming richer and more accustomed to the higher temperatures caused by global warming (Barreca et al., 2016, Carleton et al., 2018). While my results confirm that adaptation to higher mean temperatures take place, I find that higher income and mean temperatures have little effect on the harmful impact of temperature variation on mortality.

This paper contributes to the literature by bringing together the economic research on the temperature-mortality relationship with current insights from the climate sciences. There is a large economic literature concerned with estimating the costs associated with global warming. A changing climate with higher mean temperatures will affect the economy and society through many different channels, e.g. agriculture, crime, coastal storms, energy use and labour productivity (Hsiang et al., 2017). The largest cost of global warming, however, has been found to be caused by the effect of increasing temperatures on human health and mortality. Thus, an important field in this literature is the estimation of the temperature-mortality relationship, with the goal often being to predict the effect of future climate change on mortality (e.g. Carleton et al., 2018). Previous papers have found both extremely low and high temperatures to increase mortality (Deschênes and Moretti, 2009, Deschênes and Greenstone, 2011, Barreca, 2012), with the effect of temperatures on mortality tending to be larger in developing countries (Burgess et al., 2017).

A recent innovation in the literature is the use of panel data methods in the estimation of the causal relationship between climatic variables and economic variables. However, although papers in this literature have used the random variation in temperatures over time to estimate the effect of temperatures on mortality, they have not estimated the effect of temperature variation *itself* on mortality. While economists have so far not considered the economic and social impact of temperature variability, climate scientists are becoming increasingly concerned about the effect of global warming on the temperature variability. Although the effect of temperature variation on mortality has received some attention in the epidemiology literature (e.g. Zanobetti et al., 2012, Shi et al., 2015),[1] by using recent innovations from the new climate-economy literature (Dell et al., 2014), this is the first paper to offer evidence on the causal impact of temperature variation on mortality. This paper relates to an emerging literature concerned with estimating the economic and social impacts of global warming caused by other factors besides that of mean warming. Fishman (2016) estimates the impact of the temporal distribution of precipitation on crop yields, and finds that a more uneven distribution of precipitation (i.e. fewer rainy days) can overturn the benefits of higher precipitation caused by global warming on crop yields. Barreca (2012) finds that in addition to increased exposure to high temperatures, global warming can affect mortality by causing a change in humidity levels. While changes in humidity has no effect on overall mortality in the US, it will have a distributional effect by reducing mortality in the cold and dry states in the North, and increase mortality in the hot and humid states in the South.

The rest of the paper proceeds as follows. Section 2 provides a review of the liter-

[1] The epidemology literature is very different from the economic literature. In the epidemiology literature, the papers tend to be correlation analysis, analysing the survival probability of individuals, often from a sub-population (e.g. people with a chronic illness). The external validity of these studies is thus limited.

ature on the effect of global warming on temperature variability. Section 3 expands upon a Becker-Grossman style model in order to provide a conceptual framework for why temperature variability matters for human health. Section 4 explains the data used for estimation and prediction, and explains the method for estimating the relationship between temperature variability and mortality. In section 5, the estimation results from the baseline model are presented, and a simple prediction exercise on the number of temperature-induced fatalities for a counterfactual scenario is offered. Section 6 takes a closer look at adaptation to temperature variability, while section 7 investigates the robustness of the baseline model. Section 8 concludes.

2 Global warming and temperature variability

Figure 1 illustrates the difference between an increase in mean temperatures and an increase in temperature variability, caused by global warming. Temperature variability is here understood as the variance of the temperature probability distribution. The increase in the temperature variance has two effects: First, people will now be exposed to more days in the hot tail of the temperature probability distribution, and secondly, they will also be exposed to a wider range of temperatures within a given period of time. Previous studies on the temperature-mortality relationship that have predicted the effect of global warming on mortality (e.g. Carleton et al., 2018) have captured this first effect of an increase in the temperature variance, but they have not captured the second effect of being exposed to a higher temperature variability in itself.

[Figure 1 here.]

Climate scientists have argued that many of the recent extreme temperature events have been too far outside of normal temperature ranges for a simple mean-shift in the temperature distribution to explain these events (e.g. Coumou and Rahmstorf, 2012, Horton et al., 2016). While climate scientists have traditionally focused their efforts on delivering credible projections of the effect of climate change on mean temperatures, the effect of climate change on temperature variability is gaining increased attention among climate scientists (Klavans et al., 2017). One part of the literature has investigated whether global warming has affected current temperature variability.[2] However, the climate is driven by strongly nonlinear processes, thus, past changes in temperature variability are not necessarily indicative of future changes. In order to say something about future temperature variability, projections from global climate models (GCMs) are needed.

There are several theoretical reasons for believing that global warming will affect the variability of temperatures. First, there is the potential land-atmosphere feedback of heat events caused by anomalously low soil moisture; if soil moisture reaches low levels, maximum surface temperatures are less likely to be moderated through evaporative cooling (Clark et al., 2006, Coumou and Rahmstorf, 2012, Horton et al., 2016). Secondly, global warming has a larger effect on night-time cooling than day-time heating. Both model simulations and empirical analysis have shown large reductions in nocturnal cooling caused by global warming (e.g. Donat and Alexander, 2012, Kharin et al., 2013), and it has been shown that reduced nocturnal cooling has a disproportionally large effect on the occurrence and severity of heatwaves (Clark et al., 2006). A third reason is the effect of global warming on the atmospheric circulation patterns associated with heatwaves and cold spells (Meehl and Tebaldi, 2004, Sillmann et al., 2011), which can potentially cause an increase in the frequency of blocking situations.[3] Fourth, the Arctic amplification of global warming, as well as different warming rates on land than at sea, are both causing winds blowing anomalous temperatures

[2]Climate scientists have used empirical methods to investigate whether the increase in temperatures above pre-industrial levels experienced so far has had an effect on temperature variability (Della-Marta et al., 2007, Wergen and Krug, 2010, Donat and Alexander, 2012, Hansen et al., 2012). However, the results from this empirical literature is largely inconclusive. In addition, even though a place has experienced an increase (decrease) in the temperature variability so far, it does not necessarily imply that it will continue to experience increased (decreased) temperature variability in the future under additional warming.

[3]A blocking situation is when the jet stream is characterized by a strong meandering pattern that remains locked in place for a prolonged amount of time; this in turn decreases the weather variability, allowing heatwaves or cold spells the time to build up (Coumou and Rahmstorf, 2012, Horton et al., 2016).

downstream, in turn causing an increase in the occurrence of unusual temperatures (Scaife et al., 2008, Holmes et al., 2016). In addition, the Arctic sea ice loss can also influence temperature variability through a weakening of the Atlantic Thermohaline Circulation, which will reduce the oceanic fluxes of heat to high-latitude areas (Budikova, 2009).

Studies using GCMs tend to find an effect of global warming on the many different types of temperature variability (see Holmes et al. (2016) for a review). In general, there is substantial spatial heterogeneity in the effect of global warming on temperature variability, with some regions projected to experience increased temperature variability, while other regions are projected to experience a decrease in temperature variability. In addition, there is a seasonal component in the effect of global warming on temperature variability, with many regions projected to experience an increase in temperature variability in summers, and a decrease during winters (Weisheimer and Palmer, 2005, Schneider et al., 2015, Sillmann et al., 2011).[4] The early study of Zwiers et al. (1998) found that a doubling of CO2 would cause a reduction in daily minimum and maximum temperature variability in most parts of the world, with the largest reduction for daily minimum temperatures, thus causing an increase in the diurnal temperature variation. Hegerl et al. (2004) find that for large portions of the world, projected changes in temperature extremes differ substantially from projected increase in seasonal mean temperatures. For the US, both the coldest and warmest day during the year warm faster than the seasonal mean temperatures. Ballester et al. (2010) and Fischer and Schär (2010) find increased variation in daily mean temperatures for most of Europe. Clark et al. (2006) find a substantial increase in both intra-annual and interannual temperature variability in Europe, parts of North and South America, and Eastern Asia.

In conclusion, there is a large literature on the effect of global warming on temperature variability that so far has gone largely unnoticed by economists. While economic

[4] Poppick et al. (2016), however, show how seemingly innocent choices regarding model resolution and timescales can have a large effect on the projected changes in temperature variability. This is caused by different timescales and model resolutions highlighting different physical processes and sources of temperature variability.

research has highlighted the effect of exposure to low and high temperatures on mortality, we have omitted to consider the separate effect of variation in temperatures on mortality. The climate sciences, on the other hand, have grown increasingly concerned about the effect of global warming on the variability of temperatures. Although model projections are showing an effect of global warming on temperature variability in many parts of the world, GCMs are not tailored for analysing the effect of global warming on second-order moments of the temperature probability distribution such as the variance, seeing as GCMs lack many of the driving processes of extreme weather events (Fischer and Knutti, 2015, Poppick et al., 2016). Nevertheless, improving GCMs in order to deliver credible projections on the effect of global warming on future temperature variability is receiving increasing attention among climate scientists and it is becoming a promising area of research.

3 Conceptual framework

This section formalizes the relationship between temperature variability and mortality by expanding the Becker-Grossman style model of health production in Deschênes and Greenstone (2011). The conceptual framework is a simple one-period model where a representative agent jointly decides the optimal consumption of an aggregated consumption good, x_C, and the survival rate, s. The agent maximizes the utility function,

$$U = U[x_C, s] \tag{1}$$

with the mortality risk being a function of investment in health, x_H, the mean temperature, μ_T, and the temperature variance, σ_T. The production function for survival is given by,

$$s = s(x_H, \mu_T, \sigma_T) \tag{2}$$

There are many ways temperatures can affect human health (for a review, see

USGCRP (2016)). Temperatures affect human health directly by affecting the body's ability to regulate internal temperatures, causing heat stress on hot days and hypothermia on cold days. Extreme temperatures can also worsen existing conditions, such as cardiovascular and respiratory diseases. In the survival function it is assumed that $\partial s/\partial x_H > 0$, $\partial s/\partial \mu_T < 0$[5] and $\partial s/\partial \sigma_T < 0$.

There are two justifications for the assumption that an increase in the temperature variability causes a reduction in the survival rate. First, a higher variation in temperatures means that agents must invest in technologies protecting against both low and high temperatures. For a certain temperature variation it might be sufficient to invest in home insulation to protect against exposure to harmful temperatures. However, an increase in the temperature variation might expose the agent to harmfully high temperatures as well, in which case home insulation offers little protection, and technologies such as air-conditioning is needed instead. Thus, for the given level of investment in health (e.g. home insulation), the mortality risk of exposure to temperatures increases. Second, from the epidemiology literature, we known that it takes time for the human body to adjust to temperature changes (Hanna and Tait, 2015). While acclimatization to new temperatures requires active and regular exposure to such temperatures over a period of time, increased temperature variability reduces the time allowed for acclimatization, thus increasing the harmful effect of temperatures on human health.

Given income, I, and price, p, on investment in health, the agent faces the following budget constraint,

$$I - x_C - p x_H = 0 \qquad (3)$$

with the aggregated consumption good as the numeraire good. The agent maximizes utility with respect to x_C and x_H subject to equations 2 and 3. In equilibrium, the ratio of the

[5] The assumption that an increase in the mean temperature is always negative for the survival rate is a simplification. In reality, places with a low initial mean temperature could experience a decrease in mortality from an increase in temperatures (see e.g. Carleton et al., 2018).

marginal utility of consumption of x_C and x_H must be equal to the price ratio,

$$\frac{(\partial U/\partial s)(\partial s/\partial x_H)}{\partial U/\partial x_C} = p$$

For a fixed price ratio, the indirect utility function can be expressed as $V(I, \mu_T, \sigma_T)$. Consider an increase in the temperature variability holding income and mean temperature fixed. Since $\frac{\partial V}{\partial \sigma_T} \equiv \frac{\partial U}{\partial \sigma_T} = \frac{\partial U}{\partial s}\frac{\partial s}{\partial \sigma_T} < 0$, an increase in the temperature variability will, ceteris paribus, cause a decrease in utility. While the maximum survival rate attainable by the agent used to be $s^0(I/p, \mu_T, \sigma_T^0)$, for the higher level of temperature variability the maximum survival rate attainable is now $s^1(I/p, \mu_T, \sigma_T^1)$. The maximum consumption level of x_C, however, remains unaffected by the increase in temperature variability. Figure 2 illustrates this change in the budget restriction caused by the increase in temperature variation.

[Figure 2 here]

There are two effects from the increase in temperature variation. First, there is an income effect. A higher temperature variation means a reduction in the marginal utility of investing in health goods (e.g. while home insulation used to offer protection all year around, the increase in the temperature variability means that it offers protection only parts of the time). In other words, in order to maintain the same survival rate, more investment in health is needed. In addition, there is a substitution effect. Increasing the survival rate is now relatively more expensive compared to the consumption good. Agents will respond by increasing their consumption of x_C by reducing their survival rate. While the income and substitution effect pulls in different directions for x_C, causing an ambiguous effect on consumption of x_C, the income and substitution effects pulls in the same direction for the survival rate, namely a lower survival rate. For fixed income and prices, the agent is now on a lower indifference curve, and although the effect on x_C (and x_H) remains ambiguous, we can know with certainty that there has been a reduction in the survival rate of the agent.

4 Data and method

4.1 Mortality and weather data

The mortality data used in this paper is obtained from the Multiple Cause-of-Death (MCOD) files published by the National Center for Health Statistics (National Center for Health Statistics, 2018). By extracting information from death certificates filed, the MCOD files contain information about all deaths that occur within US borders. Mortality rates are constructed by combining the death counts with population estimates from the National Cancer Institute (National Cancer Institute, 2019). Using the MCOD files, a monthly mortality rate is constructed for each state in the contiguous US (i.e. the 48 adjoining US states, plus the District of Columbia). The mortality rate is defined as the number of deaths per 100 000 people in a state during a month. In addition to the all-age mortality rate, age-specific mortality rates are constructed. I follow Barreca et al. (2016), and use the following four age groups: < 1 years, 1-44 years, 45-64 years, and > 64 years.

Data on weather is extracted from the Global Historical Climate Network daily (GHCN-daily) database, which is maintained by the National Oceanic and Atmospheric Administration (Menne et al., 2012).[6] The GHCND-daily contains daily summaries from a selection of land surface stations in countries all around the world with each station subjected to a common set of quality assurance checks. The variables of interest in the daily summaries from the stations are the daily maximum temperature, minimum temperature and accumulated precipitation. The database contains in total 59 928 weather stations in the contiguous US and the District of Columbia. However, in order to reduce the measurement bias from stations going online and offline, data is extracted only from stations that report a daily summary for the variable of interest for each day within a year. If a station does not report the variable of interest for each day within a year, then all observations from

[6]Data is extracted from version 3.25 of the GHCN-daily database.

that station in that year are dropped from the sample.[7]

Two types of temperature variables are constructed: the monthly mean temperature and the monthly temperature variation. The monthly mean temperature is constructed by first taking the average of the daily maximum and minimum temperature and then counting the number of days within a month where the daily mean temperature was within a certain temperature range. This paper uses the same temperature ranges defined in Barreca et al. (2016): $< 4.5\,^{\circ}\mathrm{C}$, $26.5 - 31.5\,^{\circ}\mathrm{C}$, and $> 31.5\,^{\circ}\mathrm{C}$. A day with the mean temperature below $4.5\,^{\circ}\mathrm{C}$, between 26.5 and $31.5\,^{\circ}\mathrm{C}$ and above $31.5\,^{\circ}\mathrm{C}$ are henceforth referred to as a cold, warm and hot day, respectively. The reference category is the number of "normal" days in a month, defined as days with the mean temperature between 4.5 and $26.5\,^{\circ}\mathrm{C}$.[8]

The monthly temperature variation is defined as the standard deviation of daily mean temperatures within a month, with the daily mean temperature being the average of the daily maximum and minimum temperature. In addition, the precipitation variable is the sum of daily accumulated precipitation within a month. The temperature and precipitation variables are all measured at the station-level. County-level temperature and precipitation variables are then measured as a weighted average of observations from all weather stations within a 300 km radius of the county centroid. The weight given is the inverse of the squared distance between the station and the centroid, hence giving closer stations a higher weight. The weather variables are then aggregated up to the state-level by taking a population-weighted average across all counties within the state.[9]

The final data set contains observations on the monthly mortality rate, number of cold, warm and hot days, the standard deviation of daily mean temperatures, and accumulated precipitation, for each state in the contiguous US and the District of Columbia. The analysis in this paper is restricted to the period 1969-2004, since this is the period where

[7] On average, there are 2 967 stations that fulfilled this requirement in any given year.

[8] Defining the monthly mean temperature in this way, as opposed to e.g. the mean temperature across all days within the month, allows for a more flexible functional form estimation.

[9] This is the same procedure followed in Barreca et al. (2016), which also uses US data on the state-month level.

both population and mortality data is available.[10]

4.2 Summary statistics

Table 1 shows summary statistics for the mortality rate, temperature variation, and the number of cold, warm and hot days in the sample period 1969-2004. The averages for the temperature variation is on the monthly level, while the remaining variables are on the annual level. All averages in the table are population-weighted, and can thus be interpreted as the exposure to extreme temperatures and temperature variation experienced by the average American. As shown in column (2), the average annual mortality rate was 874.4 deaths per 100 000 people for the US in the sample period. However, behind the national estimates, there is substantial variation across the climatic regions of the US.[11] Column (1) shows that nationally, the average monthly temperature standard deviation was 3.9 °C. However, Americans in the West experienced on average a monthly temperature standard deviation of only 2.8 °C, while Americans in West North Central experienced on average a monthly temperature standard deviation of 4.9 °C.

[Table 1 here]

Columns (3)-(5) show that Americans are currently exposed to far more cold days than hot days during the year. Over the sample period, the average American experienced 74 cold days, 26.2 warm days and 1.7 hot days during the year. While people in the Southwest were, on average, exposed to 12.9 hot days during the year, most Americans rarely experienced a hot day during the year. The exposure to cold days, however, was substantially higher. While people in the Northern and Eastern part of the US experienced on average

[10] Population counts are available from 1969, while 2004 is the last year where the MCOD files contained information on the state where the death occurred. After 2004, this information was no longer made available to the public.

[11] For the definition of the nine climate regions of the US, see note below table 1.

more than 100 cold days during the year, even in the West, people were exposed on average to at least 10 cold days during the year.

[Figure 3 here]

In addition to the variation in the monthly temperature standard deviation across the climate regions of the US, there is also substantial variation in the monthly temperature standard deviation across the seasons of the year. Panel (a) and (b) in Figure 3 show the average monthly temperature standard deviation experienced by states during the sample period for summer and winter, respectively. Summer months are defined as June, July and August, while winter months are December, January and February. From the figure, we can see that the the monthly temperature standard deviation is higher during winters than summers for all states. The pattern of spatial heterogeneity also differs between the seasons, with states in the South experiencing the least variation during summer, and states in the West experiencing the least variation during winters. On average, South Dakota experienced the highest variation in summer temperatures with 3.39 °C, while North Dakota experienced the highest variation in winter temperatures with 6.82 °C.

4.3 Method

This paper estimates the causal effect of variation in temperatures on mortality by exploiting the monthly variation in temperatures and mortality within states over time, following e.g. Barreca et al. (2016). The main specification of the relationship between temperature variability and mortality is given by the following equation,

$$y_{sym} = \gamma TVAR_{sym} + \sum_j \theta^j TBIN^j_{sym} + \mathbf{X}_{sym}\beta + \alpha_{sm} + \rho_{ym} + \varepsilon_{sym} \tag{4}$$

where y_{sym} is the monthly mortality rate in state s, year y and month m. The variable of interest is $TVAR$, which is the monthly standard deviation of daily mean temperatures.

$TBIN^j_{sym}$ is the number of days in a month with the mean temperature within a certain temperature range, j. The number of temperature ranges has been restricted to three "critical" temperature ranges (and one reference temperature range) defined above as the number of cold, warm and hot days experienced by a state during a month.

Naively estimating the effect of temperature variables on mortality will lead to biased estimation, seeing as both temperatures and mortality are correlated with other confounding factors such as income, e.g. hotter states tend to be poorer, and poorer states tend to have a higher mortality rate. To avoid this confounding, I use two strategies. First, I include a rich set of fixed effects, namely a state-by-month fixed effects, α_{sm}, and a year-by-month fixed effect, ρ_{ym}. The state-by-month fixed effects are included to absorb unobserved, but permanent differences in the mortality rate between states, while allowing for state-specific characteristics in the mortality rate across the months of the year. The year-by-month fixed effects capture the pattern of seasonality in the mortality rate, as well as absorbing time shocks that are common to all states. Secondly, I include a vector of control variables, X_{sym}, which contains a quadratic function for the monthly accumulated precipitation, the share of the population in four age categories, and the log of per capita income.[12] The age shares and log of per capita income are interacted with month indicator in order to capture age- and income-specific seasonality effects that are common across all states. The vector also contains a quadratic time trend that is interacted with the state-month identifier, thus allowing each state its own trend in seasonal mortality rates.

To conclude, by including the fixed effects and control variables, the model is isolating the deviations in temperatures over time from their state-month specific means, while removing the effect of common time shocks and controlling for a time trend in the state-month specific means. The idea is that while each state has a month-specific mean temperature, and this mean temperature is correlated with other confounding factors, each state will

[12] The age shares in the four age categories, < 1 years, 1-44 years, 45-64 years, and > 64 years, are constructed by using population counts from the National Cancer Institute (2019), while the per capita income is extracted from the Bureau of Economic Analysis (2019).

experience random fluctuations over time around their month-specific mean caused by the stochastic nature of temperatures. The temperature-mortality relationship is thus identified by the presumably exogenous variation in temperatures caused by random draws from the temperature probability distribution over time. The only remaining threat to identification is the omission of any time-varying variables that are correlated with both mortality and temperatures, and that are not captured by the quadratic time trend.

5 The temperature-mortality relationship

5.1 Mean temperatures and temperature variation

Results from estimation of equation 4 are shown in Table 2.[13] Column (1) is the naive estimation of the temperature-mortality relationship. From the table, we can see that the naive estimation in column (1) greatly overestimates the effect of temperature variation on mortality. This is largely corrected for by including the state-month fixed effect in column (2). Adding the year-month fixed effect in column (3) and the vector of control variables in column (4), cause only a small decrease in the effect of temperature variation on mortality. Column (4) shows that the monthly temperature variation has a positive and statistically significant effect on mortality, with an increase in the monthly standard deviation of daily mean temperatures by 1 °C causing an additional 0.269 deaths per 100 000 people in a state.

[Table 2 here]

Column (5) shows the results from estimating the temperature-mortality relationship that has been estimated by previous studies, (e.g. Barreca et al., 2016, Karlsson and Ziebarth, 2018), namely the effect of mean temperatures on mortality. The estimates in

[13]Since both temperatures and mortality are likely to be correlated over time within states, all regressions cluster standard errors on the state-level. Arguably, there could also be some correlation across states within the same year. The main results, however, are robust to two-way clustering on the state and year level.

column (5) are in line with previous studies, which have found a positive and statistically significant effect of exposure to both high and low mean temperatures on mortality. E.g. from column (5), an additional cold day during the month will cause an additional 0.167 deaths per 100 000, while an additional hot day will cause an additional 0.266 deaths per 100 000 people.

A potential threat to identification of the models in column (4) and (5) is the confounding of the effect of mean temperatures and temperature variation on mortality. For instance, an increase in the temperature variability can cause an increase in the number of days in the tails of the temperature probability distribution. Thus, it can be argued that the adverse effect of an increase in temperature variability on mortality found in column (4) is not driven by temperature variability per se, but instead by the increase in the days with low and/or high temperatures. Similarly, the effect of cold, warm and hot days on mortality in column (5) could partly be driven by an increase in the temperature variation, and not only by exposure to days in the tails themselves.

Column (6) in Table 2 tests for the potential confounding of these two effects by simultaneously estimating the effect of mean temperatures and temperature variation on mortality. The impact on mortality of an additional cold, warm and hot day remain largely unchanged. Likewise, controlling for the exposure to extreme temperatures (i.e. cold, warm and hot days) has little effect on the impact of temperature variation on mortality. From column (6), we see that a 1 °C increase in the monthly standard deviation of daily mean temperatures causes an additional 0.223 deaths per 100 000 people, even when controlling for the potential accompanying increase in the number of cold, warm and hot days. For the remainder of the paper, column (6) is the preferred specification of the temperature-mortality relationship, seeing as it provides estimates of the separate effects of mean temperatures and temperature variation on mortality. In section 7, it is shown that the effect of temperature variation on mortality found in the baseline model is robust to an expansion of the number of temperature bins.

In addition to the overall effect of temperatures on the all-age mortality rate, previous studies have found substantial age group heterogeneity in the temperature-mortality relationship. Barreca et al. (2016) and Karlsson and Ziebarth (2018) found that while cold days affect mortality among infants and the elderly, warm and hot days mainly affect mortality among adults. Age group heterogeneity in the effect of temperature variation on mortality is investigated by estimating the model in column (6) in Table 2 separately for four different age groups. From columns (1)-(4), we can see that the effect of temperature variation on mortality broadly follows the same pattern in age heterogeneity as in mean temperatures found in previous studies. The harmful impact of temperature variation on mortality is found only among those above the age of 44, with the largest impact found among those above the age of 64. In column (4), a 1 °C increase in the monthly standard deviation of daily mean temperatures causes an additional 1.494 deaths per 100 000 people above the age of 64. This is substantially higher than the effect of temperature variation on the all-age mortality rate found above (0.223). In other words, the effects on mortality from exposure to extreme temperatures and a wider range of temperatures during a month are both mostly driven by their impact on the elderly.

[Table 3 here]

Given the small changes in the estimates in column (4) and (5), compared to column (6), in table 2, it would seem that mean temperatures and temperature variation have largely separate effects on mortality. In addition, given the magnitude of the impact of temperature variability on mortality, the existing literature on the temperature-mortality relationship has omitted an important factor, namely the temperature variation. Furthermore, Table 3 showed that is is mainly the elderly that bears the costs of a potential increase in temperature variation. While omitting the temperature variation from the temperature-mortality relationship does not seem to bias the estimates of exposure to cold, warm and hot days on mortality, it can still lead to biased predictions on the number of temperature-induced fatalities caused by global warming. This is investigated in the following prediction exercise.

5.2 Prediction exercise

While there is a good understanding of the effect of global warming on future mean temperatures, the same cannot be said for the effect of global warming on temperature variability. As discussed in section 2, projecting the effect of global warming on temperature variability is a growing and fertile area of research. However, until projections from GCMs are tailored for capturing the effect of second-order moments of the temperature probability distribution, any complex prediction analysis on the effect of temperature variability on future mortality would be premature. Instead, in order to demonstrate the potential impact of temperature variation on mortality, I offer a simple prediction exercise where I compare the changes in the number of temperature-induced fatalities caused by a one standard deviation change in the temperature variables. In this counterfactual scenario, each state experiences a one standard deviation decrease in their annual average number of cold days, and a one standard deviation increase in their average annual number of warm and hot days. In addition, all states experience a one standard deviation increase in their average monthly standard deviation of daily mean temperatures.[14]

[Figure 4 here]

Figure 4 shows the state-level changes in the temperature variables for all states for the counterfactual scenario described above. From panel (a) in the figure, we can see that states will experience an increase in the monthly standard deviation of daily mean

[14]In order to remove the effect of seasonality in the monthly temperature variation, the monthly temperature variation is calculated as the average across all months within a year, and the standard deviation is then calculated across the average monthly temperature variation in each year in the sample for each state. Furthermore, while the assumption of a decrease in the number of cold days, and an increase in the number of warm and hot days is in line with our knowledge of global warming, it is less certain whether global warming will cause an increase or decrease in the temperature variability. In fact, climate scientists have emphasized the spatial heterogeneity in the effect of global warming on temperature variability (Lehner et al., 2018), with some places experiencing an increase, and others a decrease.

temperature between $0.16 - 0.4\,^{\circ}$C. Panel (b) in the figure shows that states will experience 1-14 fewer cold days each year, while panels (c) and (d) show that states will experience 1-13 additional warm days and 0-8 additional hot days each year. In general, states with a higher mean temperature will experience the largest increase in the annual number of warm and hot days, while cooler states will experience the largest reduction in the annual number of cold days. For the monthly standard deviation of daily mean temperatures in the counterfactual scenario it is the states in the West North Central and South that experience the largest increase.

[Table 4 here]

Given the one standard deviation changes in the temperature variables, Table 4 shows the predicted changes in the average annual number of temperature-induced fatalities caused by each of the temperature variables.[15] Predictions in column (1) use the estimates from the model of the temperature-mortality relationship that omits the effect of temperature variability, while predictions in column (2) use the estimates from the full model that includes the temperature variability (columns (5) and (6) in Table 2, respectively). Columns (3)-(6) show the predicted changes in the number of temperature-induced fatalities for four different age groups using the estimates from the age-specific models in Table 3.

In column (1) in Table 4, the decrease in the number of cold days causes almost 4,000 fewer deaths each year, while the increase in the number of warm and hot days cause almost 1,800 and 800 additional deaths each year, respectively. The positive effect of a reduction in the number of cold days dominate the negative effects of an increase in the number of warm and hot days, thus causing a net reduction in the number of temperature-induced fatalities each year. We find the opposite effect, however, in column (2) when the temperature-mortality relationship is expanded to also include the effect of monthly temperature variation on mortality. While the effect of the changes in the average annual

[15] In converting the changes in the temperature variables to actual numbers of fatalities, I use the population counts from 2004, which is the last year in my sample period.

number of cold, warm and hot days on mortality remains more or less the same across columns (1) and (2), the one standard deviation increase in the monthly temperature variation in column (2) causes an additional 1,812 deaths each year. The result is now a net increase of over 400 temperature-induced fatalities each year in the counterfactual scenario. From column (6), we see that the largest number of fatalities caused by the increase in the monthly temperature variation is found among those above the age of 64 years.

[Figure 5 here]

In addition, the net effect of the changes in the temperature variables on mortality in the counterfactual scenario can also be broken down across the states. Figure 5 shows these state-level predictions. From the figure it is evident that global warming does not only have an effect on the aggregate number of temperature-induced fatalities, but it can also have a distributional effect. Figure 5 shows a clear North-South division, with states in the South experiencing a net increase in mortality, while states in the North will experience a net decrease in mortality. This is in line with previous studies, which have found that global warming will have an effect on the distribution of income in the US, causing a net gain in the northern states, and a net loss in the southern states (Hsiang et al., 2017).

While both the sign and magnitude of the effect of global warming on future temperature variability remains uncertain, this simple prediction exercise has shown how relatively small changes in the monthly temperature variation can have large impacts on the predicted number of temperature-induced fatalities. While omission of the temperature variation from the temperature mortality relationship does not seem to affect the estimated impacts of a cold, warm and hot day on mortality, it does affect the predicted number of temperature-induced fatalities in the future. Given the fact that omission of the temperature variation from the temperature-mortality relationship can lead to severely biased predictions, an important area for future research is the development of credible projections on on the effect of global warming on temperature variability.

6 Adaptation to global warming

The temperature-mortality relationship estimated above is likely to overstate the effect of global warming on mortality because it is estimated from unexpected temperature shocks. In the future, as mean temperatures continue to increase, people are likely to undertake adaptive measures to the new climate normal. Thus, estimation of equation 4 is generally thought of as an upper-bound on the mortality effect of global warming (e.g. Carleton et al., 2018). Previous papers have investigated specific adaptation measures in the temperature-mortality relationship, e.g. Deschênes and Greenstone (2011) and Barreca (2012) have estimated the relationship between temperatures and residential energy consumption, Barreca et al. (2016) has investigated the effect of residential air conditioning on the marginal effect of a hot day on mortality, while Deschênes and Moretti (2009) has considered migration as an adaptation strategy.

It is conjectured that adaptation to extreme temperatures is a function of income and mean temperatures (Carleton et al., 2018). The idea is that when people become richer, they can take more steps to protect themselves from exposure to harmful temperatures (e.g. buying air conditioning). In addition, the literature has found a lower marginal effect of extreme temperatures on mortality in places that are frequently exposed to such temperatures (Barreca et al., 2015, Karlsson and Ziebarth, 2018).[16] This is because increased exposure to extreme temperatures reduce the opportunity cost of investment in adaptation, e.g. buying air conditioning. In addition, people living in hot places will be more adapted to such temperatures compared with people living in cold places through both physiological acclimatization (Hanna and Tait, 2015) and cultural adaptation to high temperatures (e.g. siestas).

In this paper, I consider two tests of adaptation to temperature variation in the temperature-mortality relationship. First, I investigate the process of adaptation along the axes of income and mean temperatures, and second, I explore the effect of residential air con-

[16]This could be because people living in warm places have adapted to the higher temperatures, or it could be because there is a sorting of people with a high heat tolerance into warm places.

ditioning on the marginal effect of the temperature variables. Given that the goal of these analyses is to investigate heterogeneity in the temperature-mortality relationship along different measures of adaptation, the following regression models are estimated without weights (Solon et al., 2015). In addition, because of a lack of random variation in income and residential air conditioning rates within states over time, the adaptation analyses cannot claim causality. Instead, they explore the correlation between the marginal effects of temperature variation and mean temperatures with income, mean temperatures and residential air conditioning.

6.1 Mean income and temperature

In order to investigate the process of adaptation along the axes of mean income and temperature, the model in equation 4 is expanded with interactions between the temperature variables and the long-run means of state-level income and temperature,

$$y_{sym} = \mathbb{Z}_{sym} + (\boldsymbol{\delta}_0 + \boldsymbol{\delta}_1 TVAR_{sym} + \sum_j \boldsymbol{\delta}^j TBIN^j_{sym}) \times (TMEAN_{sy} + log(inc)_{sy}) \tag{5}$$

where the long-run mean income and temperature, $log(inc)_{sy}$ and $TMEAN_{sy}$, are measured as 10-year moving averages of annual log income per capita and annual mean of daily mean temperatures.[17] $\mathbb{Z}_{sym}$ contains the baseline model specified in equation 4.

Table 5 reports the estimates on the temperature variables and their interactions with mean income and temperature. In column (1), the model is estimated with interactions between the temperature variables and mean income only, while in column (2), the model is

[17] By measuring the long-run means for each state as 10-year moving averages, as opposed to e.g. the mean in the sample period, we are allowing the income distribution of US states to change over time. Given the long sample period, states that were relatively poor in 1969 are not necessarily in the bottom of the income distribution in 2004. While the distribution of states across mean temperatures remains constant over the sample period, there are in fact several states that went from being below (above) median income in 1969 to above (below) median income in 2004.

estimated with interactions between the temperature variables and mean temperature only. Column (3) shows the estimates from estimating the full model in equation 5. Although some of the coefficients on the interaction terms are not statistically significant, the sign on the coefficients are as expected.

[Table 5 here]

The coefficients on all of the interaction terms in column (1) are negative, implying a decline in the marginal effect of mean temperatures and temperature variability on mortality as income increases. The same applies for the coefficients in column (2), with the exception of the coefficient on the interaction between cold days and mean temperature. Thus, increased exposure to high temperatures is associated with a decrease in the marginal effect of warm and hot days on mortality, and an increase in the marginal effect of a cold days on mortality. The same pattern is found in column (3) when the temperature-mortality relationship is allowed to develop as a function of income and mean temperature simultaneously. While increased income is associated with a reduction in the harmful effect of temperature variation on mortality, increased mean temperature, on the other hand, seems to have little effect on the marginal effect of temperature variation. Neither of the interaction terms are found to be statistically significant.

[Figure 6 here]

Using the coefficients from column (3) in Table 5, Figure 6 illustrates the marginal effect on mortality for each of the four temperature variables along the range of long-run means in log per capita income and annual temperature observed in the sample period. The figure shows that the lowest marginal effects of warm and hot days on mortality is found in the upper right corner, which corresponds to both income and mean temperature being at their maximum values. For the effect of cold days on mortality, the lowest marginal effect is found in the upper left corner, corresponding to income and mean temperatures being at their maximum and minimum values, respectively.

While warm and hot days display substantial variation in the marginal effects along the axes of income and mean temperatures, the marginal effect of temperature variation displays less variation.[18] As an example, Figure 6 indicates the location of Washington state and Texas given their mean income and temperature in 2004. While both states have a relatively high income per capita, Texas has a significantly higher annual mean temperature than Washington state. The marginal effect of a 1 °C increase in the monthly standard deviation of daily mean temperatures is 0.118 in Washington state, compared to 0.033 in Texas. The marginal effect of experiencing an additional hot day during the month is 0.129 in Washington state, compared to -0.126 in Texas. Although the higher mean temperature in Texas is associated with a decrease in the marginal effect of both temperature variation and hot days, the decrease is more striking for the marginal effect of hot days.

This supports the conclusions from the conceptual framework in section 3, which showed that for a given level of mean temperature and income, increased variation in temperatures makes adaptation harder. Neither increased income nor increased mean temperature is associated with a strong decrease in the marginal effect of temperature variation on mortality. This implies that adaptation to increased temperature variation is relatively more difficult than adaptation to increased mean temperatures. Depending on the sign and magnitude of the effect of global warming on future temperature variability, this difference in ability for adaptation between mean temperatures and temperature variability, can have important implications for the effect of global warming on future mortality. In addition, if there is spatial heterogeneity in the effect of global warming on future temperature variability, this can have a potentially large effect on the distribution of income across states.

[18] The lowest and highest marginal effects found for the temperature variables are: TVAR = [-0.024, 0.357], cold day = [-0.028, 0.464], warm day = [-0.128, 0.425] and hot day = [-0.363, 1.263].

6.2 Residential air conditioning

In order to explore the effect of air conditioning on adaptation to temperature variation, I estimate the following model,

$$y_{sym} = \mathbb{Z}_{sym} + (\phi_0 + \phi_1 TVAR_{sym} + \sum_j \phi^j TBIN^j_{sym}) \times AC_{sy} \tag{6}$$

where AC_{sy} is the yearly penetration rate of residential air conditioning, meaning the share of households in a state with air conditioning. The data on the penetration rate of residential air conditioning for the sample period is taken from Barreca et al. (2016). Again, $\mathbb{Z}_{sym}$ contains the baseline model specified in equation 4. Table 6 reports the results from estimating the model in equation 6.

[Table 6 here]

Column (1) in Table 6 shows the estimates from the baseline model, while column (2) shows the estimates from estimating the expanded model in equation 6. In line with the previous literature, the harmful effect of warm and hot days on mortality declines when the penetration rate of residential air conditioning increases (Barreca et al., 2016). As expected, residential air conditioning has no effect on the marginal effect of cold days on mortality. Residential air conditioning does, however, have a decreasing effect on the marginal effect of temperature variation on mortality, although the effect is not found to be statistically significant.

While air conditioning was still quite rare for an American household in 1969, in 2004, a total of 29 states had achieved full penetration rate of residential air conditioning. Using the estimates from column (2), going from zero air conditioning to full penetration rate among all households in a state reduces the marginal effect of a warm and hot day by 97% $((-1.558/1.603) \times 100)$ and 101% $((-0.533/0.526) \times 100)$, respectively. The same increase in residential air conditioning, however, is associated with a decrease in the marginal effect of temperature variation on mortality by only 44% ($(-0.116/0.265) \times 100$). In other words, while the prevalence of air conditioning can more or less remove the harmful impact of high temperatures on mortality in a developed country, it offers only limited protection against increased variation in temperatures.

7 Robustness and additional heterogeneity

In this final section, I investigate the robustness of my main results found above, and additional heterogeneity in the temperature-mortality relationship. First, I investigate the robustness of my main specification to different assumptions on the functional form of the relationship between temperature variation and mortality, as well as the chosen measure of monthly temperature variation. The robustness of the temperature-mortality relationship is also tested to the specification of a dynamic model that includes lags on the temperature variables, and to an expansion of the number of temperature bins in the baseline model. Finally, I investigate the robustness of the temperature-mortality relationship over time and for different causes of deaths.

7.1 Functional form and measures of temperature variability

While the baseline model allows for a nonlinear relationship between between mean temperatures and mortality, it assumes a linear relationship between temperature variability and mortality. In order to investigate a potential nonlinear relationship between temperature variation and mortality, as well, Table 7 shows the results from different functional forms of the temperature variability variable.

[Table 7 here]

Column (1) shows the estimates from the baseline model (column (6) in Table 2), while in column (2), the model has been expanded by a quadratic term on the monthly standard deviation of daily mean temperatures. The quadratic term is both negative and statistically significant, implying an inverted u-shaped relationship between temperature variability and mortality. This relationship is plotted in Figure 7. The marginal effect of temperature variability on mortality is increasing up to approximately 9 °C, where it starts decreasing.

[Figure 7 here]

In column (3) in Table 7, I investigate whether the effect of temperature variation on mortality is different depending on whether there is an increase in temperature variation or a decrease. This is done in a two-step regression. First, the temperature variables and mortality rate is regressed on the fixed effects and control variables specified in equation 4. The residuals in the mortality rate are then regressed on the residuals in the temperature variables. By including a dummy for whether the residuals in the temperature variation are negative, and interacting it with the temperature variation, the model allows for a different effect of a negative shock and a positive shock in temperature variation.[19] Given the lack of statistical significance of the coefficient on the interaction between temperature variation and the dummy for a negative shock in column (3), it implies that an increase and decrease in temperature variability does not have a different effect on mortality.

Columns (4)-(6) in Table 7 show the results from estimating the baseline model, but using different measures of monthly temperature variation. The purpose of this exercise is to show that the results are not driven by the particular measure of monthly temperature variation adopted in the benchmark analysis. In columns (4) and (5), the temperature variation is now measured as the monthly standard deviation of daily maximum and minimum temperatures, respectively. Variation in both maximum and minimum daily temperatures has a positive and statistically significant effect on mortality, with the impact on mortality of variation in daily maximum temperatures being slightly smaller than the impact of variation

[19] The standard errors in the second step are computed by adjusting for the degrees of freedom lost in the first regressions.

in daily minimum temperatures. In column (6), monthly temperature variation is measured as the difference between the highest and lowest daily mean temperature during the month. As before, temperature variation is found to have a positive and statistically significant effect on mortality, with the estimated effects on mortality from cold, warm and hot days remaining unchanged in all model specifications. Thus, the effect of temperature variability on mortality is robust to different measures of of monthly temperature variation.

7.2 Dynamic model

The baseline model is estimated at the monthly level. However, the literature on the temperature-mortality relationship has highlighted the "harvesting effect" of exposure to harmful temperatures on mortality (e.g. Deschênes and Moretti, 2009). The harvesting effect is when exposure to such temperatures are not causing the deaths of otherwise healthy people, but instead expediting the deaths of the very ill. Thus, exposure to harmful temperatures are not so much affecting the mortality rate, as it is causing a displacement of deaths in the near-future. In order to check whether this is the case, the baseline model in equation 4 is transformed to the following dynamic model,

$$y_{sym} = \sum_{t=0}^{T} \gamma_t TVAR_{sym-t} + \sum_{t=0}^{T} \sum_{j} \theta_t^j TBIN_{sym-t}^j + \mathbf{X}_{sym}\beta + \alpha_{sm} + \rho_{ym} + \varepsilon_{sym} \tag{7}$$

which includes T number of lags on the temperature variables as explanatory variables. The sum of the coefficients on the lags in the model gives the accumulated effect on mortality from a shock in the temperature variables experienced T months ago. Table 8 shows the accumulated effect of mean temperatures and temperature variation on the mortality rate when the window of exposure is expanded up to six months. To ease comparison, column (1) reports the baseline estimates from Table 2, while columns (2)-(4) reports the estimates for the accumulated effect over 2, 3 and 6 months, respectively.

[Table 8 here]

Table 8 shows that while the harmful impact of cold days on mortality is long-lasting, the harmful impact of warm and hot days is driven mostly by near-term displacements in the mortality rate. These results are in line with previous studies (e.g. Deschênes and Moretti, 2009, Karlsson and Ziebarth, 2018). The effect of the temperature variation on mortality, however, shows a much more persistent effect on morality over time. The effect of a 1 °C increase in the monthly standard deviation of daily mean temperatures remains almost the same after six months as the effect observed after only one month. This implies that instead of expediting the death of the already ill, an increase in the monthly temperature variation is causing the deaths of people that otherwise could have lived at least 6 months longer.

7.3 Expanding the number of temperature bins

A potential threat to identification of the effect of temperature variation on mortality is failure to properly control for the effect of extreme temperatures on mortality. The baseline model in equation 4 aims at estimating the two separate effects of temperatures on mortality: (1) the effect of being exposed to a day with an extreme temperature during a month, and (2) the effect of being exposed to a wider range of temperatures during a month. In order to capture the second effect of temperatures on mortality it is imperative that the model controls for exposure to days in the tails of the temperature probability distribution since exposure to a wider range of temperatures can be correlated with the exposure to days with very low and/or very high temperatures.

The baseline model controlled for exposure to days with extreme temperatures by including the number of cold, warm and hot days experienced during a month. In order to show that the effect of temperature variation on mortality found is not driven by the inclusion of only a few and very wide temperature bins, I re-estimate the baseline model in equation 4, but where the number of temperature bins have been expanded. In the first expansion, each temperature range is now 5 °C wide, starting at −15 °C to 35 °C. This is the same bin structure used in Carleton et al. (2018). In the second expansion, each temperature range is now 1 °C wide, starting at −20 °C to 35 °C.

[Table 9 here]

Table 9 reports the estimate on the effect of temperature variation on mortality for the different bin structures. Column (1) shows the estimates from the baseline model, while column (2) and (3) show the estimate from the first and second expansion of the bin structure, respectively. The table shows slightly smaller marginal effects of temperature variation on mortality when the models is estimated with 5 °C-wide and 1 °C-wide temperature bins, compared to the baseline model. However, the confidence intervals in all three models overlap, thus the small differences found in the marginal effect of temperature variation on mortality are not statistically significant. Figure 8 plots the marginal effect on mortality from exposure to a day with the mean temperature in each of the temperature ranges for the model with the 5 °C-wide temperature bins.

[Figure 8 here]

7.4 By time period

From the analysis of adaptation in the previous section, we saw that the marginal effect of exposure to harmful temperatures on mortality decreases when income increases. The baseline model in column (6) in Table 2 is estimated using the entire sample period 1969-2004. However, it could be argued that the positive and statistically significant effect of monthly temperature variation on mortality found in the baseline model could be driven by the effect of temperature variability on mortality in the beginning of the sample period when income in the US was lower, and thus, people were more exposed to the harmful impacts of temperatures. In order to investigate this hypothesis, I split the sample period in three 12-year periods, and estimate the baseline model separately for each time period.

[Table 10 here]

Columns (1), (2) and (3) in Table 10 report the estimates for the periods 1969-1980, 1981-1992 and 1993-2004, respectively. The table shows that there has been a substantial decline in the marginal effect of warm and hot days on mortality between the two periods, with only a small decline in the marginal effect of cold days on mortality. This decline over time in the marginal effects of mean temperatures on mortality in the US has been documented by others, e.g. Barreca et al. (2015). While a reduction can also be found in the marginal effect of temperature variation on mortality, the impact of temperature variation on mortality remains substantial over time. In the period 1993-2004, a 1 °C increase in the monthly standard deviation of daily mean temperatures still caused an additional 0.151 deaths per 100 000.

7.5 Cause of death

Deschênes and Moretti (2009) found that the increase in mortality following cold days was mainly caused by an increase in cardiovascular- and respiratory-related fatalities, while Barreca (2012) and Karlsson and Ziebarth (2018) found that hot days also caused an increase in cardiovascular-related mortality. Although mean temperatures and temperature variation have been found to have an effect on the all-cause mortality rate, it does not necessarily mean that variation in temperatures affects all causes of deaths equally, nor does it mean that temperature variation and mean temperatures affect mortality through the same causes of death. In order to investigate this, I estimate the baseline model in equation 4 for the cause-specific mortality rates. The causes of deaths identified are infectious diseases, neoplasms, mental disorders, diseases of the nervous system, respiratory diseases, cardiovascular diseases and motor vehicle accidents.[20] However, while the original sample period is 1969-

[20]The ICD 9-codes used to define the causes of deaths are as following: infectious diseases = 1-139, neoplasms = 140-239, mental disorders = 290-319, diseases of the nervous system = 320-389, cardiovascular diseases = 390-459, respiratory diseases = 460-519, and motor vehicle accidents = E810-E819.

2004, in regressions using the cause-specific mortality rates the sample period is limited to 1969-1998 because of the introduction of a new classification system of diseases in 1999.

[Table 11 here]

Table 11 reports the estimates for the cause-specific mortality rates. The pattern in Table 11 is more or less as expected, with a large effect of temperature variation on respiratory and cardiovascular-related mortality in columns (5) and (6), and no effect on fatalities caused by infectious diseases in column (1). Deschênes and Moretti (2009) found a decrease in fatalities caused by traffic accident following cold days. This effect is also found in column (7), in addition to an increase in traffic accident-related mortality following warm and hot days. However, while there is a clear mechanism between extreme temperatures and traffic accidents, there is no clear mechanism between traffic accidents and temperature variation. Thus, it is comforting to see that temperature variation has no effect on fatalities caused by traffic accidents.

The effect of hot days on neoplasm-related mortality found by Karlsson and Ziebarth (2018) is not found here. Instead, column (2) shows that temperature variation has a harmful effect on neoplasm-related mortality, while column (4) shows that temperature variation also has a harmful impact on fatalities caused by diseases of the nervous system. Burke et al. (2018) found a higher suicide rate following warm temperature shocks in Mexico. A similar effect is found in column (3), with warm days affecting fatalities related to mental disorders. In addition, temperature variation is also found to have a negative impact on fatalities related to mental disorders.

8 Conclusion

This paper brings together the economic literature on the effect of global warming on temperature-induced mortality with the climate science literature. While economists have traditionally focused on the effect of mean temperatures on mortality, climate scientists have emphasized the fact that global warming might not only affect mean temperatures, but can also cause a change in future temperature variability as well. Although temperature variation has received some attention in the epidemiology literature, to the best of my knowledge, this paper is the first to estimate the causal effect of temperature variation on mortality through the use of recent innovations in the new climate-economy literature (Dell et al., 2014). This paper joins an emerging literature that is concerned with the social and economic impacts caused by a changing climate besides that of increased mean temperatures.

Using US data for the period 1969-2004, I offer three main findings. First, exposure to a wider range of temperatures during a month has a harmful effect on mortality. More specifically, I find that a 1 °C increase in the monthly standard deviation of daily mean temperatures causes an additional 0.223 deaths per 100 000 people in a state. This is comparable to the effect on mortality from experiencing an additional day with the mean temperature above 31.5 °C each month. Second, I show in a simple prediction exercises how omission of the temperature variation from the temperature-mortality relationship can lead to severally biased predictions of the number of temperature-induced fatalities caused by global warming. Third, while the literature on the temperature-mortality relationship has emphasized the possibility of adaptation to higher mean temperatures, I find less evidence of adaptation to increased temperature variability than for adaptation to higher mean temperatures. For instance, while residential air conditioning fully protects against the harmful effect of hot days on mortality, it offers only limited protection against increased variation in daily mean temperatures.

Given the main findings, this paper outlines three important areas for future research. First, although omission of temperature variation from the temperature-mortality relationship can lead to biased predictions of the effect of global warming on future mortality, at the moment we are lacking credible projections on the effect of global warming on future temperature variation. An important area for future research is to improve climate models, enabling them to deliver credible projections on the future temperature variability. Second, while this paper has found an effect of temperature variability on mortality, it is plausible that temperature variability should affect other social and economic outcomes as well, e.g. agriculture. Investigating the effect of temperature variability on these other outcomes is thus an important venue for future research. Third, the climate sciences have pointed out that global warming can affect temperature variation from the inter-annual to the diurnal level (e.g. Schär et al., 2004, Kharin et al., 2013). This paper has measured temperature variability as the within-month variation in daily temperatures. However, future research should investigate the effect of different scales of temperature variation, as it is not obvious that within-month temperature variation has the same effect on human health as for instance between-seasonal or within-day temperature variation.

Lastly, some climate scientists have argued that although global warming might affect the temperature variability, this effect is only transitory as global temperatures are moving from the old steady state to a new one (e.g. Huntingford et al., 2013). Regardless of whether this is the case or not, reaching a new steady state in global temperatures is a lengthy process. In the meantime, people will have to adapt to not only higher temperatures, but potentially also to changes in the variability of temperatures. Depending on both the sign and the magnitude of the changes in the temperature variability, this paper has shown that in the medium run there can be enormous consequences for human health and mortality.

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A Figures

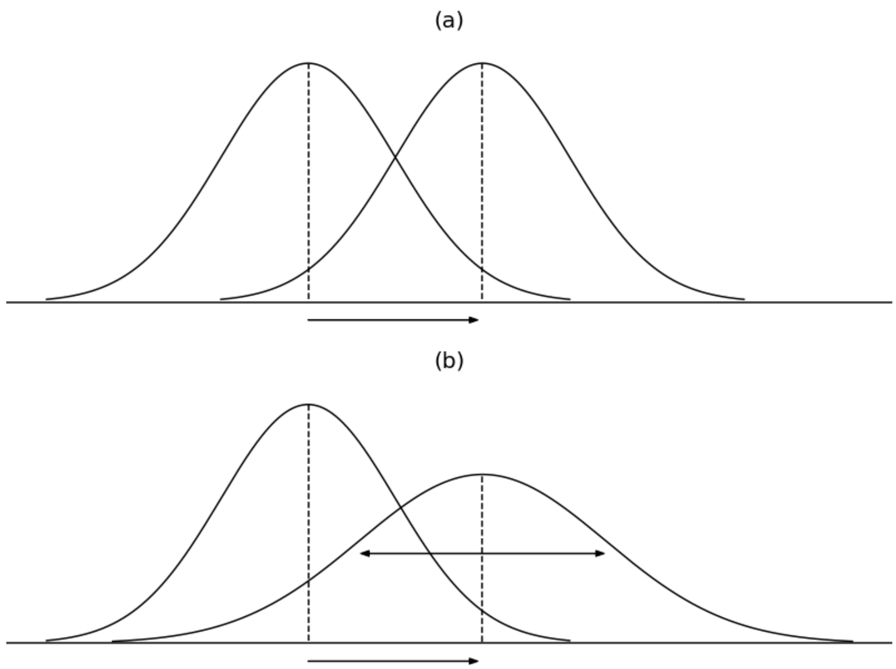

Figure 1: Change in the temperature probability distribution for (a) an increase in the mean temperature only, and for (b) an increase in the mean temperature and increased temperature variance.

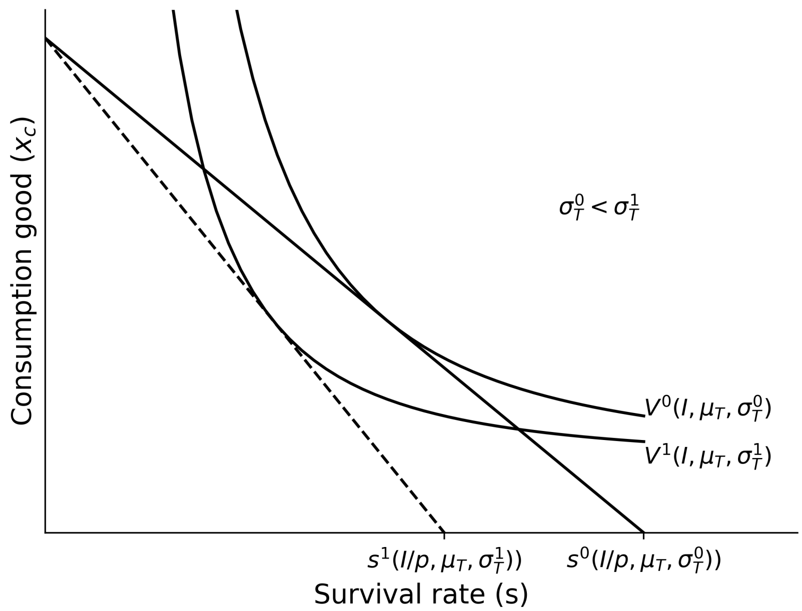

Figure 2: Optimal allocation of income on the consumption good (x_C) and survival rate (s) given income (I), prices (p), mean temperature (μ_T) and temperature variability (σ_T).

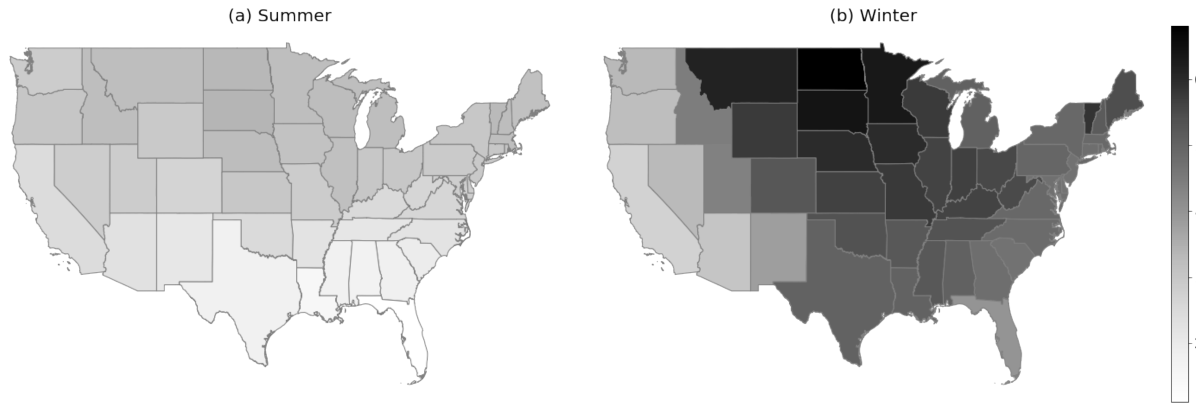

Figure 3: State-level average monthly temperature standard deviation in (a) summer (June, July and August) and (b) winter (December, January and February), 1969-2004.

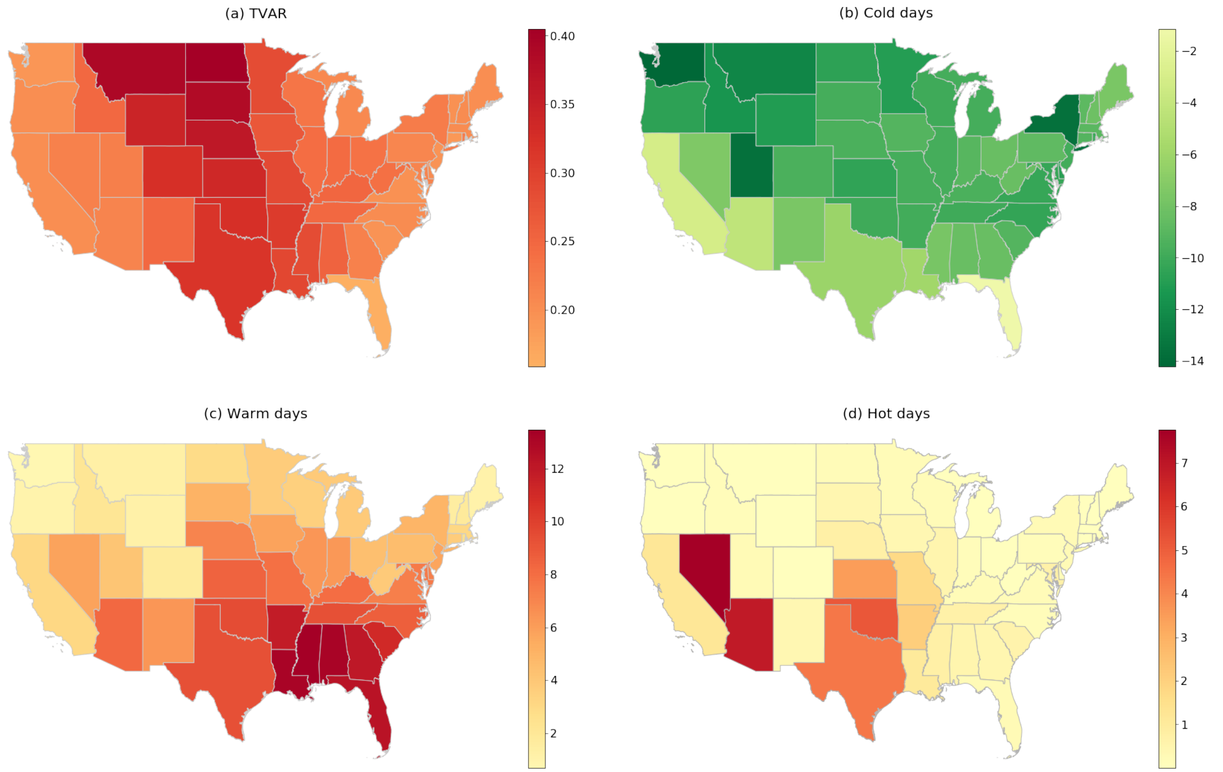

Figure 4: State-level change in temperature variables for a one-standard deviation (a) increase in the average monthly temperature variation, (b) decrease in the average annual numbers of cold days, (c) increase in the average annual number of warm days, and (d) increase in the average annual number of hot days.

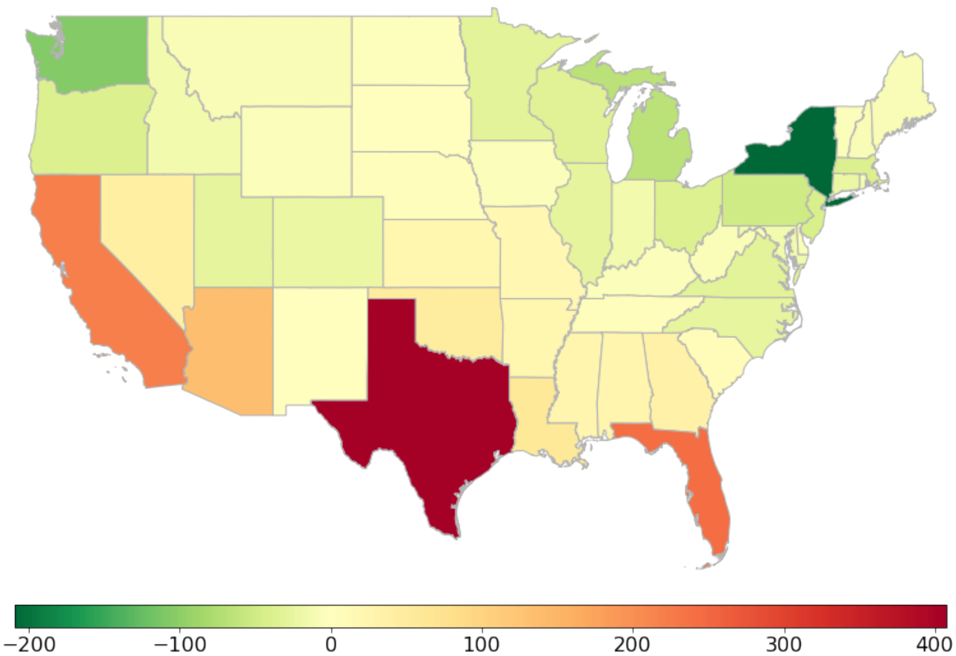

Figure 5: State-level change in the average annual number of temperature-induced fatalities caused by changes in the temperature variables in counterfactual scenario.

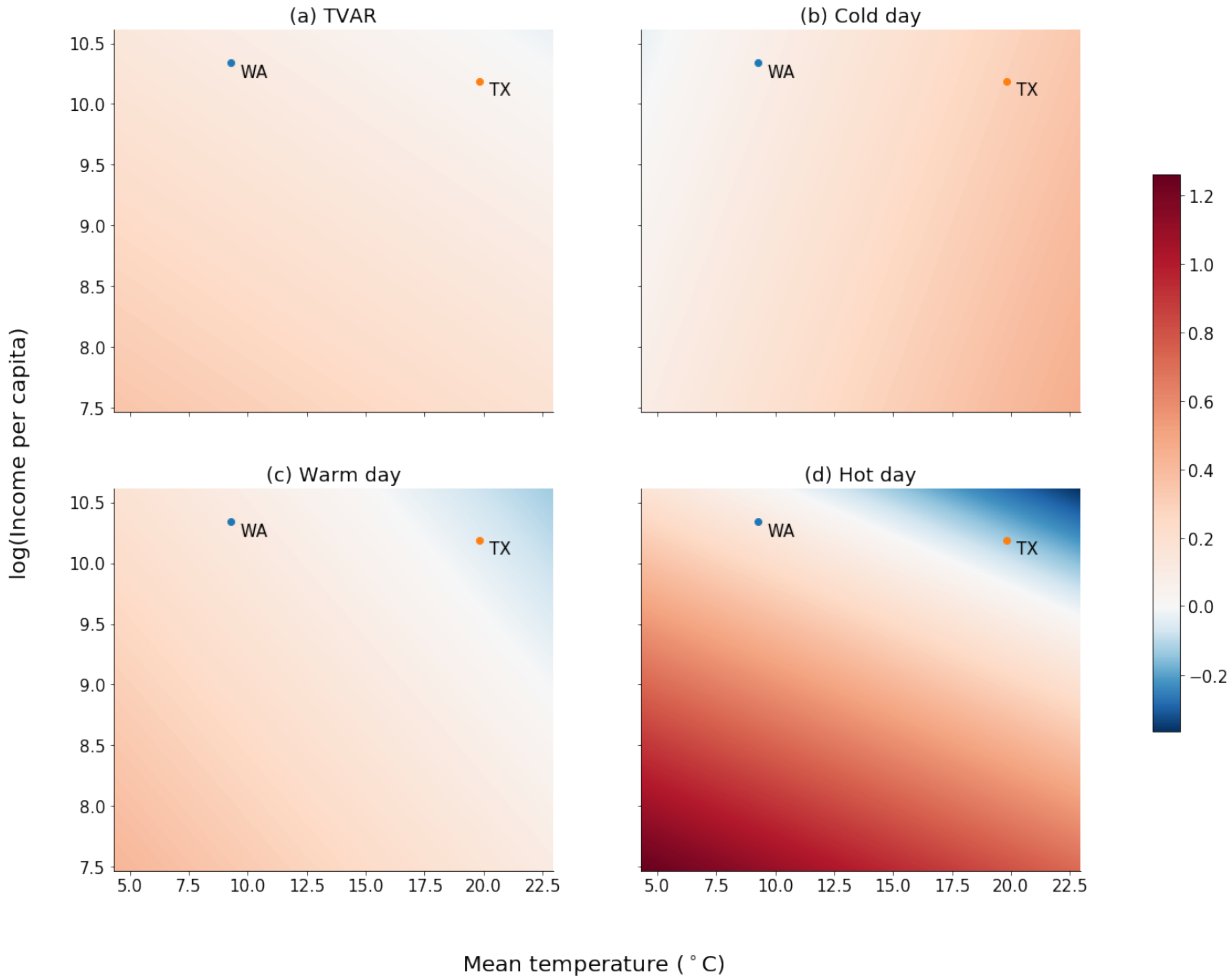

Figure 6: Marginal effects of temperature variables on the mortality rate for combinations of income and mean temperatures.

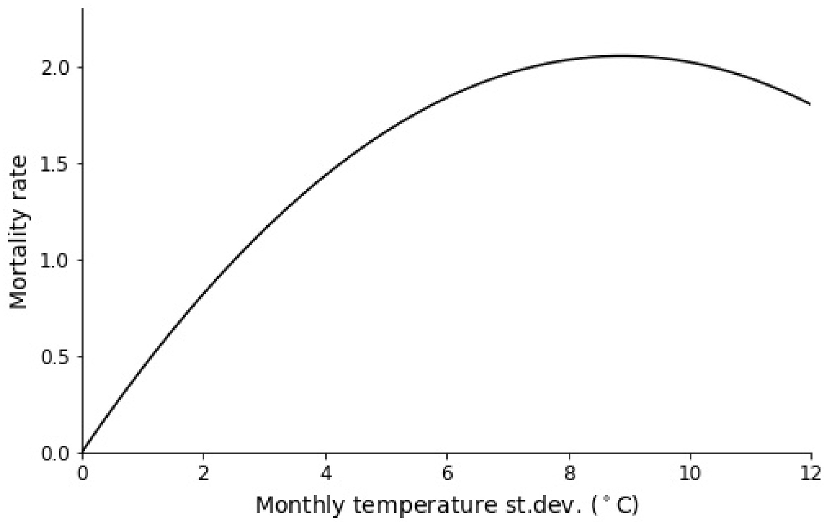

Figure 7: Marginal effect of monthly standard deviation of daily mean temperatures (TVAR) for model with quadratic term on TVAR.

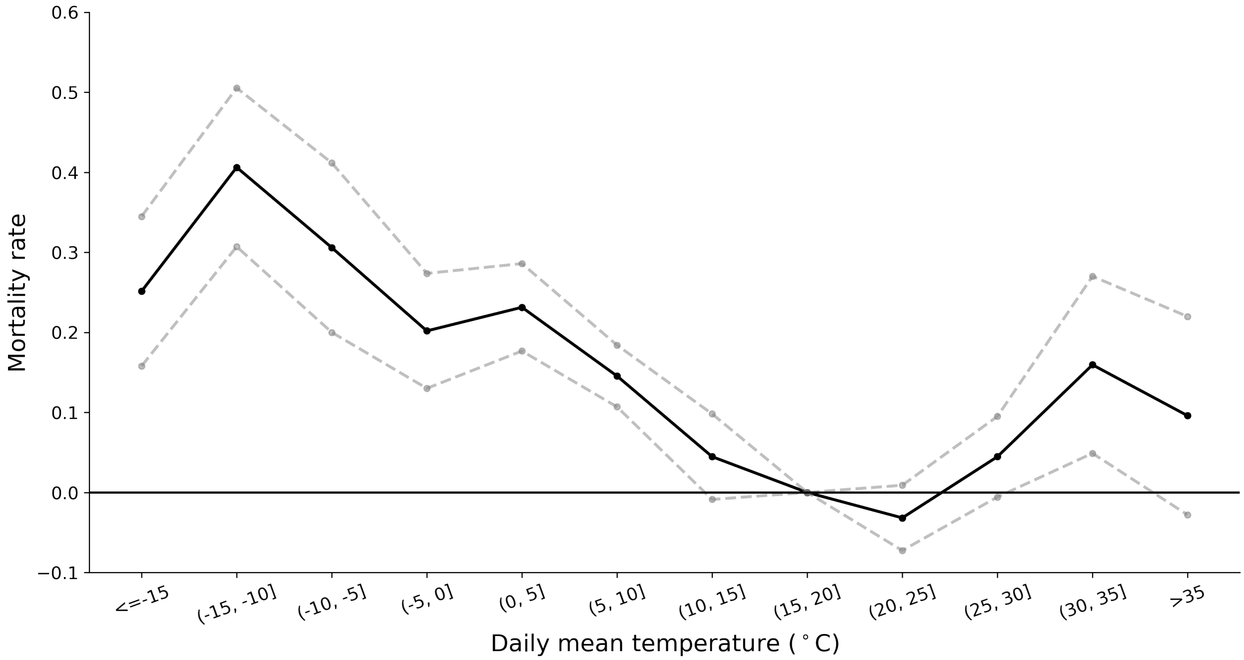

Figure 8: Marginal effect of exposure to a day in 5 °C-wide temperature ranges. The reference category is a day with the mean temperature between $15-20\,°\text{C}$. The dashed lines show the 95% confidence interval.

B Tables

Table 1: Summary statistics for the temperature variables.

	Monthly	Annual			
	(1)	(2)	(3)	(4)	(5)
	TVAR	Mortality rate	Cold days	Warm days	Hot days
National estimate	3.9	874.4	74.0	26.2	1.7
By climate region:					
Central	4.5	936.9	100.2	13.9	0.2
East North Central	4.6	858.0	139.4	5.6	0.1
Northeast	4.1	934.8	106.6	8.7	0.1
Northwest	3.2	802.7	85.4	1.8	0.1
South	3.8	838.9	29.4	72.5	3.3
Southeast	3.3	908.3	30.1	53.8	0.2
Southwest	3.6	709.4	81.3	24.7	13.4
West	2.8	739.4	11.5	18.3	5.2
West North Central	4.9	901.3	142.0	9.3	0.3

Note: All averages are population-weighted. The mortality rate is number of deaths per 100 000. TVAR is the monthly standard deviation of daily mean temperatures measured in °C. US climate regions are defined as following: Central = WV, IL, KY, OH, TN, IN, MO; East North Central = IA, WI, MI, MN; Northeast = MD, VT, CT, NJ, PA, RI, NH, DE, NY, ME, MA; Northwest = ID, OR, WA; South = OK, AR, KS, LA, TX, MS; Southeast = GA, SC, VA, NC, FL, AL; Southwest = NM, CO, AZ, UT; West = NV, CA; and West North Central = NE, ND, SD, MT, WY.

Table 2: Estimation of the temperature-mortality relationship.

	Dependent variable:					
	Mortality rate					
	(1)	(2)	(3)	(4)	(5)	(6)
TVAR	2.378**	.284***	.281***	.269***		.223***
	(.760)	(.063)	(.076)	(.034)		(.037)
Cold day					.167***	.161***
					(.014)	(.013)
Warm day					.094***	.089***
					(.015)	(.014)
Hot day					.266***	.258***
					(.075)	(.072)
State-month FE:	-	Yes	Yes	Yes	Yes	Yes
Year-month FE:	-	-	Yes	Yes	Yes	Yes
Control Variables:	-	-	-	Yes	Yes	Yes
Observations	21,168	21,168	21,168	21,168	21,168	21,168
Adjusted R^2	.096	.843	.911	.962	.963	.963

Note: Regressions are population-weighted. Standard errors are clustered by state. *p<0.05; **p<0.01; ***p<0.001

Table 3: Estimation of the temperature-mortality relationship by age-group.

	Dependent variable:			
	Mortality rate			
	(1)	(2)	(3)	(4)
	< 1 yr	1-44 yrs	45-64 yrs	> 64 yrs
TVAR	.071	.005	.245***	1.494***
	(.145)	(.009)	(.045)	(.221)
Cold day	.174*	-.006	.104***	1.198***
	(.074)	(.004)	(.016)	(.108)
Warm day	.075	.032***	.081***	.430***
	(.067)	(.006)	(.022)	(.092)
Hot day	.192	.058***	.196***	1.692**
	(.130)	(.011)	(.044)	(.555)
Observations	21,168	21,168	21,168	21,168
Adjusted R^2	.906	.865	.967	.925

Note: Regressions are population-weighted and include all fixed effects and control variables. Standard errors are clustered by state. Regressions are executed separately for each age group. *p<0.05; **p<0.01; ***p<0.001

Table 4: Predicted change in average annual number of temperature-induced fatalities in counterfactual scenario.

	All-age mortality		Age-group mortality			
	(1)	(2)	(3)	(4)	(5)	(6)
	TBIN	TBIN+TVAR	< 1 yr	1-44 yrs	45-64 yrs	> 64 yrs
TVAR	-	1,812	8	25	481	1,487
Cold days	-3,972	-3,829	-56	88	-604	-3,511
Warm days	1,773	1,679	20	374	369	1,017
Hot days	797	773	9	111	136	582
Total	-1,401	435	-20	598	382	-425

Note: Predictions based on counterfactual scenario. See text for a description of the scenario. Columns (1) and (2) show the predicted changes in temperature-induced mortality using the all-age models in column (5) and (6) in Table 2, respectively. Columns (3)-(6) use the age-specific estimates from Table 3.

Table 5: Adaptation in the temperature-mortality relationship by income and mean temperature.

	Dependent variable:		
	Mortality rate		
	(1)	(2)	(3)
TVAR	.910*	.307***	.904**
	(.387)	(.083)	(.347)
Cold day	.573**	-.066	.289
	(.207)	(.039)	(.192)
Warm day	.764***	.320***	1.058***
	(.226)	(.074)	(.230)
Hot day	3.707***	.860	3.965***
	(.681)	(.451)	(.817)
TVAR×income	-.077		-.068
	(.042)		(.041)
Cold day×income	-.045*		-.038
	(.022)		(.021)
Warm day×income	-.072**		-.075**
	(.024)		(.023)
Hot day×income	-.371***		-.345***
	(.068)		(.062)
TVAR×TMEAN		-.010	-.009
		(.008)	(.008)
Cold day×TMEAN		.020***	.020***
		(.003)	(.004)
Warm day×TMEAN		-.015**	-.017**
		(.005)	(.005)
Hot day×TMEAN		-.033	-.029
		(.024)	(.019)

continued

continuation of table

Observations	21,168	21,168	21,168
Adjusted R^2	.947	.946	.947

Note: Regression are not weighted. Regressions include all fixed effects and control variables. Standard errors are clustered by state. $^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.001$

Table 6: Adaptation in the temperature-mortality relationship by residential air conditioning.

	Dependent variable:	
	Mortality rate	
	(1)	(2)
TVAR	.223***	.265***
	(.037)	(.051)
Cold day	.161***	.137***
	(.013)	(.033)
Warm day	.089***	.526***
	(.014)	(.087)
Hot day	.258***	1.603***
	(.072)	(.264)
TVAR×AC		-.116
		(.079)
Cold day×AC		.040
		(.045)
Warm day×AC		-.533***
		(.102)
Hot day×AC		-1.558***
		(.252)
Observations	21,168	21,168
Adjusted R^2	.963	.945

Note: Regression in column (1) is weighted by population, while regression in column (2) is unweighted. Regressions include all fixed effects and control variables. Standard errors are clustered by state. *p<0.05; **p<0.01; ***p<0.001

Table 7: Robustness to functional form and different measures of monthly temperature variability.

	Dependent variable:					
	Mortality rate					
	(1)	(2)	(3)	(4)	(5)	(6)
TVAR	.223***	.462***	.232***			
	(.037)	(.116)	(.066)			
TVAR squared		-.026*				
		(.011)				
TVAR×negative			.061			
			(.074)			
Maximum TVAR				.172***		
				(.036)		
Minimum TVAR					.214***	
					(.034)	
TMEAN max-min						.057***
						(.011)
Cold day	.161***	.160***	.161***	.164***	.161***	.161***
	(.013)	(.013)	(.013)	(.013)	(.014)	(.013)
Warm day	.089***	.088***	.090***	.089***	.093***	.090***
	(.014)	(.014)	(.014)	(.014)	(.014)	(.014)
Hot day	.258***	.257***	.258***	.261***	.259***	.258***
	(.072)	(.071)	(.073)	(.073)	(.073)	(.073)
Observations	21,168	21,168	21,168	21,168	21,168	21,168
Adjusted R^2	.963	.963	.026	.963	.963	.963

Note: Regressions are population-weighted, and include all fixed effects and control variables. Standard errors are clustered by state. In column (3), the regression is executed in two steps: First, the mortality rate and temperature variables are regressed on all control variables and fixed effects. Second, the residuals in the mortality rate are regressed on the residuals in the temperature variables, while adjusting for the degrees of freedom lost in the first step. *p<0.05; **p<0.01; ***p<0.001

Table 8: Robustness to dynamic model of the temperature-mortality relationship.

	Dependent variable:			
	Mortality rate			
	(1)	(2)	(3)	(4)
	1 month	2 months	3 months	6 months
TVAR	.223***	.256***	.227**	.210*
	(.037)	(.067)	(.087)	(.094)
Cold day	.161***	.231***	.180***	.099**
	(.013)	(.023)	(.028)	(.035)
Warm day	.089***	.061**	.051*	-.031
	(.014)	(.020)	(.024)	(.033)
Hot day	.258***	.158*	.126	-.129
	(.072)	(.073)	(.065)	(.088)
Observations	21,168	21,119	21,070	20,923
Adjusted R^2	.963	.963	.963	.964

Note: Regressions are population-weighted and include all fixed effects and control variables. Standard errors are clustered by state. The number of lags on the temperature variables varies between 1-5 months, and the reported estimates in the columns are the cumulative effect over the window of exposure. *p<0.05; **p<0.01; ***p<0.001

Table 9: Robustness to expanding the number of temperature bins.

	Dependent variable:		
	Mortality rate		
	(1)	(2)	(3)
TVAR	.223***	.171***	.187***
	(.037)	(.039)	(.037)
Observations	21,168	21,168	21,168
Adjusted R^2	.963	.964	.964

Note: Column (1) is the estimate from the baseline model. In column (2), the regression includes temperature bins that are 5 °C wide, starting at −15 °C to 35 °C. In column (3), the regression includes temperature bins that are 1 °C wide, starting at −20 °C to 35 °C. Regressions are population-weighted and include all fixed effects and control variables. Standard errors are clustered by state. *p<0.05; **p<0.01; ***p<0.001

Table 10: Robustness to estimation by time period.

	Dependent variable:		
		Mortality rate	
	(1)	(2)	(3)
	1969-1980	1981-1992	1993-2004
TVAR	.335***	.166**	.151*
	(.069)	(.056)	(.072)
Cold day	.196***	.175***	.163***
	(.019)	(.025)	(.032)
Warm day	.172***	.091***	.035
	(.035)	(.026)	(.020)
Hot day	.492***	.232**	.160*
	(.118)	(.080)	(.079)
Observations	7,056	7,056	7,056
Adjusted R^2	.947	.970	.972

Note: Regressions are population-weighted and include all fixed effects and control variables. Standard errors are clustered by state. Regressions are executed separately for each time period. *p<0.05; **p<0.01; ***p<0.001

Table 11: Estimation of the temperature-mortality relationship by cause of death.

	Dependent variable:						
	Infectious disease (1)	Neo-plasms (2)	Mental disorders (3)	Nervous system (4)	Resp. disease (5)	Cardiovasc. disease (6)	Traffic accidents (7)
TVAR	.0003	.025**	.005*	.009***	.037***	.155***	.002
	(.001)	(.009)	(.002)	(.003)	(.009)	(.009)	(.004)
Cold day	-.0001	.005	.001	.004***	.025***	.106***	-.009***
	(.0005)	(.004)	(.001)	(.001)	(.004)	(.004)	(.001)
Warm day	-.0002	.004	.002*	.004*	.003	.044***	.006**
	(.0005)	(.003)	(.001)	(.002)	(.003)	(.003)	(.002)
Hot day	-.001	-.010	.005	.001	.002	.129***	.017**
	(.003)	(.013)	(.004)	(.005)	(.008)	(.013)	(.006)
Observations	17,640	17,640	17,640	17,640	17,640	17,640	17,640
Adjusted R^2	.598	.950	.902	.916	.893	.967	.848

Note: Regressions are population-weighted and include all fixed effects and control variables. Standard errors are clustered by state. *p<0.05; **p<0.01; ***p<0.001