Deadly Variation: The Effect of Temperature Variability on Mortality*

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Abstract

While economists have focused on the effect of mean temperatures on mortality, climate scientists have emphasized that global warming might not only lead to an increase in mean temperatures, but can potentially also affect temperature variability. 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 variability on mortality can severely bias our predictions on the number of temperature-induced fatalities caused by global warming, and (3) adaptation to increased temperature variability is more difficult than adaptation to increased mean temperatures.

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1 Introduction

This past decade has been the warmest one ever on record with almost every year being warmer than the previous one (WMO, 2019). However, human-induced climate change, also known as global warming, is not only causing an increase in the global mean temperature, but it is also causing an increase in the probability and severity of extreme heat events (Coumou and Rahmstorf, 2012). The start of this century has been unprecedented in terms of extreme weather events, with many recent extreme heat events being far outside of the previous temperature distribution. As a case in point, in 2003, large parts of Europe was struck by a heat wave so severe that it is believed to have led to more than 70,000 premature deaths (Robine et al., 2008). Despite an only modest increase in the mean temperature above pre-industrial levels at the time, temperatures during the heat wave beat the previous record by 3 °C (Schär et al., 2004). Furthermore, in just a decade there was a tenfold increase in the probability of experiencing another heat event as severe as the one in 2003 (Christidis, Jones, and Stott, 2015). This dramatic increase in the probability and severity of extreme heat events has led climate scientists to question whether global warming is leading to a simple increase in mean temperatures, or whether it is also affecting temperature variability. While it has been established with a high degree of certainty that global warming will cause increased mean temperatures (IPCC, 2014), there is less certainty regarding the effect of global warming on temperature variability. This is, however, a question of increasing concern and research among climate scientists (Klavans et al., 2017).

I investigate the effect of temperature variability on mortality by exploiting the plausibly random variation in daily temperatures to identify the effect of being exposed to more variation in daily temperatures, while controlling for exposure to days with extreme temperatures. Using a within-state identification strategy as in Barreca et al. (2016), I estimate the effect of monthly 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. Second, I show in a simple prediction exercise how omitting the effect of temperature variability from the temperature-mortality relationship can severely bias our predictions on the number of temperature-induced fatalities caused by global warming. Third, I find that adaptation to increased temperature variability is more difficult than adaptation to increased mean temperatures. Although there are technologies that can protect against 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). I find that while residential air-conditioning fully removes the harmful impact of exposure to high temperatures, it provides only partial protection against temperature variation. Previous studies have also 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). I find that higher income and mean temperatures have little effect on the harmful impact of monthly temperature variability on mortality.

There is a large economic literature concerned with estimating the costs associated with global warming. While 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 has been found to be caused by the effect of increasing temperatures on human mortality. Thus, an important topic 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 exposure to extreme mean 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).

This paper makes two main contributions to this literature. First, although the effect of temperature variability 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, Jones, and Olken, 2014), this is the first paper to offer evidence on the causal impact of temperature variability on mortality. Second, this paper contributes to the literature by bringing together the economic research on the temperature-mortality relationship with current research in the climate sciences. Although papers on the temperature-mortality relationship has relied on the random variation in temperatures over time for identification, they have not estimated the effect of temperature variation *itself* on mortality. There has so far been little concern among economists about the economic and social impact of temperature variability, whereas climate scientists, on the other hand, are becoming increasingly concerned about the effect of global warming on temperature variability. While the effect of exposure to extreme mean temperatures on human health has received considerable attention, temperature variability also matters by affecting the marginal utility of investing in adaptation. The marginal utility from investing in e.g. air-conditioning is higher for people living in hot places who will benefit from their air-conditioning all year round, compared to people living in places exposed to both cold and hot days who will only benefit from air-conditioning part of the time.

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. For instance, Fishman (2016) estimates the impact of the temporal distribution of

[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.

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, while Barreca (2012) finds that global warming can affect mortality by also causing a change in humidity levels. This literature demonstrates that in order to estimate the true social cost of carbon, it is important to consider the many other consequences of global warming besides mean warming.

The rest of the paper proceeds as follows. Section 2 provides a review of the literature 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 the strategy for estimating the relationship between temperature variability and mortality. In section 5, the estimation results from the benchmark analysis are presented, and a simple prediction exercise on the number of temperature-induced fatalities by the end of the century is offered. Section 6 takes a closer look at adaptation to temperature variability, while section 7 investigates robustness and heterogeneity in the estimated impact of temperature variability on mortality. 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 over 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, namely increased exposure to hot days, but they have not captured the second effect of being exposed to a wider range of temperatures 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 probability 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, Brown, and Murphy, 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

[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, Sato, and Ruedy, 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.

shown that reduced nocturnal cooling has a disproportionally large effect on the occurrence and severity of heatwaves (Clark, Brown, and Murphy, 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 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 future temperature variability (see Holmes et al. (2016) for a review). There is usually a lot of 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 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, Bischoff, and Płotka, 2015, Sillmann et al., 2011).[4] The early study of Zwiers and Kharin (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 in daily minimum temperatures, thus causing an increase in diurnal temperature variability. Hegerl et al. (2004) find that for large portions of the world, projected changes in temper-

[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).

[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.

ature extremes differ substantially from projected increases in seasonal mean temperatures. For the US, both the coldest and warmest day during the year warm faster than the seasonal mean temperatures. Ballester, Giorgi, and Rodó (2010) and Fischer and Schär (2010) find increased variation in daily mean temperatures for most of Europe. Clark, Brown, and Murphy (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 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 temperature variability. Although model projections are showing an effect of global warming on temperature variability in many parts of the world, GCMs are not yet 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 an active and growing area of research among climate scientists.

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 standard deviation, σ^T. The production function for survival is given by,

$$s = s(x_H, \mu^T, \sigma^T) \tag{2}$$

where 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 is a clear link between exposure to extreme temperatures and mortality (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. However, for the agents in the model, variation in temperatures also matters. More variation in temperatures around the mean means that agents must invest in technologies protecting against a wider range of temperatures. For a certain temperature variability it might be sufficient to invest in home insulation to protect against exposure to harmful temperatures. However, an increase in temperature variability 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, i.e. home insulation, the mortality risk of exposure to temperatures increases. The critical point is that while agents living in a hot place will benefit from e.g. air-conditioning all year round, agents living in places exposed to both cool and hot weather will only benefit from air-conditioning part of the time. An increase in temperature variability will therefore reduce the marginal utility of investing in adaptation

[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).

to temperatures.[6]

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

$$I - x_C - px_H = 0 \tag{3}$$

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 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 standard deviation, σ^T, 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 σ^T will, ceteris paribus, cause a decrease in utility. While the maximum survival rate attainable by the agent used to be $s_0(I/p, \mu^T, \sigma_0^T)$, for the higher level of σ^T the maximum survival rate attainable is now $s_1(I/p, \mu^T, \sigma_1^T)$. The maximum consumption level of x_C, however, remains unaffected by the increase in σ^T. Figure 2 illustrates this change in the budget restriction caused by the increase in σ^T.

[Figure 2 here]

There are two effects from the increase in the temperature standard deviation. First, there is an income effect. A higher σ^T means a reduction in the marginal utility of investing in health goods (e.g. while air-conditioning used to offer protection all year round, the increase in the temperature standard deviation means that it offers protection only parts

[6] An additional explanation offered by the epidemiology literature is physiological acclimatization. Humans can adjust to changes in temperature, however, this is a process that requires time (Hanna and Tait, 2015). While acclimatization to new temperatures requires active and regular exposure to such temperatures over an extended period of time, increased temperature variability reduces the time allowed for acclimatization, thus increasing the harmful effect of temperatures on human health.

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 effects pull in different directions for x_C, causing an ambiguous effect on consumption of x_C, they pull in the same direction for the survival rate, namely a reduced 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 know with certainty that the agent now faces a higher mortality risk.

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 (2018). By extracting information from death certificates filed, the MCOD files contain information about all deaths occuring on US territories. Mortality rates are constructed by combining the death counts with population estimates from the 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 District of Columbia), with the mortality rate defined as the number of deaths occurring in a state in a month per 100,000 people.[7]

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).[8] The GHCN-daily database contains daily summaries

[7]The data is compiled on the state level because of a policy change that made county information in the public use mortality data unavailable after 1988 for counties with a population below 100,000.

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

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 precipitation. The database contains in total 59,928 weather stations in the contiguous US. However, in order to reduce the measurement bias from stations going online and offline (Auffhammer et al., 2013), 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 fulfill this criterion, then all observations from that station in that year are dropped from the sample.[9]

Two types of temperature variables are constructed: the monthly temperature standard deviation and the monthly mean temperature. The monthly temperature standard deviation is defined as the standard deviation of daily mean temperatures within a month, with the daily mean temperature calculated as the average of the daily maximum and minimum temperature. This variable corresponds to the parameter σ^T in the conceptual framework presented in the previous section.[10] 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 in a month with the daily mean temperature within a certain temperature range, also known as temperature bins. In the benchmark analysis, I use the three critical temperature ranges defined in Barreca et al. (2016): $< 4.5\,°\mathrm{C}$, $26.5 - 31.5\,°\mathrm{C}$, and $> 31.5\,°\mathrm{C}$. A day with the mean temperature below 4.5 °C, between 26.5 and 31.5 °C, and above 31.5 °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 °C.[11] In addition, precipitation is measured as a second order polynomial in the

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

[10] In section 7, I check the robustness of my benchmark analysis to different measures of the monthly temperature variation.

[11] 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. In section 7, I check the robustness of my benchmark analysis to an increase in the number of temperature bins and to measuring the mean temperature as a fourth order polynomial function.

monthly sum of daily accumulated precipitation.[12]

All temperature and precipitation variables are measured at the station level. County level temperature and precipitation variables are then calculated 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.[13] The final data set contains observations on the mortality rate, temperature standard deviation, number of cold, warm and hot days, and accumulated precipitation, for each state in each month in the contiguous US. The analysis in this paper is restricted to the period 1969-2004 since this is the period with both population and mortality data available.[14]

4.2 Summary statistics

Table 1 shows summary statistics for the mortality rate and temperature variables on the national level and for the different climate regions of the US over the sample period 1969-2004. All averages in the table are population-weighted and can therefore be interpreted as the exposure to extreme temperatures and temperature variability for the average American. Column (1) shows the average monthly temperature standard deviation, σ^T. The average American was exposed to a monthly σ^T of 3.9 °C. Columns (2)-(4) show the average annual number of cold, warm and hot days, respectively. Over the sample period, the average

[12]The precipitation variable is constructed by first calculating the second order polynomial for each day at the station level. The polynomial is then aggregated up to the state level (see the text for details), at which point the daily precipitation polynomial is summed across all days in a month. Under the assumption that weather events are additive, this transformation of the precipitation variable up to the state-month level preserves the nonlinear relationship between mortality and precipitation that occurs on the station-day level (Hsiang, 2016)

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

[14]Population counts are available from 1969 and onwards, 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.

American experienced 74 cold days, 26.2 warm days and 1.7 hot days during the year, thus, the average American was exposed to far more cold days than hot ones during the year. Column (5) shows that the average annual mortality rate was 874.4 deaths per 100,000 people for the US over the sample period.

[Table 1 here]

There is, however, substantial variation in exposure to temperature variability and days with extreme temperatures across the climate regions of the US.[15] While people in the West were exposed to an average monthly σ^T of only 2.8 °C, people in West North Central were on average exposed to a monthly σ^T of almost 5 °C. All climate regions were on average exposed to cold days during the year, with people in the Northern and Eastern part of the US exposed on average to more than 100 such days during the year, and even in the West, people were on average exposed to at least 11 cold days during the year. When it comes to hot days, on the other hand, most people rarely experienced a hot day during the year, with the notable exception of people in the Southwest who were on average exposed to 13.4 such days during the year.

[Figure 3 here]

In addition to the variation in the monthly σ^T across the climate regions of the US, there is also substantial variation in the monthly σ^T across the seasons of the year. Panel (a) and (b) in Figure 3 show the average monthly σ^T experienced by states over the sample period for summer and winter months, respectively.[16] The figure shows that the monthly σ^T is higher during winter months than during summer months in all states, however, the difference in the monthly σ^T between winter and summers is generally low for states in the Western part of the US. The pattern of spatial heterogeneity also differs between the seasons,

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

[16] Summer months are defined as June, July and August, while winter months are December, January and February.

with the states experiencing the lowest σ^T found in the South during summers and in the West during winters. The lowest σ^T during summers is found in Florida with an average monthly σ^T of only 1.1 °C, while the highest σ^T during summers is found in South Dakota with an average monthly σ^T of 3.4 °C. The highest σ^T during winters is found in North Dakota with an average monthly σ^T of 6.8 °C, while the lowest σ^T during winters is found in California with an average monthly σ^T of only 2.7 °C.

4.3 Estimation strategy

I estimate the causal effect of monthly temperature variability 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,

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

where y_{sym} is the monthly mortality rate in state s, year y and month m. The variable of interest is σ^T_{sym}, which is the monthly temperature standard deviation. $TBIN^j_{sym}$ is the number of days in a month with the mean temperature within a certain temperature range, j. The number of temperature bins 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 people in a state during the 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 e.g. income (hotter states tend to be poorer, and poorer states tend to have a higher mortality rate). To avoid this confounding, I employ two strategies. First, I include a rich set of fixed effects, namely a state-by-month fixed effect, α_{sm}, and a year-by-month fixed effect, ρ_{ym}. The state-by-month fixed effect is 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 effect captures 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, $\mathbf{X}_{sym}$, which contains a second order polynomial in the monthly accumulated precipitation, the share of state population in four age categories, and the log of per capita income.[17] 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 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.

By including these 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 temperature probability distribution, and this distribution is correlated with other confounding factors, each state will over time experience random fluctuations around their month-specific mean caused by the stochastic nature of temperatures. The temperature-mortality relationship is thus identified by the presumably exogenous variation over time in temperatures caused by random draws from the location-specific temperature probability distribution. 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.

[17] The four age groups are: < 1 year, 1-44 years, 45-64 years, and > 64 years. They are constructed by using population counts from the National Cancer Institute (2019). The per capita income is extracted from the Bureau of Economic Analysis (2019).

5 The temperature-mortality relationship

5.1 Mean temperatures and temperature variability

Results from estimation of equation (4) are shown in Table 2.[18] Column (1) is the naive estimation of the temperature-mortality relationship, which leads to an overestimation of the effect of temperature variability 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 small additional decreases in the impact of the monthly σ^T on mortality. Column (4) shows that the monthly σ^T has a positive and statistically significant effect on mortality, with an increase in the monthly σ^T 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 investigated previously by the literature, namely the effect of exposure to extreme mean temperatures on mortality. In column (5), an additional cold day during the month causes an additional 0.167 deaths per 100,000, while an additional hot day during the month causes an additional 0.266 deaths per 100,000 people. The magnitude of these estimates are in line with previous studies, which have found a positive and statistically significant effect of exposure to days with both a high and low mean temperature on mortality (e.g. Barreca et al., 2016, Karlsson and Ziebarth, 2018).

A potential threat to identification of the models in columns (4) and (5) is the confounding of the effect of exposure to increased temperature variability with the effect of exposure to days with an extreme mean temperature. Since an increase in the monthly temperature standard deviation can cause an increase in the number of days in the tails of

[18] 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.

the temperature probability distribution, it can be argued that the impact of the monthly σ^T on mortality found in column (4) is not driven by temperature variability per se, but instead by the accompanying increase in the days with low and/or high mean temperatures. Similarly, the effect of cold, warm and hot days on mortality found in column (5) could partly be driven by increased σ^T, 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 effects of exposure to extreme mean temperatures and temperature variability on mortality. The impact on mortality of an additional cold, warm and hot day remains largely unchanged, e.g. an additional hot day during the month causes an additional 0.258 deaths per 100,000. Likewise, controlling for the exposure to extreme mean temperatures (i.e. cold, warm and hot days) has little effect on the impact of the monthly temperature standard deviation on mortality. Column (6) shows that a 1 °C increase in the monthly σ^T causes an additional 0.223 deaths per 100,000 people, even when controlling for the potential increase in the number of cold, warm and hot days. The marginal effect of σ^T on mortality is thus comparable to the impact on mortality from experiencing an additional hot day during the month, which previous studies on the temperature-mortality relationship have focused on (e.g. Barreca et al., 2016). Since column (6) provides estimates of the separate effects of temperature variability and exposure to extreme mean temperatures on mortality, this is the preferred specification of the temperature-mortality relationship for the remainder of the paper.[19]

5.2 Prediction exercise

Given the magnitude of the impact on mortality from exposure to increased temperature variability, the existing literature on the temperature-mortality relationship has omitted an important component of this relationship. The consequences of this omission is explored in

[19]In section 7, I investigate the robustness of my benchmark analysis to the functional form and measure of monthly temperature variation chosen in the preferred specification.

the following prediction exercise. Temperature projections for the end of the century are collected from the Global Daily Downscaled Projections (GDDP) data created by NASA Earth Exchange (Thrasher et al., 2012). The NEX-GDDP data is compiled from the General Circulation Model runs conducted under the Coupled Model Intercomparison Project Phase 5, and it consists of high-resolution ($0.25\,^{\circ} \times 0.25\,^{\circ}$) bias-corrected climate projections from 21 different climate models throughout the year 2099. I collect temperature projections from all of the models in the NEX-GDDP data for the RCP8.5 emission scenario, which corresponds to a mean global surface warming of approximately $4-6\,^{\circ}$C above pre-industrial levels by the end of the century. I define global warming as the difference in the average annual number of cold, warm and hot days for each state in the period 2070-2099 compared to the baseline period 1969-2004.[20,21]

[Table 3 here]

Panel A in Table 3 shows a population-weighted average of the projected changes in the number of cold, warm and hot days for the US as a whole.[22] The NEX-GDDP data projects that the average American will be exposed to 38.4 fewer cold days, 39.6 additional warm days and 19.9 additional hot days each year by the end of the century. There is, however, substantial variations across states in the projected changes in the number of cold, warm and hot days (see Appendix C for state specific projections). Panel B in Table 3 shows the mortality impacts of these projected changes in the number of cold, warm and hot days

[20]Daily mean temperatures at each grid point is calculated as the average across the 21 climate models in the NEX-GDDP data. Daily mean temperatures are then aggregated up to the county level by taking the average across all grid points that fall within a county. A population-weighted average is then taken across all counties within a state. The population weights used is the share of US population in each county in 2004, which implies the assumption that the distribution of people in the US remains the same after 2004. Global warming is then defined as the difference in the average annual number of cold, warm and hot days between the periods 2070-2099 and 1969-2004.

[21]The final data set contains temperature projections for all areas in the sample used for estimation except District of Colombia. Even though the NEX-GDDP data is of a high-resolution, there are no grid cells that fall within the district.

[22]This is a weighted average of the difference in the number of cold, warm and hot days across all states, using the average state population in the baseline period 1969-2004 as weights.

using the estimates from the preferred specification in column (6) in Table 2. The decrease in the number of cold days reduces mortality by 26,607 fewer deaths each year, while the increases in the number of warm and hot days increase mortality by an additional 15,168 and 22,096 deaths each year, respectively. Using projected population counts from United Nations (2017), these estimates take into account population growth in the US throughout the century.[23] The net effect is an increase in the number of temperature-induced fatalities by approximately 10,500 each year. The increase, however, is not statistically significant. Furthermore, since states do not experience uniform changes in the number of cold, warm and hot days, this national estimate is masking large distributional effects between states (see Appendix C for state specific mortality estimates).

[Figure 4 here]

While we have 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 active area of research among climate scientists, however, projections from climate models are not yet tailored for capturing the effect of global warming on second-order moments of the temperature probability distribution. Sidestepping this issue, Figure 4 illustrates the additional effect on the number of temperature-induced fatalities for hypothetical changes in the monthly temperature standard deviation by the end of the century. Table 3 showed that under the assumption of no changes in the monthly σ^T, the increase in mean temperatures will cause an increase in mortality by approximately 10,500 additional fatalities each year. Figure 4 shows that a 1 °C increase in the monthly σ^T will cause a doubling in this predicted increase in the annual number of temperature-induced fatalities, while a 1 °C decrease will fully counteract the predicted increase in mortality caused

[23]According to these projected population counts, average population in the 48 adjoining US states in the period 2070-2099 will be 430,371,246. However, the mortality predictions are based on the assumption of constant distribution of people across states and age groups between the periods 1969-2004 and 2070-2099.

by increased mean temperatures. Even for much smaller changes in the monthly temperature standard deviation there can be a substantial effect on predicted future mortality. If the monthly σ^T were to increase by only 0.4 °C, that would still cause an additional 5,000 predicted fatalities each year, incidentally also making the predicted increase in the annual number of temperature-induced fatalities by the end of the century statistically significant. Figure 4 illustrates that even small changes in the monthly temperature standard deviation can have a large impact on the predicted effect of global warming on mortality, thus highlighting the importance of improving climate models in order to deliver credible projections on future temperature variability.

6 Adaptation to global warming

The temperature-mortality relationship estimated in the previous section 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 perceived 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 against 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).[24] This is because increased exposure to extreme temperatures reduce the opportunity cost of investment in adaptation. 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 section, I consider two tests of adaptation to temperature variability 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-conditioning on the marginal effect of the temperature variables. Given that the goal of this analysis is to investigate heterogeneity in the temperature-mortality relationship along different axes of adaptation, the following regression models are estimated without weights (Solon, Haider, and Wooldridge, 2015). In addition, because of a lack of random variation in income and residential air-conditioning rates within states over time, the adaptation analysis cannot claim causality. Instead, it explores the correlation between the temperature variables 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. In equation (5), the long-run mean income, $log(inc_{pc})$, and temperature, $TMEAN$, are measured as 10-year moving averages of annual log income per capita and annual mean of daily mean temperatures.[25]

[24] 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.

[25] By measuring the long-run means for each state as 10-year moving averages, as opposed to e.g. the mean over the sample period, I allow 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

$\mathbb{Z}_{sym}$ contains the terms from the baseline model specified in equation (4).

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

Table 4 reports the results from estimating the model in equation (5). In column (1), the model is estimated with interactions between the temperature variables and mean income only, while in column (2), the model is 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 all as expected.

[Table 4 here]

The coefficients on all of the interaction terms in column (1) are negative, implying a decline in the marginal effects of the monthly σ^T and days with extreme mean temperature 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, a higher annual mean temperature is associated with a decrease in the marginal effects of a warm and hot day on mortality, and an increase in the marginal effect of a cold day 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 impact of the monthly σ^T on mortality, increased annual mean temperature, on the other hand, seems to have little effect on the harmful impact of monthly σ^T. Neither of the interaction terms, however, are statistically significant.

Using the coefficients from column (3) in Table 4, Figure 5 illustrates the marginal effects on mortality for each of the four temperature variables along the range of the long-run

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.

means of log per capita income and annual mean temperature observed in the sample period. The figure shows that the lowest marginal effects of a warm and hot day on mortality are found in the upper right corner, which corresponds to both income and mean temperature being at their maximum values. The lowest marginal effect of a cold day on mortality, on the other hand, is found in the upper left corner, corresponding to income and mean temperature being at their maximum and minimum values, respectively. While the marginal effects of a warm and hot day on mortality display substantial variation along the axes of income and mean temperature, the marginal effect of the monthly σ^T displays substantially less variation.[26]

[Figure 5 here]

As an example, Figure 5 indicates the location of Washington 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. The marginal effect of a 1 °C increase in the monthly σ^T is an additional 0.118 deaths per 100,000 people in Washington, compared to 0.033 in Texas. The marginal effect of experiencing an additional hot day during the month is an additional 0.129 deaths per 100,000 people in Washington, compared to -0.126 in Texas. Although the higher mean temperature in Texas is associated with a decrease in the marginal effects of both the monthly temperature standard deviation and a hot day, the decrease is more striking for the marginal effect of a hot day.

This supports the conclusions from the conceptual framework in section 3, which showed that for a given level of income and mean temperature, increased temperature variability makes adaptation harder. Neither increased income nor increased mean temperature is associated with a strong decrease in the marginal effect of the monthly σ^T on mortality. This implies that adaptation to increased temperature variability is relatively more difficult than adaptation to increased mean temperatures. Depending on the sign and magnitude of

[26]The range of the marginal effects for the temperature variables are: σ^T = [-0.024, 0.357], cold day = [-0.028, 0.464], warm day = [-0.128, 0.425] and hot day = [-0.363, 1.263].

the effect of global warming on future temperature variability, this difference in the ability to adapt to increased temperature variability and increased mean temperatures can have important implications for the effect of global warming on future mortality.[27]

6.2 Residential air-conditioning

In order to explore the effect of air-conditioning on adaptation to the monthly temperature standard deviation, I estimate the following model,

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

where the temperature variables, σ^T_{sym} and $\sum_j TBIN^j_{sym}$, are interacted with AC_{sy}, which is the share of households in state s and year y with air-conditioning. Data on the share of households with air-conditioning over the sample period is taken from Barreca et al. (2016). Again, $\mathbb{Z}_{sym}$ contains the terms from the baseline model specified in equation (4).

[Table 5 here]

Table 5 reports the results from estimating the model in equation (6). Column (1) shows the estimates from the baseline model in equation (4), while column (2) shows the estimates from estimating the expanded model in equation (6). In line with the previous literature, the harmful impacts of a warm and hot day on mortality decline when the share of households with air-conditioning increases (Barreca et al., 2016). As expected, residential air-conditioning has no effect on the marginal effect of a cold day on mortality. Although the coefficient on the interaction between σ^T and the share of households with air-conditioning is negative, the effect is small and statistically insignificant.

[27]In addition, if there is spatial heterogeneity in the effect of global warming on future temperature variability, this can potentially have a large effect on the distribution of income across states.

While air-conditioning was still quite rare for an American household in 1969, in 2004, a total of 29 states had achieved full coverage of residential air-conditioning. Using the estimates from column (2), going from zero air-conditioning to full coverage among households in a state reduces the marginal effects on mortality 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 the monthly σ^T 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 on mortality from exposure to days with high temperatures, it offers only limited protection against exposure to increased temperature variability.

7 Robustness and additional heterogeneity

7.1 Functional form and measure of temperature variation

The preferred specification of column (6) in Table 2 aims at separating the effect of being exposed to a wider range of temperatures during the month from the effect of being exposed to days with extreme mean temperatures. In order to capture this latter effect of temperatures on mortality it is imperative that the model properly controls for exposure to days in the tails of the temperature probability distribution. I therefore re-estimate the model in equation (4), but where the number of temperature bins have been expanded. Column (1) in Table 6 reports the estimate from a model where each temperature bin is $1\,^{\circ}\mathrm{C}$ wide, starting at $-20\,^{\circ}\mathrm{C}$ to $+35\,^{\circ}\mathrm{C}$, while column (2) reports the estimate from a model where exposure to days with extreme temperatures has been estimated through a fourth order polynomial in the daily mean temperature.[28] Although columns (1) and (2) show a slight decrease in the

[28] The fourth order polynomial in daily mean temperatures is calculated in the same way as the precipitation variable: the polynomial is first calculated at the station-day level, and then aggregated up to the state level where the daily polynomial is summed up across all days in a month. See footnote 12 for more details.

impact of the monthly σ^T on mortality compared to the baseline estimate in column (6) in Table 2, the confidence intervals from all three models overlap.

[Table 6 here]

Columns (3)-(5) in Table 6 investigate different functional forms on the effect of the monthly temperature standard deviation on mortality. In column (3), the model has been expanded by a quadratic term on the monthly σ^T. The quadratic term is negative and statistically significant, implying a positive but decreasing marginal effect of the monthly temperature standard deviation on mortality. This relationship is plotted in Figure 6. In column (4), I investigate whether the effect of σ^T on mortality is different depending on whether there is an increase in σ^T or a decrease.[29] Given the lack of statistical significance of the coefficient on the interaction between the monthly σ^T and the dummy for a negative shock, it implies that an increase and decrease in monthly temperature variability does not have a different effect on mortality.

Figure 3 showed that the monthly σ^T is on average higher during winter than summer. It could be that the effect of monthly temperature variability on mortality is lower when the natural temperature variation is higher. Column (5) tests this hypothesis by estimating the model using only summer and winter months and by including an interaction between the weather variables and a winter dummy. The marginal effect of the monthly σ^T on mortality becomes almost three times as large during summer compared to the benchmark analysis, while the coefficient on the interaction between the monthly σ^T and the winter dummy is negative and statistically significant. This implies that temperature variability is in fact more harmful during summer when natural variability is low, compared to winter.[30]

[29]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 monthly σ^T are negative, and interacting it with the monthly σ^T, the model allows for a different effect of a negative shock and a positive shock in σ^T. The standard errors in the second step are computed by adjusting for the degrees of freedom lost in the first regressions.

[30]This could be important for predictions since global warming might affect summer and winter temper-

[Figure 6 here]

In order to show that the results from my benchmark analysis are not driven by the particular measure of monthly temperature variability adopted, columns (6)-(8) in Table 6 report the estimates from estimating the model in equation (4) using different measures of monthly temperature variation. In columns (6) and (7), temperature variability is now measured as the monthly standard deviation of daily maximum and minimum temperatures, respectively, while in column (8), monthly temperature variability is measured as the difference between the highest and lowest daily mean temperature during the month. All measures of monthly temperature variability have a positive and statistically significant effect on the mortality rate.[31]

7.2 By age group and cause of death

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, Karlsson and Ziebarth, 2018).[32] Panel A in Table 7 shows the estimates from estimating the baseline model in equation (4) separately for four different age groups.[33] The harmful impact of monthly σ^T on mortality is found mainly among those above the age of 44, with the largest impact found among those above the age of 64. I estimate that a 1 °C increase in the monthly σ^T causes an additional 1.494 deaths per 100,000 people above the age of 64, which is substantially higher than the effect of σ^T on the all-age mortality rate found in the benchmark analysis. In other words, the impact on mortality from exposure to

ature variability differently (Schneider, Bischoff, and Płotka, 2015).

[31]In addition, the estimated effects on mortality from being exposed to cold, warm and hot days (not reported in the table) remain unchanged in all model specifications in columns (3)-(8), with the exception of column (5).

[32]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.

[33]I follow Barreca et al. (2016), and construct age-specific mortality rates for the following age groups: $<$ 1 year, 1-44 years, 45-64 years, and $>$ 64 years.

days with extreme temperatures and to increased temperature variability during the month are both driven mostly by their impact on the elderly.

[Table 7 here]

The literature has also found that exposure to extreme temperatures does not affect all causes of deaths equally. 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 caused an increase in cardiovascular-related mortality. In order to investigate heterogeneity in the effect of temperature variability on mortality, I estimate the baseline model separately for different 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.[34] Panel B in Table 7 reports the estimates for the cause-specific mortality rates, and it shows that the harmful impact of monthly σ^T on mortality is largely driven by its effect on respiratory- and cardiovascular-related mortality.

In addition, Burke et al. (2018) found a higher suicide rate following warm temperature shocks in Mexico. A similar effect is found in Table 7 with exposure to both hot days and increased monthly σ^T affecting fatalities related to mental disorders. I also find that exposure to increased monthly σ^T slightly increases mortality related to neoplasms and diseases of the nervous system. Lastly, it is comforting to see that temperature variation has no effect on fatalities caused by traffic accidents. Previous studies have found an effect of exposure to extreme temperatures on traffic accidents (e.g. Deschênes and Moretti, 2009). However, while there is a clear mechanism between days with extreme temperatures

[34] 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. While the original sample period is 1969-2004, 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.

and traffic accidents, there is no clear mechanism between traffic accidents and temperature variability.

[Table 6 here]

7.3 By time period and dynamic model

Table 8 investigates the robustness of the benchmark analysis to estimating the model for different time periods and by including lagged exposure to the temperature variables. The analysis of adaptation in the previous section showed that the marginal effects of the temperature variables on mortality decrease as income increases. The preferred specification in column (6) in Table 2 is estimated using the entire sample period 1969-2004. However, it could be argued that the marginal effect of the monthly σ^T on mortality found in the benchmark analysis is 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 equation (4) separately for each time period.

[Table 8 here]

Panel A in Table 8 reports the estimates for the periods 1969-1980, 1981-1992 and 1993-2004. Previous studies have documented a decline in the marginal effect of exposure to extreme temperatures on mortality in the US (e.g. Barreca et al., 2015). While panel A confirms this sharp decline in the marginal effect of exposure to days with high temperatures on mortality over the second half of the previous century, only a slight decline is found in the marginal effect of the monthly σ^T on mortality. The impact of temperature variability on mortality remains substantial over time, and by the end of the sample period a 1 °C increase in the monthly σ^T still caused an additional 0.151 deaths per 100,000 people.

Panel B in Table 8 investigates the presence of "harvesting" in the effect of temperature variability on mortality. Harvesting occurs when exposure to harmful temperatures are not causing the deaths of otherwise healthy people, but instead expediting the deaths of the very ill (Deschênes and Moretti, 2009). Thus, exposure to harmful temperatures is not so much increasing mortality as causing a displacement of deaths in the near-future. In order to investigate harvesting in the impact of the monthly σ^T on mortality, I transform the baseline model in equation (4) to the following dynamic model,

$$y_{sym} = \sum_{t=0}^{T} \gamma_t \sigma^T_{sym-t} + \sum_{t=0}^{T} \sum_{j} \theta^j_t TBIN^j_{sym-t} + \mathbf{X}_{sym}\beta + \alpha_{sm} + \rho_{ym} + \varepsilon_{sym} \tag{7}$$

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. Estimates in Panel B are the accumulated effects on mortality from exposure to a shock in the temperature variables experienced up to six months ago.

Panel B confirms the finding from the literature that while the effect of exposure to 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 (e.g. Deschênes and Moretti, 2009, Karlsson and Ziebarth, 2018). The impact of the monthly σ^T on mortality, however, shows a much more persistent effect on mortality over time. The effect of a 1 °C increase in the monthly σ^T remains almost the same after six months as the effect observed after only one month. This implies that instead of causing a short-term displacement of deaths, an increase in the monthly σ^T is causing the deaths of people that otherwise could have lived at least 6 months longer.

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. The relationship between exposure to days with extreme temperatures and mortality is generally well-understood. However, exposure to increased temperature variability also matters for human health and mortality because increased variation around the mean temperature reduces the marginal utility of investing in adaptation.

By combining US data for the period 1969-2004 with recent innovations from the new climate-economy literature (Dell, Jones, and Olken, 2014), I demonstrate the deadly impact of within-month variation in temperatures. 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 impact on mortality from experiencing an additional day with the mean temperature above 31.5 °C. The literature on the temperature-mortality relationship has emphasized the possibility of adaptation to higher mean temperatures. I find, however, less evidence of adaptation to increased monthly temperature variability than of adaptation to higher mean temperatures, e.g. while residential air-conditioning fully protects against the harmful effect of days with high temperatures on mortality, it offers only limited protection against increased monthly temperature variability. In addition, higher income and mean temperatures have little effect on the harmful impact of exposure to monthly temperature variability on mortality.

In a simple prediction exercise, I show how even small changes in the monthly temperature standard deviation can have large impacts on the predicted number of future temperature-induced fatalities. Given that we are currently lacking credible projections on the effect of global warming on future temperature variability, an important area for future research is thus to improve climate models, enabling them to deliver credible projections on second-order moments of the future temperature probability distribution. While this paper has measured temperature variability as the within-month variation in daily mean temperatures, the climate sciences have pointed out that global warming can affect temperature variability from the inter-annual to the diurnal level (e.g. Schär et al., 2004, Kharin et al., 2013). Future research should therefore investigate the effect of different scales of temperature variability. In addition, while this paper has found an effect of temperature variability on mortality, it is plausible that it could also affect other social and economic outcomes as well, e.g. agriculture, making the investigation of the impact of temperature variability on these other outcomes an important venue for future research.

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 mean temperatures, but potentially also to changes in the variability of temperatures. Depending on both the sign and the magnitude of the changes in future temperature variability, this paper has shown that there can be enormous consequences for human health and mortality in the medium run.

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A Figures

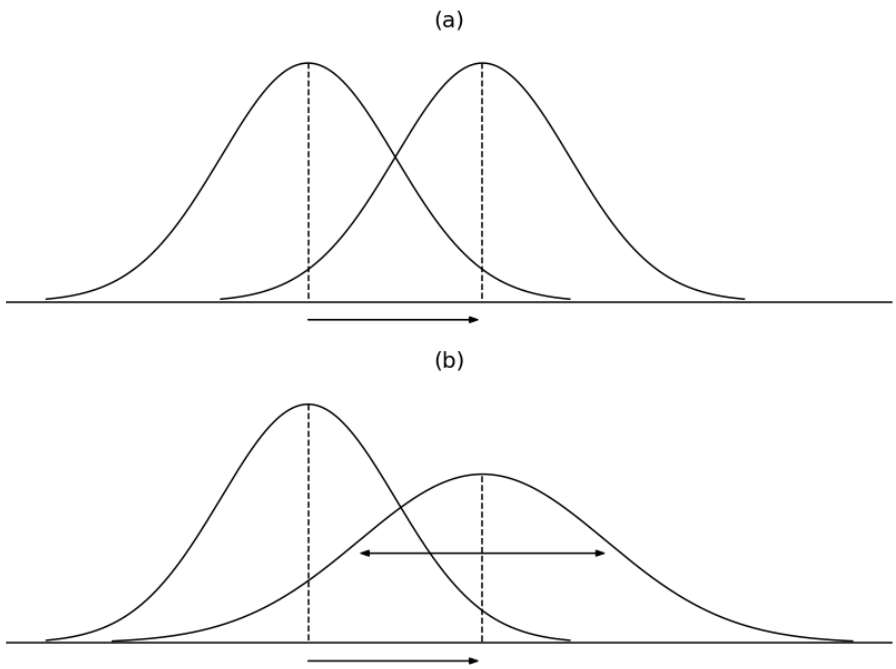

Figure 1: Change in the temperature probability distribution for (a) an increase in the mean temperature only, and for (b) an increase in the mean temperature and increased temperature variance.

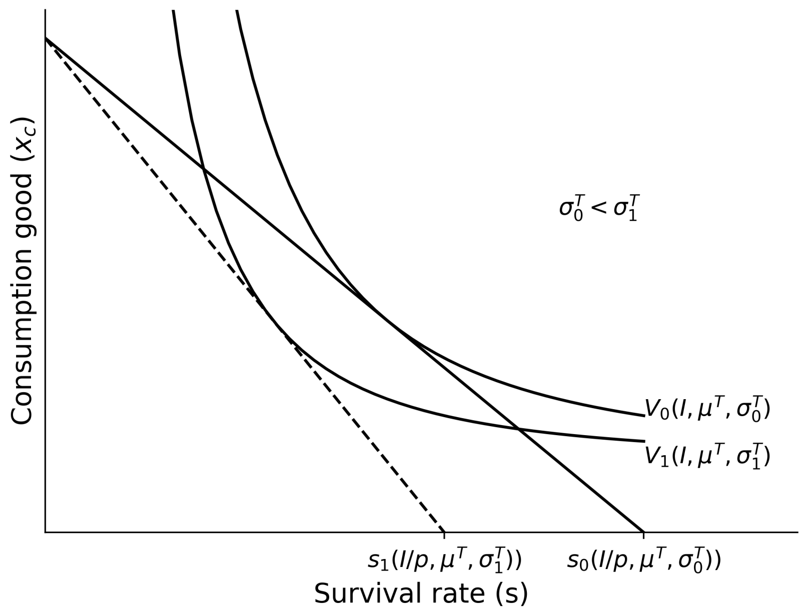

Figure 2: Optimal allocation of income on the consumption good (x_C) and survival rate (s) given income (I), prices (p), mean temperature (μ^T) and temperature standard deviation (σ^T).

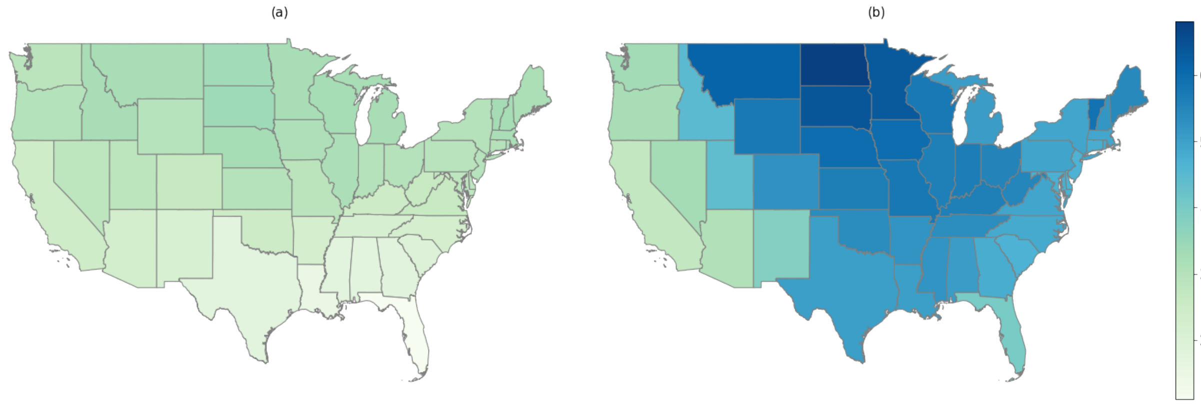

Figure 3: State-level average monthly temperature standard deviation (σ^T) in (a) summer (June, July and August) and (b) winter (December, January and February), 1969-2004.

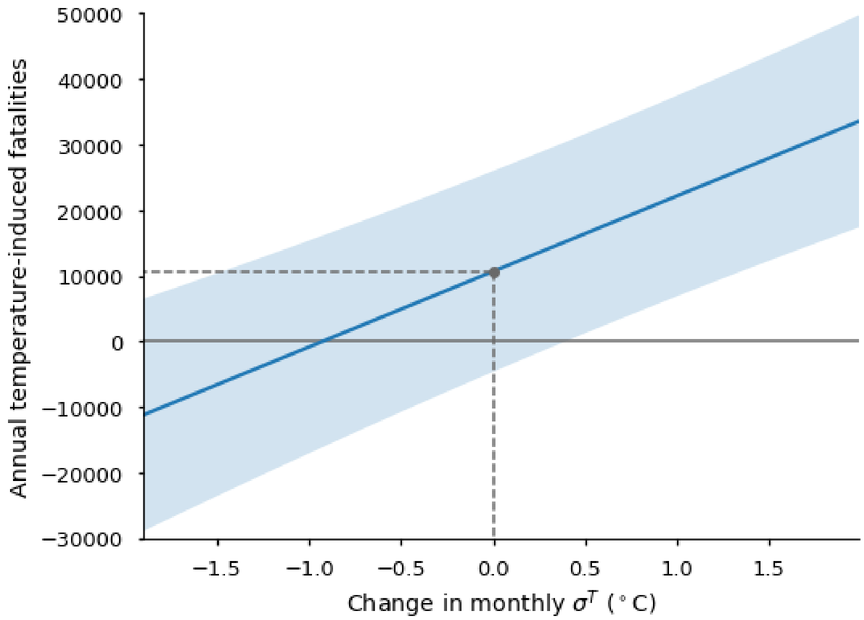

Figure 4: Predicted annual number of temperature-induced fatalities in 2070-2099, compared to 1969-2004, for hypothetical changes in the monthly temperature standard deviation (σ^T). Shaded light blue area indicates the 95% confidence interval, and dotted lines indicate scenario with no change in the monthly temperature standard deviation. See the text for more details.

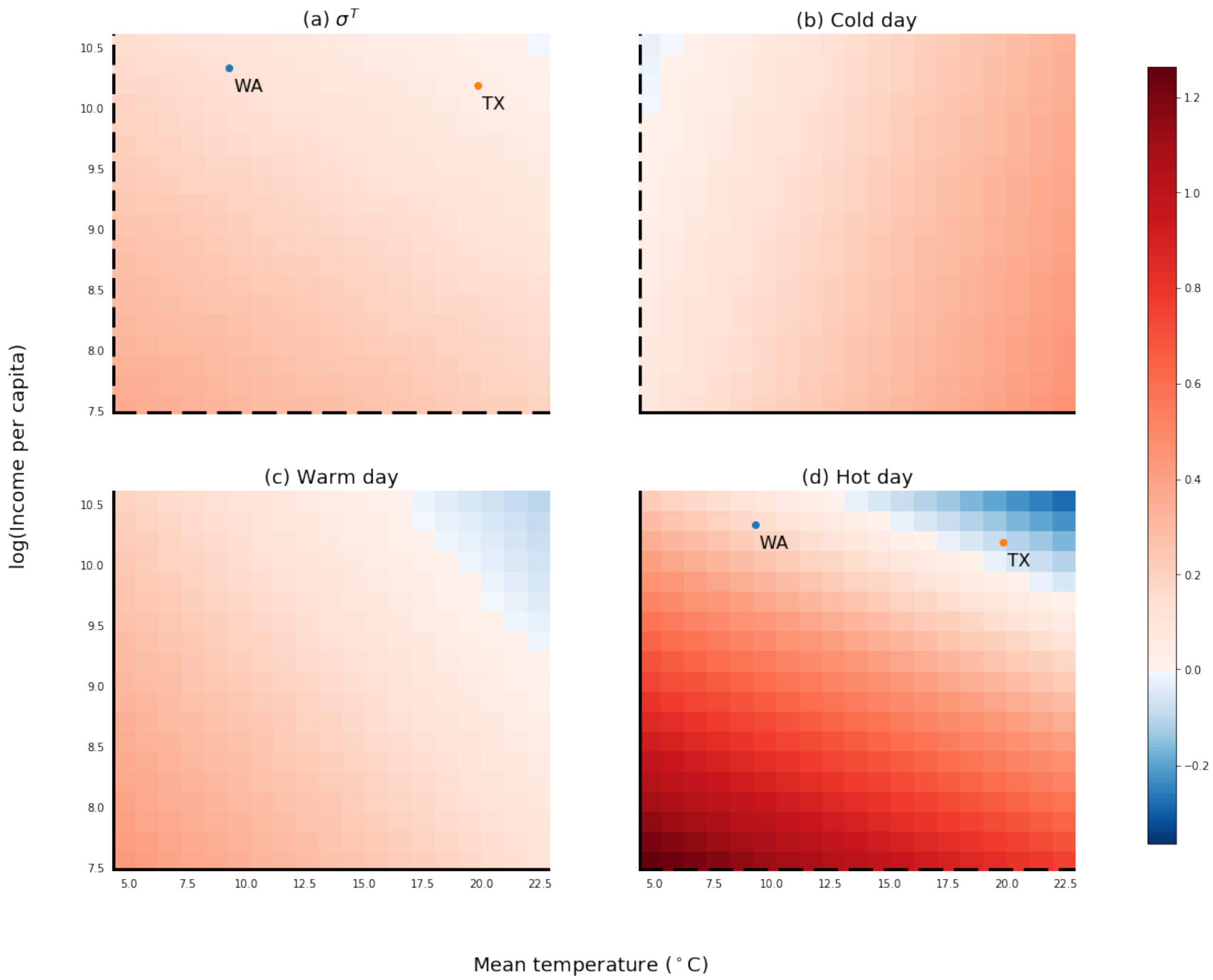

Figure 5: Marginal effects of temperature variables on mortality for combinations of income and annual mean temperatures. Solid lines on axis indicates statistical significance on at least the 5% level. See the text for more details.

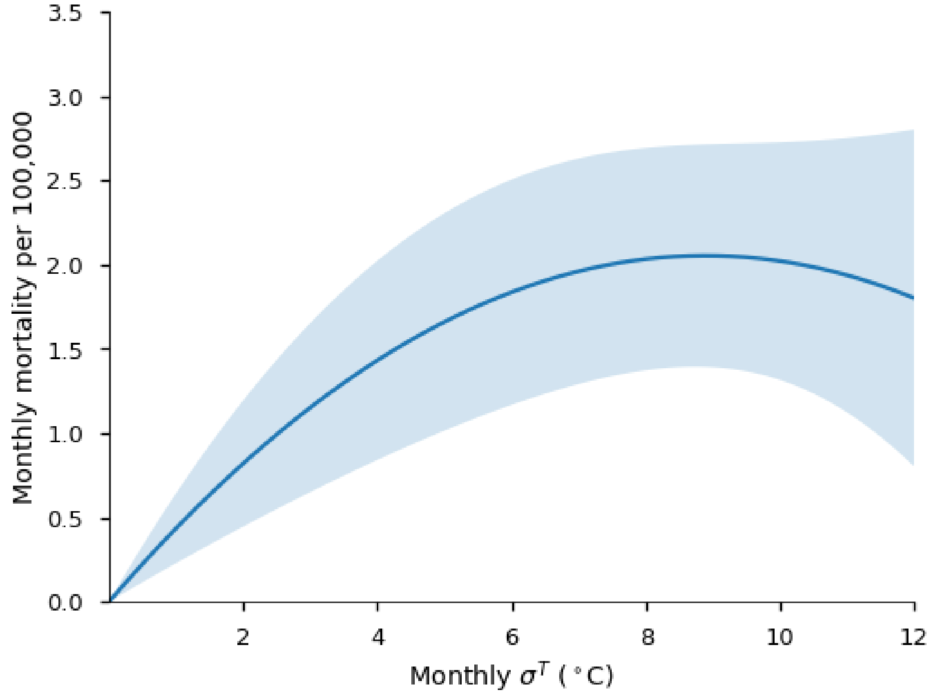

Figure 6: Marginal effect of the monthly temperature standard deviation (σ^T) on mortality for model with quadratic term on σ^T in column (3) in Table 6. Shaded light blue area indicates the 95% confidence interval.

B Tables

Table 1: Summary statistics for the temperature variables.

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

Note: All averages are population-weighted. σ^T is the monthly standard deviation of daily mean temperatures measured in °C. The mortality rate is number of deaths per 100,000. 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: Estimates of the impact of exposure to monthly temperature variability and extreme temperatures on monthly mortality rate.

	Dependent variable:					
	Monthly mortality per 100,000					
	(1)	(2)	(3)	(4)	(5)	(6)
σ^T	2.378**	.284***	.281***	.269***		.223***
	(.760)	(.063)	(.076)	(.034)		(.037)
Cold days					.167***	.161***
					(.014)	(.013)
Warm days					.094***	.089***
					(.015)	(.014)
Hot days					.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 (in parenthesis) are clustered by state. *p<0.05; **p<0.01; ***p<0.001

Table 3: Estimates of the impact of global warming on annual temperatures and number of temperature-induced fatalities by 2070-2099, compared to 1969-2004.

Cold days:	Warm days:	Hot days:	Total impact:
Panel A: Projected change in days per year			
-38.4	39.6	19.9	4.8 °C
Panel B: Impact on number of temperature-induced fatalities per year			
-26,607***	15,168***	22,096**	10,656
(2,197)	(2,451)	(6,185)	(7,811)

Note: Projected changes in panel A are defined as the difference in the national average of the annual number of cold, warm and hot days between the periods 2070-2099 and 1969-2004, with each state weighted by its average population during the period 1969-2004. Mortality impacts in panel B are calculated by multiplying the predicted changes in panel A with the estimates from column (6) in Table 2. Mortality predictions are given as the change in the average annual number of temperature-induced fatalities. Standard errors (in parentheses) are clustered at the state level and take climate change predictions and population growth as constants. *p<0.05; **p<0.01; ***p<0.001

Table 4: Adaptation in the impact of exposure to monthly temperature variability and extreme temperatures on monthly mortality rate, by income and mean temperature.

	Dependent variable:		
	Monthly mortality per 100,000		
	(1)	(2)	(3)
σ^T	.910*	.307***	.904**
	(.387)	(.083)	(.347)
Cold days	.573**	-.066	.289
	(.207)	(.039)	(.192)
Warm days	.764***	.320***	1.058***
	(.226)	(.074)	(.230)
Hot days	3.707***	.860	3.965***
	(.681)	(.451)	(.817)
$\sigma^T \times log(inc_{pc})$	-.077		-.068
	(.042)		(.041)
Cold days $\times$ $log(inc_{pc})$	-.045*		-.038
	(.022)		(.021)
Warm days $\times$ $log(inc_{pc})$	-.072**		-.075**
	(.024)		(.023)
Hot days $\times$ $log(inc_{pc})$	-.371***		-.345***
	(.068)		(.062)
$\sigma^T \times TMEAN$		-.010	-.009
		(.008)	(.008)
Cold days $\times$ $TMEAN$		.020***	.020***
		(.003)	(.004)
Warm days $\times$ $TMEAN$		-.015**	-.017**
		(.005)	(.005)
Hot days $\times$ $TMEAN$		-.033	-.029
		(.024)	(.019)

continued

continuation of table

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

Note: Regressions are not weighted. Regressions include all fixed effects and control variables specified in equation (4). Standard errors (in parenthesis) are clustered by state. $^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.001$

Table 5: Adaptation in the impact of exposure to monthly temperature variability and extreme temperatures on monthly mortality rate, by residential air-conditioning.

	Dependent variable:	
	Monthly mortality per 100,000	
	(1)	(2)
σ^T	.223***	.265***
	(.037)	(.051)
Cold days	.161***	.137***
	(.013)	(.033)
Warm days	.089***	.526***
	(.014)	(.087)
Hot days	.258***	1.603***
	(.072)	(.264)
$\sigma^T \times AC$		-.116
		(.079)
Cold days $\times$ AC		.040
		(.045)
Warm days $\times$ AC		-.533***
		(.102)
Hot days $\times$ 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 specified in equation (4). Standard errors (in parenthesis) are clustered by state. $^{*}p<0.05$; $^{**}p<0.01$; $^{***}p<0.001$

Table 6: Estimates of the impact of exposure to monthly temperature variability on monthly mortality rate for alternative measures and functional forms of monthly temperature variation.

	Dependent variable:							
	Monthly mortality per 100,000							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
σ^T	.187***	.190***	.462***	.232***	.632***			
	(.037)	(.036)	(.116)	(.067)	(.096)			
σ^T squared			-.026*					
			(.011)					
$\sigma^T \times$negative				.061				
				(.074)				
$\sigma^T \times$winter					-.275*			
					(.132)			
Maximum σ^T						.172***		
						(.036)		
Minimum σ^T							.214***	
							(.034)	
TMEAN max-min								.057***
								(.011)
Observations	21,168	21,168	21,168	21,168	10,584	21,168	21,168	21,168
Adjusted R^2	.964	.964	.963	.026	.959	.963	.963	.963

Note: Regressions are population-weighted. Regressions include all fixed effects and control variables specified in equation (4). Standard errors (in parenthesis) are clustered by state. In columns (1) and (2), exposure to extreme temperature is estimated by temperature bins that are 1 °C wide from -20 °C to $+35$ °C, and by a fourth order polynomial in the daily mean temperature, respectively. In column (4), 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 including an interaction with a dummy for a negative shock in σ^T. In column (5), the regression is executed using state-month observations only from summer and winter months, and interacting all weather variables with a dummy for winter. Columns (6)-(8) use alternative measures for the monthly temperature variation. See the text for more details. *p<0.05; **p<0.01; ***p<0.001

Table 7: Estimates of the impact of exposure to monthly temperature variability and extreme temperatures on monthly mortality rate, by age group and cause of death.

	σ^T	Cold days	Warm days	Hot days
Panel A: By age group				
Infants	.071	.174*	.075	.192
	(.145)	(.074)	(.067)	(.130)
1-44	.005	-.006	.032***	.058***
	(.009)	(.004)	(.006)	(.011)
45-64	.245***	.104***	.081***	.196***
	(.045)	(.016)	(.022)	(.044)
65 +	1.494***	1.198***	.430***	1.692**
	(.221)	(.108)	(.092)	(.555)
Panel B: By cause of death				
Infectious disease	.0003	-.0001	-.0002	-.001
	(.001)	(.0005)	(.0005)	(.003)
Neoplasms	.025**	.005	.004	-.010
	(.009)	(.004)	(.003)	(.013)
Mental disorders	.005*	.001	.002*	.005
	(.002)	(.001)	(.001)	(.004)
Nervous system	.009***	.004***	.004*	.001
	(.003)	(.001)	(.002)	(.005)
Respiratory disease	.037***	.025***	.003	.002
	(.009)	(.004)	(.003)	(.008)
Cardiovascular disease	.155***	.106***	.044***	.129***
	(.009)	(.004)	(.003)	(.013)
Traffic accidents	.002	-.009***	.006**	.017**
	(.004)	(.001)	(.002)	(.006)

Note: Regressions include all fixed effects and control variables specified in equation (4). Standard errors (in parenthesis) are clustered by state. In panel A, the sample size is 21,168 state-month observations and regressions are executed separately for each of the age groups. Regressions are weighted by state population in the relevant age group. In panel B, the sample size is 17,640 state-month observations, and regressions are executed separately for each of the all-age cause-specific mortality rates. Regressions are weighted by total state population. *p<0.05; **p<0.01; ***p<0.001

Table 8: Estimates of the impact of exposure to monthly temperature variability and extreme temperatures on monthly mortality rate, by time period and for dynamic model with lagged exposure.

	σ^T	Cold days	Warm days	Hot days
Panel A: By time period				
1969-1980	.335***	.196***	.172***	.492***
	(.069)	(.019)	(.035)	(.118)
1981-1992	.166**	.175***	.091***	.232**
	(.056)	(.025)	(.026)	(.080)
1993-2004	.151*	.163***	.035	.160*
	(.072)	(.032)	(.020)	(.079)
Panel B: Dynamic model with lagged exposure				
2 months	.256***	.231***	.061**	.158*
	(.067)	(.023)	(.020)	(.073)
3 months	.227**	.180***	.051*	.126
	(.087)	(.028)	(.024)	(.065)
6 months	.210*	.099**	-.031	-.129
	(.094)	(.035)	(.033)	(.088)

Note: Regressions are population-weighted. Regressions include all fixed effects and control variables specified in equation (4). Standard errors (in parenthesis) are clustered by state. In panel A, regressions are executed separately for each of the time periods. The sample size is 7,056 state-month observations in each time period. In panel B, estimation is expanded with lagged exposure in the temperature variables as specified in equation (7). Panel B reports the cumulative effect for each of the lengths of lagged exposure, and the sample size varies between 21,119 and 20,923 state-month observations. *p<0.05; **p<0.01; ***p<0.001

C Appendix

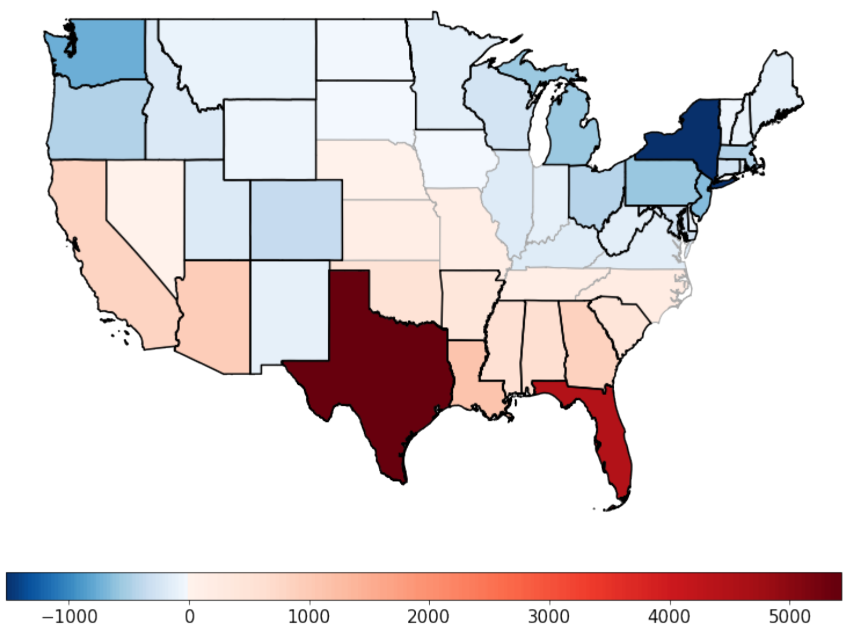

Figure 7: Predicted state level change in average annual number of temperature-induced fatalities between the periods 2070-2099 and 1969-2004. States with a statistically significant change in mortality on at least the 5 % level are outlined in black.

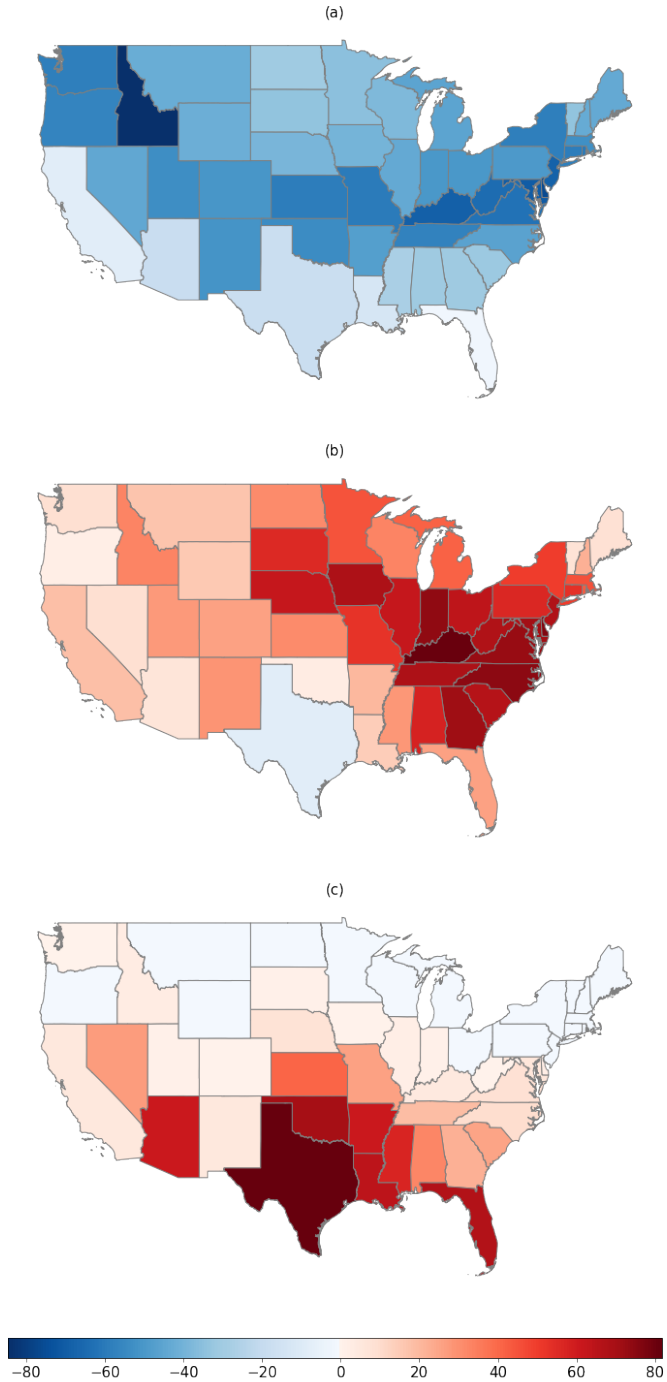

Figure 8: Projected state level change in average annual number of (a) cold days, (b) warm days, and (c) hot days, between the periods 2070-2099 and 1969-2004.