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Climate Change, Humidity, and Mortality in the United States

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Abstract

This paper estimates the effects of temperature and humidity on mortality rates in the United States (c. 1968–2002) in order to provide insight into the potential health impacts of climate change. I find that humidity, like temperature, is an important determinant of mortality. Coupled with Hadley CM3 climate-change predictions, my estimates imply that mortality rates are likely to increase by about 1.3 percent by the end of the 21st century (c. 2070–2099). Although small on the aggregate, the bias from omitting humidity has significant implications for evaluating the distributional impacts of climate change on health.

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Climate Change, Humidity, and Mortality in the United States*

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Abstract

This paper estimates the effects of temperature and humidity on mortality rates in the United States (c. 1968-2002) in order to provide insight into the potential health impacts of climate change. I find that humidity, like temperature, is an important determinant of mortality. Coupled with Hadley CM3 climate-change predictions, my estimates imply that mortality rates are likely to increase by approximately 0.9 percent by the end of the 21st century, with Southern states incurring the largest burden. Although small on the aggregate, the bias from omitting humidity has important implications for evaluating the distributional impacts of climate change on health.

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1 Introduction

The earth's climate is expected to become hotter and more humid in the coming century due to man-made pollution. The goal of this paper is to determine to what extent these climatic changes will affect human health conditions in the United States. Although previous research has estimated the potential health costs of warming temperatures (e.g., Deschênes and Greenstone, 2007), this study is the first to examine the impact of rising humidity levels. I use a within-county identification strategy to estimate the effects of temperature and humidity on monthly mortality rates over a 35-year period (c. 1968-2002). I then make end-of-the-21st-century projections using my mortality estimates and "business-as-usual" scenario from the Hadley CM3 climate model. In addition to contributing to the evaluation of optimal climate-change mitigation policies, my research adds to the literature on the importance of the weather, and in particular humidity, as a determinant of human health and welfare.

The expected net effect of climate change on mortality is ambiguous prima facie. Exposure to extreme temperatures and/or extreme humidity levels increases the risk of mortality mostly through impacts on the cardiovascular and respiratory systems.[1] In the coming century, the weather is expected to become "more extreme" during summer months (i.e., hotter and more humid) but "less extreme" during winter months (i.e., less cold and less dry).[2] As such, mortality rates are likely to increase during summer months but decrease during winter months. In simple terms, this study determines the net effect of these climatic changes on mortality.

Although the focus of this paper is on mortality, I also estimate the effects of climate change on energy consumption. Heating, cooling, dehumidification, and humidification represent

[1] This is discussed in greater detail in the "The Relationship Between Temperature, Humidity, and Mortality" section below.
[2] Among others, Gaffen and Ross (1999), Willett *et al*. (2007), and IPCC (2007) document these climatic changes.

an important channel through which individuals can mitigate the effects of adverse weather conditions. Incorporating the costs of this self-protection is important for developing credible estimates of the "heath-related" costs of climate change (Deschênes and Greenstone, 2007).

In this paper, I make two key contributions to the literature: First, I provide comprehensive estimates of the effects of humidity on mortality (in addition to estimating the effects of temperature on mortality). As Schwartz *et al.* (2004) note, "the effects of humidity on mortality have received little investigation." Conversely, the effects of temperature have received much more attention in the literature.[3] Furthermore, the humidity-mortality studies that do exist are subject to concerns of external validity because they rely on datasets with small sample sizes. Using 35 years of weather and mortality data from over 350 counties in the United States, my work is the first to provide extensive evidence that humidity is, in fact, an important determinant of mortality. As a noteworthy contribution to the health literature, I also show that low-humidity levels are a strong predictor of influenza-related deaths.

For the second contribution of this paper, I incorporate the effects of humidity when projecting the impact of climate change on mortality rates in the United States. My study builds on recent research by Deschênes and Greenstone (2007a) (hereafter DG) who examine the impact of changing temperatures on mortality rates in the United States. In short, they present compelling evidence that the temperature-mortality relationship is U-shaped.[4] Using climate-change predictions from the Hadley CM3 climate model, DG project that mortality rates may

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[3] See Deschênes and Greenstone (2007) for a comprehensive review of the epidemiological studies that examine the health effects of temperature.

[4] DG find that both "cold" temperatures (e.g., below 40°F) and "hot" temperatures (e.g., above 80°F) cause significant increases in mortality. Deschênes and Moretti (2007) also explore the effects of temperature on mortality rates in the United States. Unlike DG, the focus of Deschênes and Moretti is to estimate the inter-temporal mortality displacement effects from exposure to hot or cold temperatures. They find that cold temperatures (e.g., below 30°F) have a large cumulative effect on mortality rates but hot temperatures (e.g., above 80°F) exhibit more of a culling effect.

increase by about 1.7 percent in the coming century.[5] However, DG's results are potentially biased because they fail to control for humidity (due to data constraints). My paper shows that the bias from omitting humidity is small on the aggregate for the United States. Failing to account for humidity is more important in the context of predicting the distributional impacts of climate change.

The mortality data and the weather data used in my analysis were constructed from the National Center for Health Statistics' Multiple Causes of Death (MCOD) files and the National Climatic Data Center's Global Summary of the Day (GSOD) files, respectively. The MCOD files provide me with information on the mortality counts for counties with over 100,000 inhabitants from 1968 through 2002. I construct county-by-month mortality rates using mortality counts from the MCOD files and population estimates from the National Cancer Institute. The GSOD files are organized by weather station and day. I aggregate the station-day data to the county-month level using inverse-distance weights between the station and the geographic centroid of each county. My sample consists of 361 counties. For my study, the key weather variables of interest are: daily mean temperature and daily specific humidity.[6]

There are three main empirical challenges with identifying the causal effects of temperature and humidity on mortality.[7] First, individuals select their area of residence based on a host of factors, which include socioeconomic status, underlying health capital, and preference for certain climates. To the extent that these factors are correlated, this sorting is likely to bias estimates. Second, weather may affect the inter-temporal distribution of deaths in the short term, while having little substantive effect on the mortality rate over a longer time horizon. This could

[5] DG also evaluate the effects of climate change using the CCSM 3 climate model. They find that mortality rates only increase by 0.5 percent using the CCSM 3 climate model. I cannot use the CCSM 3 climate model since daily humidity is not a reported variable.
[6] Specific humidity is measured in grams of water vapor per kilogram of air.
[7] These limitations are eloquently discussed in DG.

potentially lead to overstating the adverse effects of climate change on human health conditions given hot weather is more likely to exhibit a “harvesting” phenomenon (Deschênes and Moretti, 2007). Third, temperature and humidity likely have nonlinear effects on mortality. Failing to account for these nonlinear effects may produce biased estimates in the context of predicting the consequences of increasing temperatures and humidity levels.

My research design addresses these three concerns in the following ways: First, I include a robust set of fixed effects in order to disentangle the causal effects of weather from other factors. I have unrestricted county-by-calendar-month fixed effects to account for the possibility that individuals with unobservable predispositions to certain climates select into different states. I include county-by-calendar-month specific quadratic time trends in order to address the possibility that there are unobservable county-level compositional changes that are also correlated with climatic trends.[8] Second, I use a two-month moving average in order to account for potential inter-temporal effects of temperature and/or humidity. Third, I allow the mortality effects of temperature and humidity to vary by 10°F bins and 2 grams-of-water-vapor bins, respectively. In addition, I estimate a model with temperature-humidity interaction terms to allow for the possibility that high-humidity levels exacerbate the adverse effects of hot temperatures.

For my energy consumption analysis, I use state-year per capita energy consumption data from the Energy Information Administration (c. 1968-2002). I rely on a qualitatively similar identification strategy to the one outlined above, while accounting for the fact that the energy data is at the state-year level (as opposed to county-month level). That is, I include year fixed effects, state fixed effects, and state-specific quadratic time trends. As such, my energy

[8] Note that the county-specific quadratic trends vary by calendar month to account for selection, over time, by individuals with unobservable tastes for a particular seasons of weather.

consumption estimates can also be interpreted as causal since the identifying variation comes from plausibly exogenous within-state variation in temperature and humidity levels.

It is important to highlight the limitations of my research design in the context of measuring the impacts of climate change. On one hand, I may overstate the direct effects because my estimates are derived from unanticipated weather shocks. Since climate change is anticipated, individuals may be able to mitigate the adverse health effects of temperature and humidity changes by adapting health-saving technologies (e.g., dehumidifiers) or by migrating to more favorable climates.[9] On the other hand, I potentially understate the health impacts of climate change because I ignore morbidity and weather-related natural disasters (e.g., hurricanes).[10]

There are four important results from my mortality analyses: First, both temperature and humidity are important determinants of mortality. Specifically, the temperature-mortality relationship and the humidity-mortality relationship are both U-shaped and large in magnitude at the extremes.[11] Second, my results indicate that temperature and humidity have a large impact on cardiovascular-related and influenza-related mortalities. Third, temperature and humidity mostly impact mortality rates for individuals over the age of 45. Fourth, the impacts of high humidity levels are exacerbated by high temperatures.

Using climate-change predictions from the "business-as-usual" scenario (A1F1) in the Hadley CM3 climate model, I project that mortality rates are likely to increase by about 0.9 percent, or a loss of approximately 510,000 life years, in the United States by the end of the 21st century. Assuming the statistical value of one life year is $100,000, my results suggest that the

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[9] Any conscious choice to "adapt" a new technology would necessarily be less costly than the alternative (DG). Also, epidemiological evidence suggests that the human physiology is itself capably of adapting to different climates (Pan *et al.*, 1995).
[10] In addition, predicting the indirect health impacts (e.g., via agriculture output or weather-related natural disasters) is outside the scope of this research. For example, Deschênes and Greenstone (2007b) and Schlenker and Roberts (2008) estimate the effects of climate change on agriculture output in the United States.
[11] That is, mortality rates decrease as the temperature (humidity) increases until some threshold temperature (humidity) level is reached; after which, mortality rates increase as the temperature (humidity) increases.

United States may have $57 billion added costs in terms of additional mortalities. Without controlling for humidity, I only estimate a 0.8 percent increase in mortality, suggesting that omitting humidity leads to only a small underestimate of the mortality impact of climate change.[12]

I also find the per capita energy consumption is likely to increase by 5.7 percent, or 11.7 quads of BTU, which would raise the health-related costs of climate change an additional $89 billion. Without controlling for humidity, I only find a 3.3 percent increase in energy consumption (or 6.8 quads of BTU).[13] The bias from failing to account for humidity is economically meaningful: the energy costs of climate change are underestimated by $38 billion.

Importantly, omitting humidity causes meaningful biases when evaluating the distributional impacts of climate change. The costs of climate change are overestimated in areas with cold and dry climates (e.g., the Northeast), but underestimated in areas with hot and humid climates (e.g., the South). This fact suggests that the adverse effects of climate change are going to be borne even more disproportionately by poorer areas of the United States. Consequently, incorporating the effects of humidity has important implications for devising both efficient and equitable climate-change policies.

On the whole, my results suggest that humidity, like temperature, is an important determinant of human health and welfare. To the extent possible, future research should account for increasing humidity levels when evaluating the effects of climate change.

[12] My "temperature only" projections are somewhat smaller than those found by DG (i.e., 1.7 percent increase), though the difference between our projections is not statistically significant at conventional levels. The differences may be explained by the fact that I use county-month level variation, while DG rely on county-year level variation. And, my sample consists of only 361 counties, while DG have information on over 3,000 counties. Note that when I estimate a model with county-year variation, my estimates are too imprecise to meaningfully compare to DG's estimates.

[13] When I omit humidity, my energy-consumption projections are qualitatively similar to DG , who project about a 4.9 quad increase.

2 Understanding Humidity

In this section, I discuss the physical aspects of humidity that are relevant to my identification strategy. Specifically, I explain: (a) the preferred measures of humidity, and (b) the physical determinants of humidity.

2.1 Measures of Humidity

Humidity is a measure of the amount of water vapor in the air. The most commonly used measures are: dew point, water vapor pressure, specific humidity, and relative humidity. These four measures are highly correlated when controlling for temperature because of their physical and mechanical relationships. As such, models that include more than one measure of humidity risk identification off functional form assumptions and/or measurement error. I opt to include specific humidity in my core specification over the other measures for two reasons: first, specific humidity is not mechanically determined by temperature (unlike relative humidity).[14] Second, specific humidity is easy to conceptualize; i.e., specific humidity is defined as the number of grams of water vapor in a one-kilogram parcel of air, which is commonly written as “g/kg”.[15] For simplicity, I use “humidity” interchangeably with “specific humidity” for the remainder of the paper.

2.2 Physical Determinants of Humidity

[14] Measurement error in temperature is negatively correlated with measurement error in relative humidity since temperature enters positively into the denominator of the equation for relative humidity.

[15] Dew point is the temperature at which the water vapor in the air condenses, water vapor pressure is the atmospheric pressure exerted by the water vapor in the air and relative humidity is the actual vapor pressure divided by the saturation vapor pressure. Note that there is a subtle difference between specific humidity and absolute humidity. That is, absolute humidity is the number of grams of water vapor per one cubic meter (volume) of air. Absolute humidity is not a commonly used because the volume of a parcel of air changes when the surrounding air pressure changes, and not necessarily when there is an increase in water vapor content (Ahrens, 2009).

In order to better understand the identifying variation in my model, this sub-section briefly discusses the physical determinants of humidity. Water molecules on the earth's surface accelerate (as do other molecules) as the air temperature rises. As a result, these accelerated water molecules are more likely to "break free" from other water molecules and become water vapor (Ahrens, 2009). Conversely, as the temperature cools water vapor is more likely to condense and turn to its liquid or solid state. Conditional on the temperature, humidity levels increase when there is more surface water because the stock of potentially evaporable water molecules is greater.[16]

In sum, humidity is an increasing function of the temperature and the stock of surface water.[17] To illustrate these relationships, Figure 1 shows the raw correlation between daily mean temperature and daily mean humidity in New Orleans and Phoenix, respectively, in 2002. As hypothesized, there is a positive relationship between temperature and humidity in both cities. Conditional on temperature, New Orleans has higher humidity levels than Phoenix since New Orleans is mostly surrounded by water and Phoenix is located in the desert.

The fact that temperature and humidity are physically related has two important implications for identification. First, models that estimate the effect of temperature on mortality without controlling for humidity are potentially biased. The degree of the bias is a function of geographic differences in the temperature-humidity gradient and/or changes in the temperature-humidity gradient over time. At the extreme, there would be no bias from omitting humidity if the temperature-humidity gradient was identical everywhere and fixed over time. In reality, the potential for bias is non-negligible since: (a) the temperature-humidity gradient varies geographically, as illustrated by Figure 1, and (b) the temperature-humidity gradient is expected

[16] Higher humidity levels in themselves may cause warmer temperatures because water vapor in the air traps infrared energy on the surface (Ahrens, 2009). This is sometimes referred to as a "feedback mechanism."
[17] Vegetation can also affect humidity levels through transpiration (Ahrens, 2009).

to vary in the coming century due to changes in the frequency, intensity, and distribution of rainfall.[18]

Second, models that control for both temperature and humidity are identified by cross-sectional differences in the temperature-humidity gradient and changes in the temperature-humidity gradient over time.[19] As such, studies with small samples sizes, like many previous epidemiological studies, are likely to have little identifying variation from which to distinguish the effects of humidity from temperature. For example, Braga *et al.* (2002) and Schwartz *et al.* (2004) rely on mortality data from only 12 metropolitan counties. Note that my study overcomes this challenge by using 35 years of weather and mortality data for over 350 counties the United States.

3 The Relationship Between Temperature, Humidity, and Mortality

In this section I briefly review the mechanisms through which temperature and humidity are thought to affect the human physiology. In addition, I discuss how these mechanisms affect my choice of identification strategy.

Extreme temperatures are dangerous because they place stress on the cardiovascular, respiratory, and cerebrovascular systems. Specifically, an individual's blood pressure, blood viscosity, and heart rate adjust as the temperature deviates from "comfortable" conditions (Keatinge *et al.*, 1984). Breathing cold air in itself can lead to bronchial constriction (Martens, 1998). In general, previous studies have noted that cold temperatures have a larger impact on mortality rates than hot temperatures. Furthermore, hot temperatures are more likely to affect the

[18] For example, the Hadley CM3 model predicts fewer days with rainfall, but more rainfall conditional on there being rain.
[19] In a previous draft of this paper, I demonstrate that the temperature-humidity gradient is not itself correlated with important omitted variables by estimating the relationship between temperature, humidity, and the unemployment rate at the state-month level.

inter-temporal distribution of mortality, or to “harvest”, than cold temperatures (Deschênes and Moretti, 2007).

Humidity can affect the human physiology through a variety of mechanisms. On one hand, low-humidity levels can also lead to dehydration as well as promote the spread of pollutants (Xie *et al.*, 2007). Airborne diseases, like influenza, are also more likely to be transmitted at low-humidity levels (Lowen *et al.*, 2007; Shaman and Kohn, 2009). On the other hand, high-humidity levels exacerbate the effects of heat stress because humidity impairs the body’s ability to sweat and cool itself (Ahrens, 2009). High-humidity levels can affect respiratory health since they promote the spread of bacteria, fungi, and dust mites (Baughman and Erans, 1996). Despite these hypothesized mechanisms, the impacts of humidity on mortality have not been well established in the epidemiological literature (Schwartz *et al.*, 2004).

In sum, the temperature-mortality relationship and the humidity-mortality relationship are both most likely nonlinear. As such, I use an empirical specification that allows the mortality effects to vary depending on whether the temperature or humidity falls in one of several 10°F or two-grams-of-water-vapor bins, respectively. In addition, I include controls for "dangerous" temperature-humidity combinations to test whether high-humidity levels significantly exacerbate the adverse effects of high temperatures.

4 Data

I use mortality data from the National Center for Health Statistics' Multiple Causes of Death (MCOD) files and weather data from the National Climatic Data Center's Global Summary of the Day (GSOD) files in my analysis. These data cover the period between 1968 and 2002 and are organized into 151,620 county-month cells (i.e., 361 counties times 420 months). I also match the NCDC data to state-year energy consumption data from the Energy Information Administration (EIA). The EIA data have 1,785 state-year observations (i.e., 50 states plus the District of Columbia times 35 years).

4.1 Multiple Causes of Death

The MCOD data files are full censuses of the deaths that occurred in the United States.[20] I first construct all-cause and cause-specific mortality counts by county of residence and month of death.[21] I then calculate county-by-month mortality rates per 100,000 inhabitants using state-year population estimates from the National Cancer Institute.[22] For a separate set of analyses presented in Appendix Table 1, I also construct county-month mortality rates by different age groups (i.e., under 1, 1-4, 5-14, 15-24, 25-34, 35-44, 45-54, 55-64, 65-74, 75-84, and over 85 years of age).

It is important to note that I rely on a select sample of counties since, subsequent to 1989, counties with fewer than 100,000 inhabitants are not identified in the public-use MCOD data. Nonetheless, the set of 361 represent close to 70 percent of the entire population of the United States.[23] As a robustness check, I show that my results are qualitatively similar when I use state-level variation and include the entire sample of deaths in the MCOD data.

4.2 Global Summary of the Day

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[20] The 1972 MCOD file, which is a 50 percent sample, is the only exception.

[21] Information on day of death is only available from 1972 through 1988. Although information on state of *occurrence* is available, I organize the mortality data by state of *residence* because the former is potentially endogenous.

[22] The NCI population data is available from 1969 onwards. For simplicity, I assume that the county populations in 1968 are identical to 1969.

[23] The MCOD data actually identify 404 counties. In order to have a balanced panel, I drop 43 counties that do not have a weather stations within 50 miles of the county centroid throughout the 1968-2002 period.

The Global Summary of the Day (GSOD) files report detailed weather information by weather station and day and are available every year that the MCOD data is available (i.e. 1968-2002). Weather variables in the GSOD files include: mean temperature, dew point, station pressure, sea level pressure, and total precipitation, among other things. Although not reported in the GSOD files, I calculate specific humidity using a standard meteorological formula and information on dew point and air pressure.[24] Also, the GSOD files include an unbalanced panel of weather stations; I use all stations that report weather information each year to make the most of the available data.[25] From the GSOD station-day data, I construct (aggregated) county-month weather variables using 50-mile inverse-distance weights.[26]

4.3 Climate-change predictions

I use climate change predictions from the United Kingdom Meteorological Office's Hadley Centre. Following DG, I rely on the "business-as-usual" (A1F1) scenario predictions of the Hadley CM3 climate model for the years 2070 through 2099. The Hadley CM3 model predictions are widely used by climate-change researchers.[27] Also, the business-as-usual scenario assumes there is little or no additional effort (e.g., policy initiatives) to mitigate man-made pollution. The Hadley CM3 model reports daily mean temperature, daily specific humidity, and

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[24] Specific humidity is a function of the dew point and station pressure (NOAA, 2008a). Note that station pressure is not available for many observations. When this occurs, I use the sea level pressure adjusted to the weather station's elevation using a standard meteorological formula (NOAA, 2008b). When neither station- nor sea-level pressure is available, I use the average sea-level pressure for the entire state adjusted to the station's elevation. When dew point is missing, however, I drop the station-day observation from my sample. If dew point is missing more than 50 percent of the year, I drop all observations for that station-year. Also, prior to 1973 relatively few weather stations recorded total precipitation, although these stations did record whether there was any rainfall. I assign the average daily precipitation for that year (conditional on there being some precipitation) to those station-days that report having rainfall, but are missing the actual amount of precipitation.

[25] For example, there were approximately 550 reporting stations in 1968, 1,130 in 1978, 1,330 in 1998, and 1,640 in 2002.

[26] The construction of the state-month weather variables is discussed more formally in the methodology section below.

[27] See IPCC (2007), Schlenker and Roberts (2008), and Stern (2008), for example.

total precipitation at several points across the United States that are separated by 2.5° latitude and 3.75° longitude grids. I create county-level variables from the Hadley CM3 A1F1 predictions using inverse-distance weights of the population (in 2000) within each grid section.[28]

4.4 Energy consumption data

The EIA reports total energy consumption in British Thermal Units (BTU) for the residential sector by state and year between 1968 and 2002. I create per capita energy consumption data using population estimates provided by the EIA. Following DG, I focus on the residential sector because the elasticity of energy consumption with respect to the weather is likely to be greater than in other sectors.

5 Estimation Strategy

5.1 The Reduced-Form Model

I estimate the effects of temperature and humidity on mortality via ordinary-least-squares using the following model:

$$(1)\ \mathrm{MORT}_{cmy} = \sum_{b} \beta^{b}\,\mathrm{TEMP}_{cmy}^{b} + \sum_{b'} \propto^{b'}\,\mathrm{HUMID}_{cmy}^{b'} + \mathrm{PRCP}_{cmy}\,\partial + \mu_{my} + \varphi_{cm}$$
$$+ \delta_{cm}\mathrm{YEAR} + \pi_{cm}\mathrm{YEAR}^{2} + e_{kym}\ ,$$

where MORT is the monthly mortality rate (per 100,000 inhabitants) in county c, year y, and calendar month m; TEMP is the set of temperature variables that indicate the fraction of days county c is exposed to mean temperatures in a given 10°F bin b (e.g. 50-60°F); HUMID is the set

[28] More formally, I construct county-level weather variables by taking an inverse-distance weighted average of the weather information at the four grid points closest to the county centroid. Then, I aggregate the county-level weather variables to the state, division and national level using county population estimates for 2000. Note that the county population estimates and the county centroid information comes from the Census 2000 United States Gazetteer Files (U.S. Census Bureau, 2007).

of humidity variables that indicate the fraction of days county c is exposed to mean humidity levels in a given 2-grams-of-water-vapor bin b' (e.g. 2-4 g/kg); PRCP is a vector of controls for precipitation[29]; μ is a set of unrestricted time effects; φ is a set of unrestricted county by calendar month fixed effects; δ YEAR and π $YEAR^2$ are sets of unrestricted county by calendar month quadratic time trends.[30] I cluster the standard errors on state of residence to account for the possibility that e is correlated within states.[31] Also, I weight equation (1) by the county population in 2000.

The inclusion of the county-by-calendar-month fixed effects accounts for any fixed differences between states and fixed seasonal differences within states that may be correlated with unobservable factors (e.g., seasonal income). Adding county-by-calendar-month quadratic time trends allows me to control for the possibility that within-county compositional changes (e.g., as a result of migration) are correlated with gradual climatic changes.

The TEMP and HUMID variables are two-month moving averages that are constructed by aggregating a station-day indicator variable to the county-month level using inverse distance weights of the population within 50 miles of each weather station. For example, I define TEMP=40-50°F, or "exposure" to temperatures between 40 and 50°F in county c in year y and month m, as follows:

$$(2)\ \mathrm{TEMP}_{cym}^{b} = \frac{\left(\Sigma_i \frac{\left(\Sigma_d^D \mathrm{DUM}_{icdmy}^{b}\right)}{D_{my}} + \frac{\left(\Sigma_{d'}^{D'} \mathrm{DUM}_{icd',m-1,y}^{b}\right)}{D_{m-1,y}}\right)}{2} \omega_{icy} ,$$

where DUM is an indicator variable set to one if the daily mean temperature is in bin b, or between 40 and 50°F in this case, on day d of month m (or day d' of month m minus one) of year

[29] I control for the fraction of days state k is exposed to precipitation in a given 0.2-inch bin, for precipitation levels between 0.0 and 1.0 inches per day. Fraction of days with precipitation levels above 1.0 inch is also included as a control.
[30] As a robustness check, I use only county-month linear time trends. The results are qualitatively similar.
[31] For example, public health resources, which also affect mortality rates, are potentially correlated over time within states.

y at station i; ω is the inverse-distance weight between weather station i and the county c centroid for all counties, where ω is set to zero for all weather stations that are: further than 50 miles away from the centroid of county c, or not in operation during year y[32]; and D is the number of calendar days (i.e., 28, 29, 30, or 31 days) in month m (or D' in month m minus one) of year y. The other temperature and humidity variables are constructed similarly to TEMP=40-50°F using equation (2).

Note that I use a two-month moving average for temperature and humidity in order to mitigate any inter-temporal mortality effects. I use a two-month moving average because previous studies find that weather may have a harvesting effect for up to 30 days (Deschênes and Moretti, 2007). As a robustness check, I show that temperature and humidity have little effect on the cancer death rate, or deaths that would have occurred in the short-term regardless of the weather. Also, my results are similar when I use more complex moving averages, like a 30-day moving average, or when I use a three-month moving average.

The various temperature and humidity bins allow for the possibility that the temperature-mortality and the humidity-mortality relationships are non-linear. For example, previous researchers have noted U-shaped, V-shaped, and J-shaped relationships between temperature and mortality (Pan et al., 1995; Schwartz et al., 2004). The optimal number of bins requires that I balance model flexibility and statistical precision. With this in mind, I divide TEMP into 10°F bins, with less than 0°F and greater than 90°F at the extremes (i.e., <0, 0-10, 10-20, 20-30, 30-40, 40-50, 50-60, 60-70, 70-80, 80-90, and >90°F). HUMID is divided into two-grams-of-water-vapor bins, with 0 to 2 and greater than 18 grams of water vapor at the extremes (i.e., 0-2, 2-4, 4-6, 6-8, 8-10, 10-12, 12-14, 14-16, 16-18, >18 grams of water vapor per one kilogram air.

[32] The weighting scheme follows the approach outlined in Hanigan *et al.* (2006) and is such that the sum of all weights ω equals one.

In equation (1), omitted weather dummy-bins are TEMP = 60-70°F and HUMID = 8-10 g/kg. By dropping these particular variables, the remaining temperature and humidity parameters can be thought of as deviations from more "comfortable" conditions.

Also, I incorporate temperature-humidity interaction terms in various robustness checks to allow for the possibility that high humidity levels exacerbate the effects of high temperatures. Specifically, I interact a dummy variable for whether the temperature is above 80°F with each humidity bin, for those 2 g/kg humidity bins above 10 g/kg. I also control for temperatures above 80°F and 90°F, respectively, interacted with a continuous measure of the humidity level. My results are qualitatively similar, though I do find evidence that the mortality impacts of high temperatures are worsened by high-humidity levels.

5.2 Effects on energy consumption

Using EIA data, I estimate the effects of temperature and humidity on per capita energy consumption in the residential sector. The unit of observation in the EIA data is at the state-year level so I must rely on a model different than equation (1). As such, I estimate the following reduced-form model:

$$(3)\ C_{ky} = \sum_b \beta^b\, TEMP_{ky}^b + \sum_{b'} \propto^{b'} HUMID_{ky}^{b'} + PRCP_{ky}\,\gamma + \mu_y + \delta_k YEAR + \pi_k YEAR^2 + e_{kym}\,,$$

where C is the per capita energy consumption in the residential sector in state k and year y; TEMP, HUMID, and PRCP are as in equation (2) except they are aggregated to the state-year level using county-populations as weights; year fixed effects (μ) control for macro-level shocks; and state-specific quadratic time trends (YEAR and $YEAR^2$) are included to account for the possibility that trends in energy consumption are spuriously correlated with state-specific climatic trends.[33]

6 Results: the effects of temperature and humidity on mortality

6.1 Summary Statistics

Figure 2 presents population-weighted histograms of the daily temperature and daily humidity data, respectively, for the years 1968 through 2002. In general, both the temperature and humidity distributions are unimodal. However, temperature appears to be more left-skewed while humidity is more right-skewed. The fact that there are relatively few observations at the tails of the distributions suggests the effects of extreme temperatures and extreme humidity levels are likely to be less precisely estimated.

Table 1 provides summary statistics by region of residence (i.e., Northeast, Midwest, South, and West). In general, the South and the West are relatively warmer than the Northeast and the Midwest. Also, the South has significantly more high-humidity days than the other three regions. The West has the lowest monthly mortality rate among the four regions (i.e., around 60 deaths per 100,000 inhabitants).

Figure 3 shows that the mortality rate is inversely related to the average monthly temperature and average monthly humidity levels for the whole of my sample. For example, average temperature and average humidity levels both peak in August, while the monthly mortality rate peaks in January. Figure 3 provides suggestive evidence that winter weather conditions (e.g., cold and dry weather) are more dangerous to the human physiology than summer weather conditions (e.g., hot and humid weather). However, inferring causality from these seasonal relationships is unsound because there may be fixed differences across seasons (e.g., nutritional intake, income) that vary by county. Importantly, my model abstracts from any

[33] My results are robust to the exclusion of state-specific quadratic trends.

variation in the mortality rate that may be spuriously correlated with unobservable seasonal factors that are fixed within each county. As such, the results of the regressions below can be interpreted as causal.

6.2 Main Results

As a reference point, I start by regressing the vector of temperature variables (TEMP) on the monthly mortality rates without controlling for humidity. As shown in column (1) of Table 2, both temperatures below 50ºF and temperatures above 90°F cause significant increases in the mortality rate (relative to temperatures between 60 and 70ºF). For example, exposure to one additional month with temperatures between 30 and 40ºF causes an additional 8.73 deaths per 100,000 inhabitants. Exposure to one month with temperatures above 90 ºF causes an additional 4.98 deaths per 100,000 inhabitants. These effects are large in relation to the average monthly mortality rate for my sample of 68.7. Despite differences in data, my column (1) estimates are qualitatively similar to DG's estimates of the temperature-mortality relationship.

Without controlling for temperature, the humidity-mortality relationship follows a similar pattern to the temperature-mortality estimates. That is, column (2) shows that there is mostly a negative correlation between humidity and mortality rates at low-levels of humidity. For example, exposure to one month with humidity levels between 2 and 4 g/kg causes 6.60 additional deaths per 100,000 inhabitants (relative to 8-10 g/kg). Also, exposure to high humidity levels (e.g., above 18 g/kg) predicts modestly higher mortality rates.

To identify the joint effects of temperature and the effects of humidity on mortality, column (3) includes both TEMP and HUMID as regressors. There are three key findings worth highlighting from the column (3) estimates:

First, the coefficients on low temperatures and low-humidity levels are smaller in magnitude than their respective column (1) and column (2) counterparts. For example, the coefficient on TEMP=30-40 and the coefficient on HUMID=2-4 are both about 40 percent smaller. The fact that the F-statistic on the vector of temperature variables and the vector of humidity variables are 15.76 and 26.11, respectively, suggests that including humidity is at least statistically important. However, the economic magnitude of the bias from neglecting humidity (or temperature) when evaluating the effects of climate change is not readily apparent since temperature and humidity are strongly correlated. As I will show below, the bias from neglecting humidity is insignificant on the aggregate, but important when determining the distributional impacts of climate change.

Second, despite their diminished magnitude, both cold temperatures and low-humidity levels are still important determinants of mortality. That is, the coefficient estimates are still positive, large, and statistically significant at low temperatures and low-humidity levels. For example, one additional month with humidity levels between 2 and 4 g/kg causes an additional 4.30 deaths per 100,000 inhabitants (relative to 8-10 g/kg).

Third, the effect of temperatures above 90ºF is still positive, statistically significant, and large in magnitude. The coefficient on humidity levels above 18 g/kg is still positive, moderately large, and statistically significant at conventional levels.

To provide for easier interpretation, I translate the coefficients in column (3) into percentage changes in the annual mortality rate from exposure to *one additional day* per year in a given temperature or humidity bin. These estimates, which are presented in Figure 4, show that one additional day per year between 30 and 40ºF causes the annual mortality rate to increase by approximately 0.02 percent (relative to 60-70ºF). As Figure 4 illustrates, the temperature-mortality relationship and the humidity-mortality relationship are both roughly U-shaped. That is, mortality rates decrease as the temperature (humidity) increases until some threshold temperature (humidity) level is reached; after which, mortality rates increase as the temperature (humidity) increases. My estimates imply that the "ideal" temperature is between 70 and 80ºF and the "ideal" humidity level is between 10 and 12 g/kg.[34]

As an aside, Figure 4 suggests that there may be a positive relationship between mortality at temperatures below 30ºF, although the parameter estimates are imprecise. The positive relationship is driven to some extent by the fact that motor-vehicle fatalities decrease as the temperature declines below 40ºF.[35]

6.3 By Cause of Death

Figure 5 analyzes the effects of temperature and humidity on two of the most prominent causes of death: cardiovascular disease and cancer.[36] For cardiovascular deaths (Panel A), the temperature-mortality relationship and the humidity-mortality relationship is roughly U-shaped. I find that temperature and humidity have little effect on deaths from cancer (Panel B), which suggests that my identification strategy has effectively mitigated potential biases from inter-temporal displacement effects (Deschênes and Moretti, 2007).

Figure 6 examines the effects of temperature and humidity on influenza-related mortalities. Here, I define a death as "influenza-related" when influenza is reported as a primary *or* secondary cause of death. I use this approach given the primary cause of influenza-related

[34] Note that my research design produces local-average-treatment-effects. As such, my estimates provide only suggestive evidence regarding the benefits of being consistently exposed to certain weather conditions.
[35] In results not reported, I find a strong positive relationship between temperature and motor vehicle fatalities for all temperatures below 50ºF. (Humidity is not a strong predictor of motor vehicle fatalities.) This finding is consistent with a study by Eisenberg and Warner (2005), which shows that fatal accidents decline after snowfalls, despite an increase in non-fatal accidents.
[36] Cardiovascular and cancer deaths represent about 65 percent of all causes of death. Also, this analysis categorizes death by their "primary" cause so the categories are mutually exclusive.

fatalities is frequently listed as cardiovascular disease (Mdjid *et al.*, 2004). My results show a statistically significant and economically meaningful relationship between low-humidity levels and influenza-related fatalities. For example, one additional day with humidity levels between 0 and 2 g/kg causes a 1.0 percent increase in the mortality rate. The temperature estimates are generally imprecise at the low end of the temperature distribution; though, I find that temperatures between 30 and 50°F have a significant impact on influenza-related mortality rates. To my knowledge, this is the first study to demonstrate the relationship between humidity and influenza using human subjects.[37] Although further exploration on the humidity-influenza relationship is warranted, such an endeavor is outside the scope of this work.

6.4 By Age Group

I find that mortality rates for people over 45 years of age are most sensitive to temperature and humidity changes.[38] (See Appendix Table 1.) In general, these age-group-specific estimates show a U-shaped temperature-mortality and a U-shaped humidity-mortality relationship. This finding confirms that my core model, which pools all age groups into one, is not biased by age-specific compositional changes.

6.5 Other Robustness Checks

To account for the possibility that humidity exacerbates the effects of heat stress, I first include controls for days with temperatures above 80°F *interacted with* each humidity bin for all

[37] My results complement the animal study conducted by Lowan *et al.* (2007), which showed that relative humidity was an important predictor of influenza transmission. Shaman and Kohn (2009) re-evaluated the Lowan *et al.* study and showed that absolute humidity measures, like specific humidity, did even better at explaining the influenza transmission.

[38] As an aside, I find that low-humidity levels actually predict *fewer* infant deaths than moderate- or high-humidity levels.

humidity levels above 10 g/kg. Also, I include controls for days with temperatures above 80°F and 90°F, respectively, interacted with a linear measure of humidity.[39] In general, I find support for the hypothesis that high humidity levels can worsen the effects of high temperatures. (See Appendix Table 2.)

Also, I divide my sample into two groups based on the number of days per year the temperature is above 65°F. The results are qualitatively similar for the group of "hot counties" and the group of "cold counties". (See Appendix Figure 1.)

As a check on my county-month model, I estimate the effects of exposure to temperature and humidity using data at the state-month level. Recall that due to data constraints in the MCOD files, I only have identifiers for counties with over 100,000 inhabitants. With the state-month model, I can include all deaths reported in the MCOD files. Both models produce nearly identical estimates. (See Appendix Figure 2.) The only meaningful difference is that the estimated effects of temperatures above 90°F are smaller in magnitude in the county model; this suggests, if anything, that I am slightly underestimating the costs of climate change.

Also, I estimate a model using diurnal temperatures. In this specification, I find slightly larger impacts on mortality rates at high temperatures. (See Appendix Figure 3.)

Although there is some loss of precision, my results are qualitatively similar when I use 5°F bins and one-gram-of-water-vapor bins. (See Appendix Figure 4.)

My results are qualitatively similar when I use the log of the monthly mortality rate as my dependent variable. I examine the sensitivity of my results to varying the set of fixed effects by replacing the (county by calendar month) quadratic trends with linear trends. I vary the moving average in equation (2) to 30 days and three months, respectively. (See Appendix Table 3.)

[39] In these specification checks, humidity enters in as a continuous variable. I have tried allowing for non-linear effects of humidity; the results are qualitatively similar.

7 Results: The effects of temperature and humidity on energy consumption

My energy estimates, which are presented in Figure 7, show a roughly U-shaped temperature-energy consumption relationship. For example, one additional day per year with temperatures between 30 and 40°F causes annual per capita energy consumption in the residential sector to increase by 0.2 percent (relative to temperatures between 60 and 70°F). One additional day per year with temperatures above 90°F causes energy consumption to increase by 0.1 percent.

Energy consumption increases at high-humidity levels. However, there is little or no change in energy consumption at low-humidity levels. For example, one additional day per year with humidity levels between 14 and 16 g/kg causes annual energy consumption to increase by almost 0.1 percent (relative to 8-10 g/kg). One additional day per year with humidity levels between 0 and 2 g/kg has no discernable effect on energy consumption.

On the surface, the unresponsiveness of energy consumption to low-humidity levels can be explained by the fact that relatively few households in the United States own humidifiers. According to the EIA, only 15 percent of all households had humidifiers in 2001 (EIA, 2009). Conversely, the increase in energy consumption at high-humidity levels is likely due to increased use of air conditioners, which about 76 percent of all households possessed in 2001 (EIA, 2009).[40]

As an important aside, the fact that energy consumption is unresponsive to low-humidity levels has important implications for public-health policy. According to my core mortality

[40] As Steadman (1979) notes, high humidity levels raise the "apparent temperature", which can be mitigated by reducing either: (a) the actual temperature (e.g., via air conditioning), or (b) the humidity level (e.g., via dehumidifiers). A more thorough examination of the factors that explain why energy consumption increases at high- but not low-humidity levels is worthy of study, but outside the scope of this paper.

estimates (Figure 4), humidity levels below 6 g/kg cause a large increase in mortality rates. However, there is little apparent self-protection, in the form of increased energy consumption, from these dangerous humidity levels. To the extent that humidifiers (or other technologies) can mitigate the adverse health effects of low-humidity levels, then policy intervention may have significant economic returns. Moreover, such policy intervention may help prevent influenza-related deaths, which are more prevalent at low-humidity levels. And, if influenza deaths are strongly correlated with influenza morbidity, then policy intervention may also help to mitigate the costs of a future influenza epidemic.

8 The Effects of Climate Change on Mortality and Energy Consumption

8.1 Welfare valuations

The A1F1 scenario of the Hadley CM3 model predicts significantly more hot and humid weather by the end of the 21st century. Figure 8 illustrates the difference in the daily temperature and daily humidity distributions between the GSOD sample period (c. 1968-2002) and the Hadley CM3 sample period (c. 2070-2099) for the entire United States. For example, the United States will experience approximately 20 fewer days between 60 and 70ºF and 40 more days over 90ºF per year on average by the end of the 21st century. And, there will be approximately 10 fewer days with humidity levels below 2 g/kg and nearly 50 more days with humidity levels above 18 g/kg per year on average.

Coupled with my core temperature-mortality and humidity-mortality estimates (Figure 4), I project that mortality rates are likely to increase approximately 0.9 percent, or nearly 23 thousand additional deaths, by the end of the 21st century (c. 2070-2099).[41] Using my age-specific estimates (Appendix Table 1) and life expectancy estimates for the year 2000 from the

[41] I hold the United States population constant at 300 million for simplicity.

Center for Disease Control and Prevention (2010), I find that each additional death is associated with approximately 25 years of lost life on average.[42] Assuming a statistical value of a life-year of $100,000 (as done by DG and others) and 25 years of lost life per additional death, my estimates imply that climate change will cost the United States approximately $57 billion dollars in terms of lost life. Also, the projected increase in mortality rates is statistically significant from zero at conventional levels.[43]

Furthermore, I project that there will be a 5.7 percent increase in energy consumption in the residential sector. (Or, an increase of 11.7 quadrillion BTUs.) Assuming a price per quadrillion BTU of $7.6 million (in 2006$), as done by DG, this translates into an additional $89 billion in energy expenditure per year. My energy-cost projection is statistically significant from zero at the 10-percent level.[44]

Together, the health-related costs of climate change (in terms of mortality and energy consumption) are $147 billion dollars per year. Put another way, this translates into a loss of about $490 per capita per year ($147 billion divided by 300 million inhabitants). This is a modest cost relative to the United States' baseline income per capita of around $35 thousand (BEA, 2009).

8.2 Discussion: Importance of controlling for humidity

On the aggregate, excluding humidity causes me to understate the mortality costs of climate change by a small amount. I estimate only a 0.8 percent increase in mortality rates when

[42] Note that DG find that each male fatality is associated with approximately 27 lost life years, and each female fatality is associated with approximately 15 lost life years on average.
[43] My mortality projections are more precisely estimated than those of DG since I pool all age groups in my core analyses. When I project the mortality impacts of climate change on each age group, as done by DG, my results are considerably more imprecise.
[44] My energy projections are more imprecise than DG's projections. This discrepancy may be the result of measurement error since the GSOD data has relatively fewer weather stations than the Summary of the Day files, which is what DG use.

I fail to control for humidity, as opposed to a 0.9 percent increase in mortality in my core model (see Panel B of Table 3). With regards to energy consumption, the bias from omitting humidity is much larger. A model that omits humidity finds only a 3.3 percent increase, as opposed to 5.7 percent increase, in energy consumption. Although statistically insignificant at conventional levels, the bias is economically meaningful: omitting humidity underestimates the welfare costs of climate change by about $45 billion.

Incorporating humidity is more important in the context of evaluating the distributional impacts of climate change. Projecting the change in mortality rates by Census Division, Table 4 column (1) shows that the adverse impacts of climate change are concentrated in the South, where the climate is hotter and more humid on average.[45] Conversely, most northern areas of the United States are expected to see a decrease in mortality rates. Omitting humidity (column 2) causes me to noticeably underestimate the mortality costs of climate change in southern areas but slightly overestimate the benefits of climate change in northern areas.[46] For example, the West South Central Division (where Louisiana is located, for one) is expected to see a 2.6 percent increase in mortality rates with my core model, but only a 2.0 percent increase when omitting humidity. Conversely, the New England Division (where New York is located) has a projected 1.1 percent decrease in mortality with my core model, as opposed to only a 0.7 percent decrease without controlling for humidity.[47]

Given poverty is more concentrated in the South (Census Bureau, 2009), my results suggest that omitting humidity underestimates the extent to which the poor will be impacted by

[45] With respect to energy consumption, the distributional impacts of climate change would follow a similar pattern (results not reported).
[46] State-specific projections are available upon request.
[47] The distributional bias is even greater when evaluating the effects of climate change at the state level. For example, ignoring humidity underestimates the mortality impacts on Florida and Louisiana by over one percentage point.

climate change. As an important aside, these projections imply that accounting for humidity may be even more important when evaluating the distributional effects of climate-change across countries with disparate climates.

8.3 Robustness Checks

As a robustness check, I also project the impacts of climate change using a model that relies on diurnal temperatures (instead of daily mean temperatures) and a model that incorporates temperature-humidity interactions.[48] These robustness checks, which are presented in Table 3, indicate that my core estimates are potentially underestimating the aggregate costs of climate change still. The diurnal-temperature model (column 3) predicts a 1.3 percent increase in mortality, and the model with temperature-humidity interactions (column 4) predicts a 1.5 percent increase in mortality for the entire United States.

In addition, these models suggest that I am underestimating the distributional impacts of climate change as well. For example, a model with temperature-humidity interactions projects a 4.7 percent increase in mortality rates in the West South Central, as opposed to a 2.6 percent increase with my core model, and opposed to a 2.0 percent increase with a model that excludes humidity. As such, these robustness checks suggest that my core analyses may represent a more conservative estimate of the costs of climate change.

9 Conclusions

My research explores the impacts of temperature and humidity on some of the health-related costs of climate change for the United States. To my knowledge, this is the first study to

[48] In the temperature-humidity interaction model, I interact a dummy for temperatures above 80°F and a dummy for temperatures above 90°F with the linear measure of humidity.

provide comprehensive evidence that humidity, like temperature, is an important determinant of mortality. Under a "business-as-usual" climate-change scenario, I find there will be an increase in mortality rates of around 0.9 percent by the end of the 21st century. Also, I project a 5.7 percent increase in energy expenditure in the residential sector. Omitting humidity causes me to underestimate the mortality costs of climate change by a small amount, and underestimate the energy costs of climate change by a relatively large amount.

My research shows that controlling for humidity is particularly important in the context of predicting the *distributional* effects of climate change. Specifically, omitting humidity causes me to underestimate the costs of climate change in areas with hot and humid climates, but overestimate the costs in areas with cold and dry climates. Given poverty rates are positively correlated with hot and humid climates both within the United States and around the world, my paper suggests that controlling for humidity has important implications for devising optimal climate-change policies that address concerns of fairness and equity.

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Figure 1

Daily mean temperature (ºF) and daily mean specific humidity (g/kg), New Orleans and Phoenix by day, 2002 only

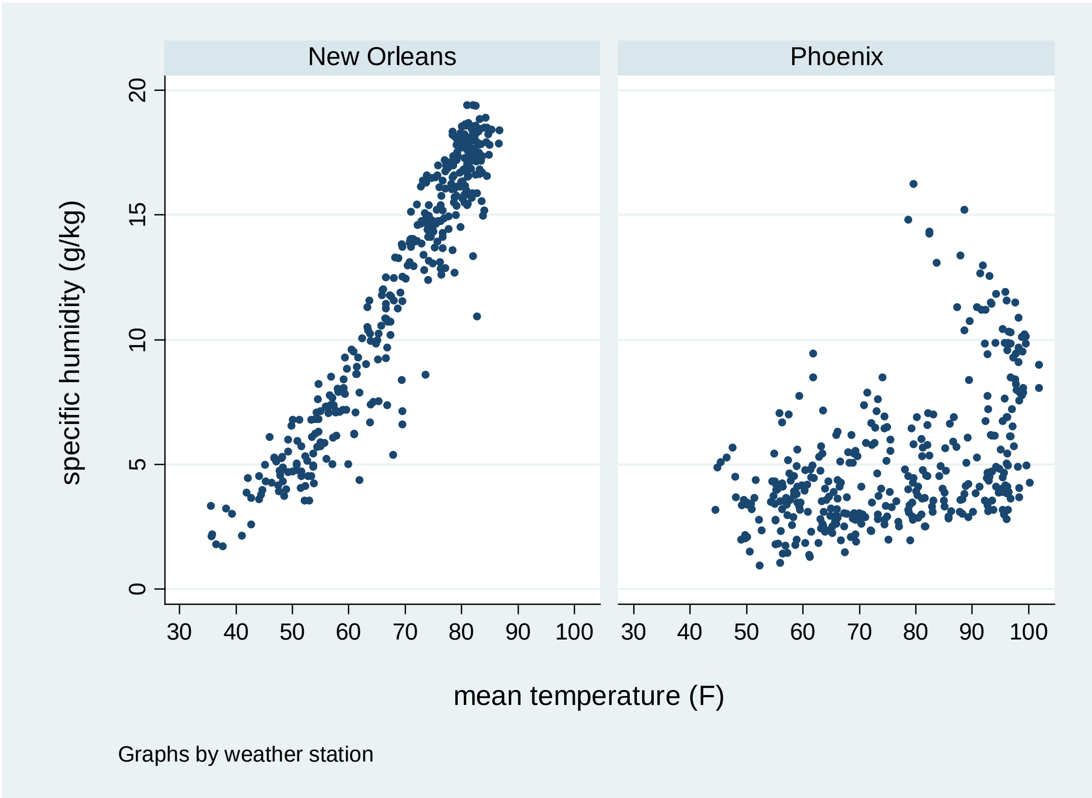
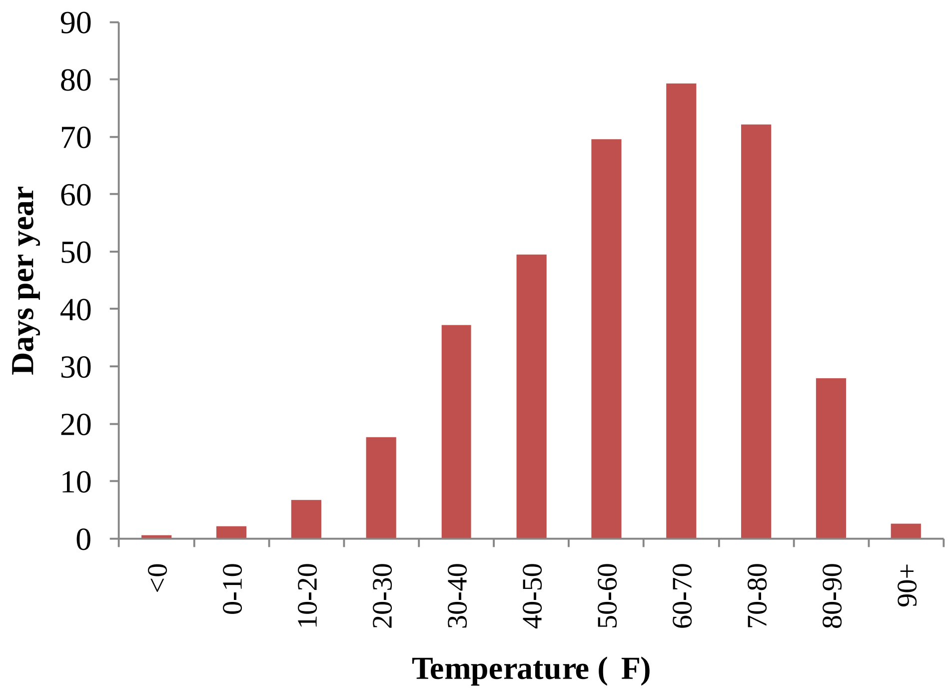
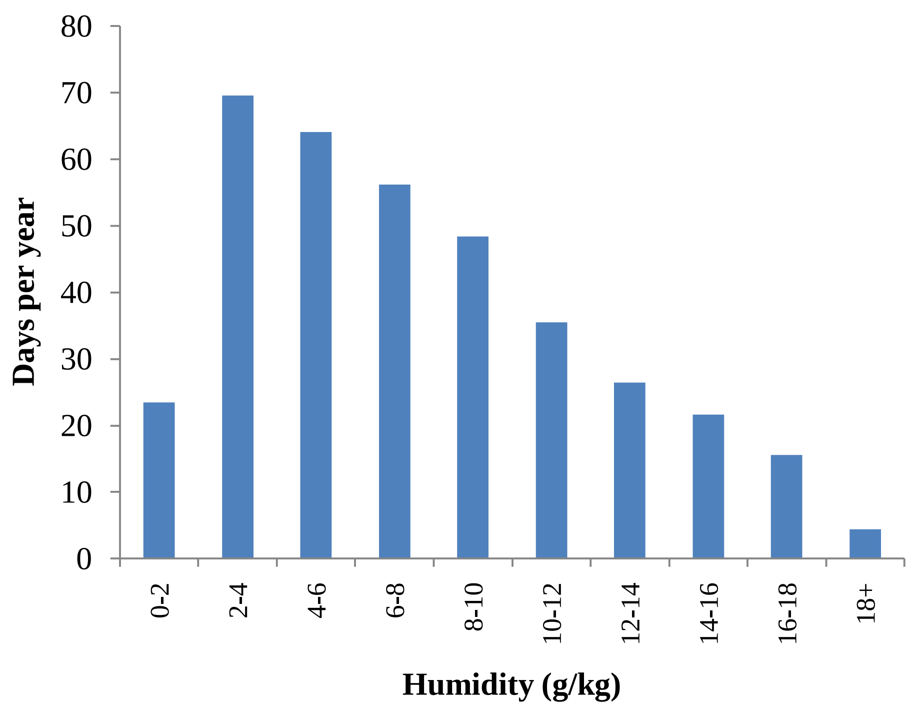


Figure 2
Daily distribution of temperature and humidity,
Core sample of 361 counties, 1968-2002

Panel A: Daily mean temperatures by 10ºF increments



Panel B: Daily mean specific humidity by 2 g/kg increments

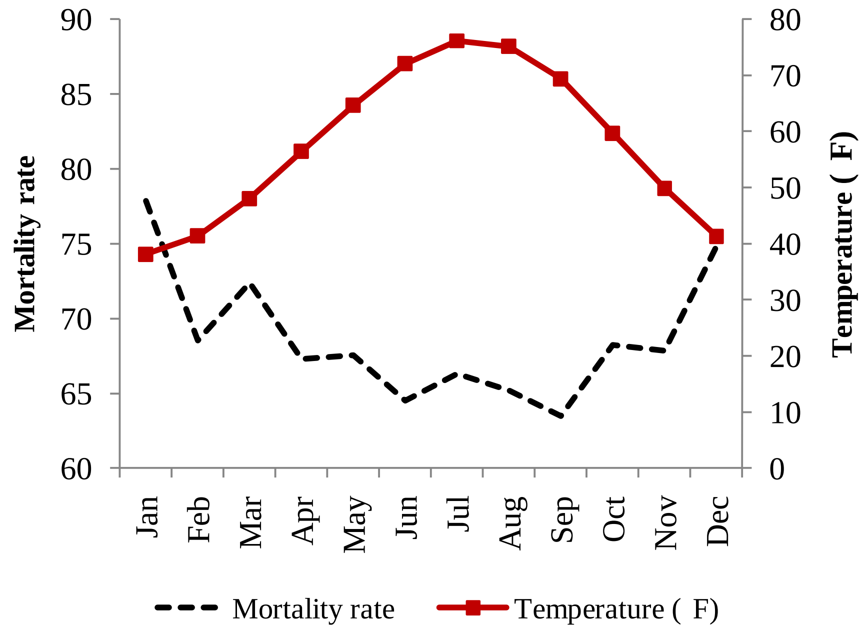


Notes: Frequencies were computed using county populations in the year 2000 as weights.

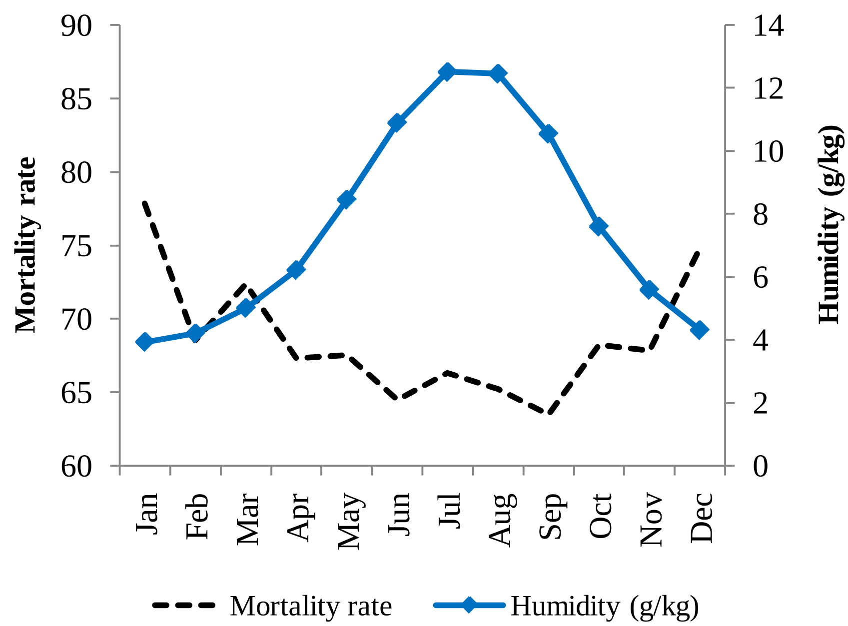
Figure 3

Mean monthly mortality rate, mean monthly temperature and mean monthly humidity, Core sample of 361 counties, 1968-2002

Panel A: Temperature



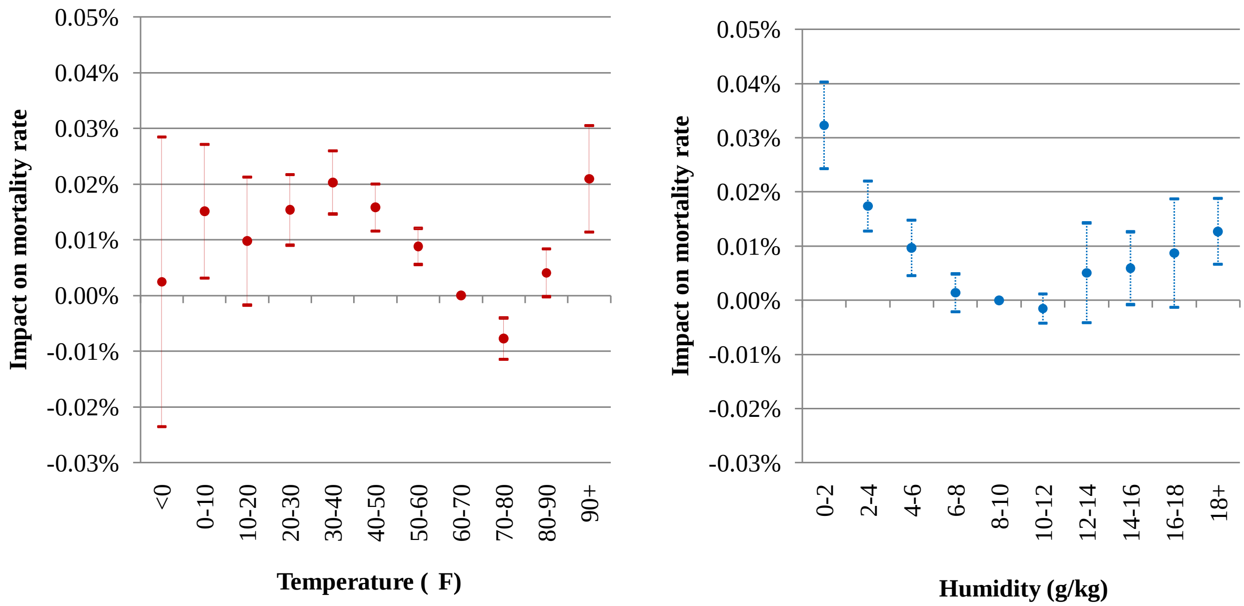
Panel B: Humidity



Notes: Calculations made using county populations in the year 2000 as weights.

Figure 4

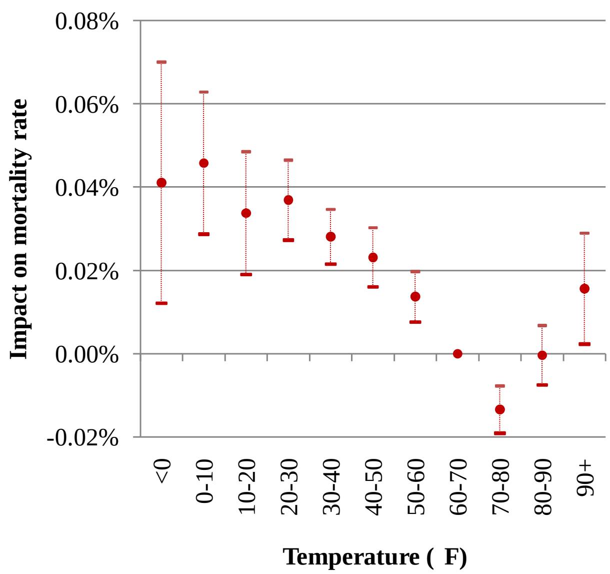
Main results, the percentage change in the annual mortality rate from one additional day within a given temperature or humidity bin relative to 60-70ºF and 8-10 g/kg, respectively

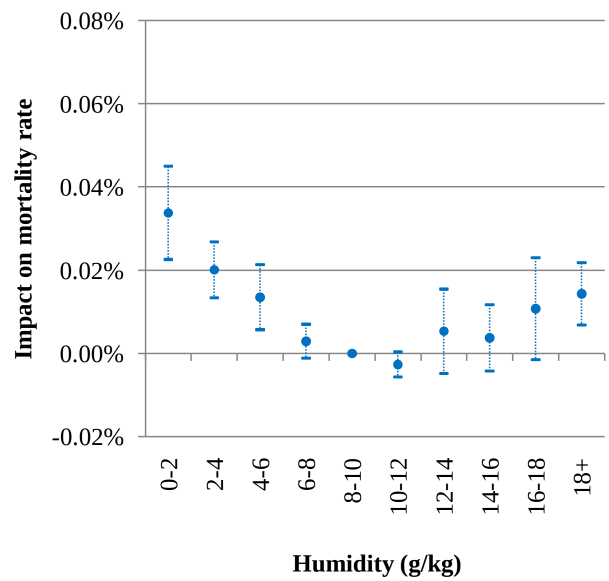


Notes: Regression coefficients from Table 1, column (3), are normalized based on the average mortality rate (per 100,000) for the 361 counties in my sample between 1968 and 2002. The dots represent the point estimates and the brackets represent the 95% confidence interval.

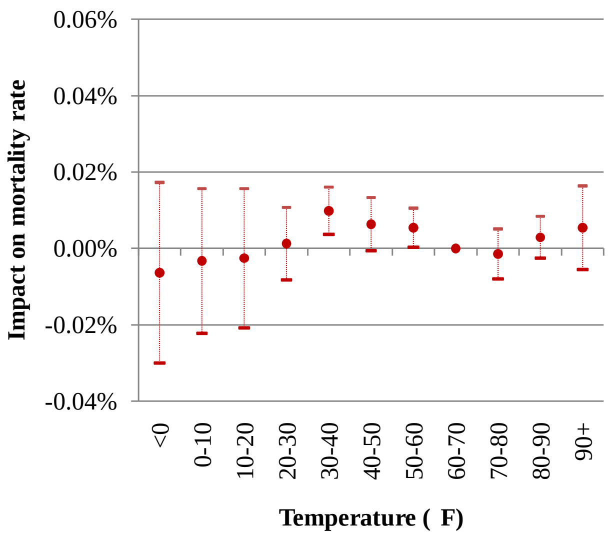
Figure 5
By primary cause of death, the percentage change in the annual mortality rate from one additional day within a given temperature or humidity bin relative to 60-70ºF and 8-10 g/kg, respectively

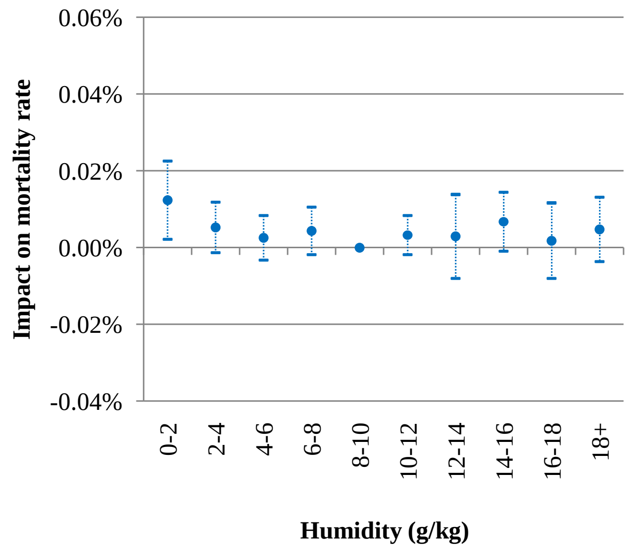
Panel A: Primary cause is cardiovasular





Panel B: Primary cause is cancer

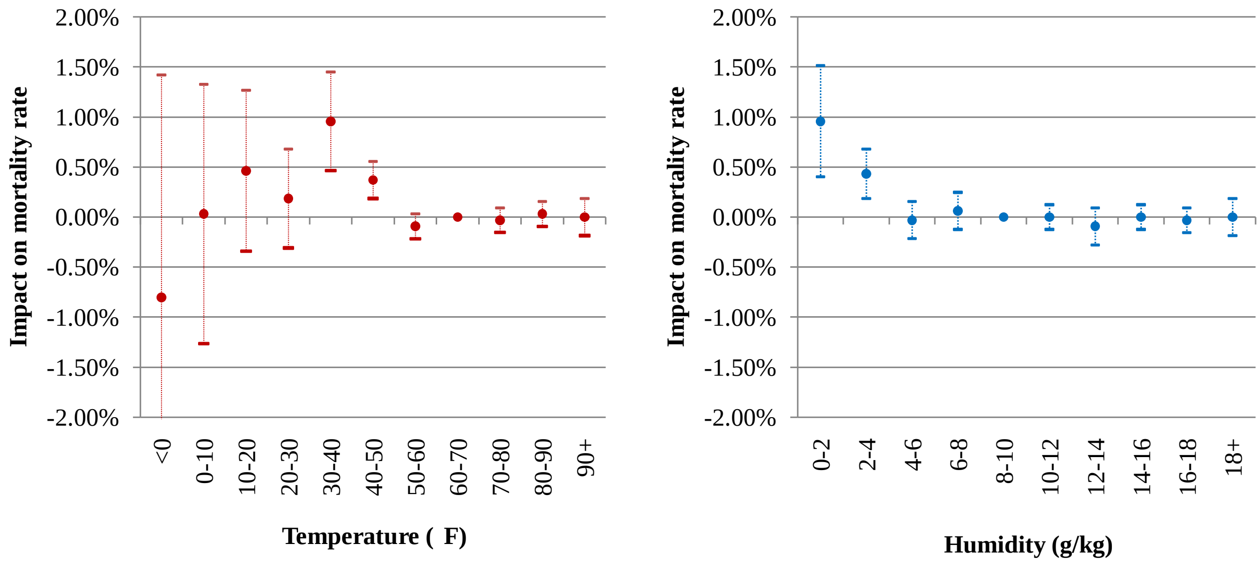




Notes: See the notes to Figure 4. Axes vary across Panel A and Panel B.

Figure 6

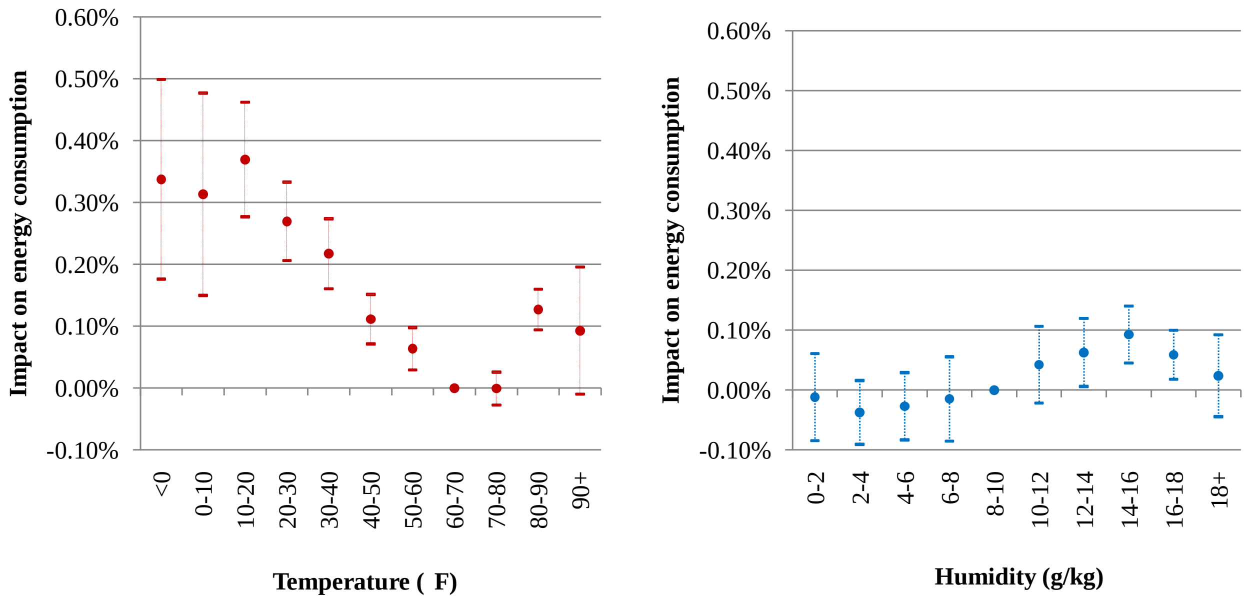
For influenza-related fatalities, the percentage change in the annual mortality rate from one additional day within a given temperature or humidity bin relative to 60-70ºF and 8-10 g/kg, respectively



Notes: See the notes to Figure 4. The standard errors on the coefficient for temperatures below 0°F are too large to be illustrated here. Influenza-related fatalities are defined as any death where influenza is listed as a primary or secondary cause of death.

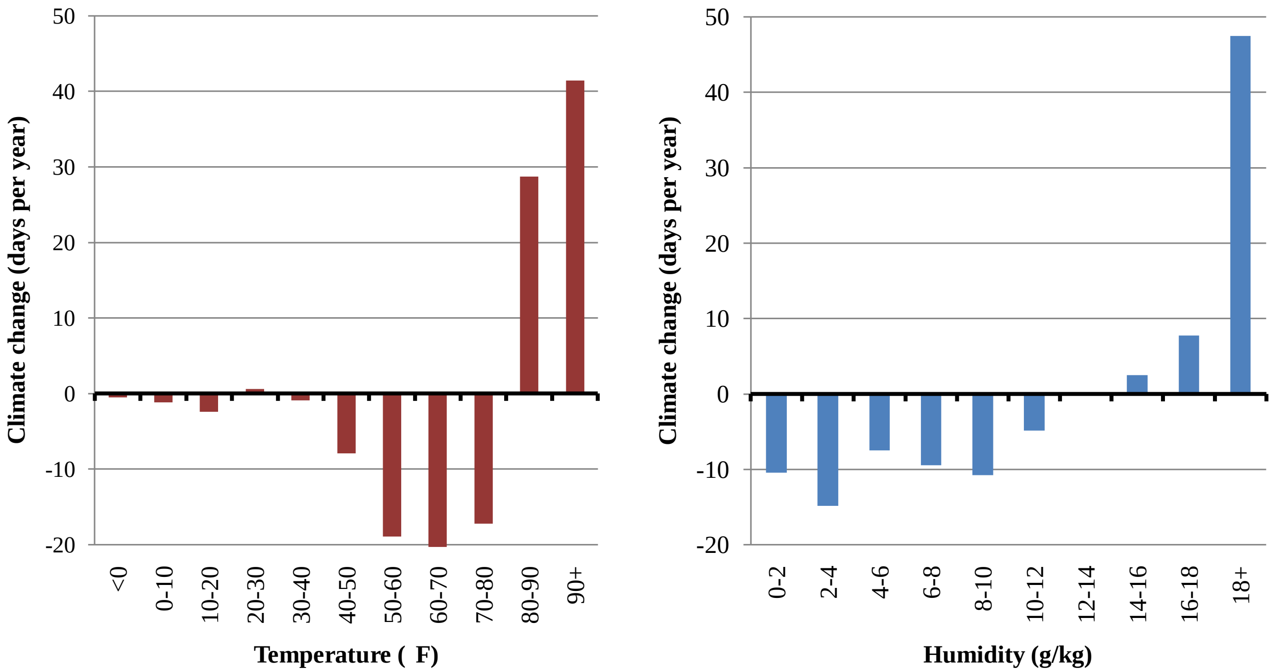
Figure 7

The percentage change in annual per capita energy consumption in the residential sector from one additional day within a given temperature or humidity bin relative to 60-70ºF and 8-10 g/kg, respectively



Notes: The dotted lines represent the 95% confidence interval.

Figure 8
Climatic changes (in days per year) between the 1968-2002 period and the 2070-2099 period,
A1F1 scenario of the Hadley CM3 climate-change model



Notes: The changes were estimated using county population in 2000 as weights. While my core analyses relies on only 361 counties, the calculations here rely on all counties in the United States.

Table 1
Summary of monthly means
Core sample of 361 counties, 1968-2002

		Region			
	Entire U.S.	North-east	Mid-west	South	West
Monthly mortality rate (per 100,000), by cause of death					
All causes	68.7	77.7	70.0	67.7	61.5
Cardiovascular	31.3	36.9	32.6	29.8	27.3
Cancer	15.3	18.0	15.5	14.8	13.4
Respiratory	4.5	4.9	4.5	4.1	4.6
Motor vehicle	1.5	1.2	1.3	1.7	1.6
Temperature (ºF) indicator variables					
TEMP = <0	0.00	0.001	0.006	0.000	0.000
TEMP = 0-10	0.01	0.007	0.018	0.000	0.001
TEMP = 10-20	0.02	0.031	0.045	0.003	0.003
TEMP = 20-30	0.05	0.086	0.096	0.017	0.013
TEMP = 30-40	0.10	0.165	0.166	0.060	0.044
TEMP = 40-50	0.14	0.169	0.140	0.113	0.128
TEMP = 50-60	0.19	0.164	0.144	0.150	0.291
TEMP = 60-70	0.22	0.185	0.174	0.195	0.300
TEMP = 70-80	0.20	0.166	0.173	0.288	0.146
TEMP = 80-90	0.08	0.025	0.036	0.169	0.053
TEMP = 90+	0.01	0.000	0.001	0.004	0.021
Humidity (g/kg) indicator variables					
HUMID = 0-2	0.06	0.119	0.111	0.028	0.020
HUMID = 2-4	0.19	0.254	0.263	0.127	0.148
HUMID = 4-6	0.18	0.165	0.163	0.129	0.242
HUMID = 6-8	0.15	0.123	0.114	0.108	0.259
HUMID = 8-10	0.13	0.110	0.106	0.104	0.202
HUMID = 10-12	0.10	0.094	0.091	0.106	0.095
HUMID = 12-14	0.07	0.073	0.073	0.115	0.028
HUMID = 14-16	0.06	0.046	0.052	0.128	0.004
HUMID = 16-18	0.04	0.015	0.022	0.119	0.001
HUMID = 18+	0.01	0.001	0.005	0.037	0.000

Notes: Means were calculated using the county population in the year 2000 as weights.

Table 2

Main results, outcome = monthly mortality rate (per 100,000 inhabitants), 1968-2002

	(1)	(2)	(3)
Specification:	TEMP only	HUMID only	TEMP + HUMID
TEMP = <0	8.25		0.61
	(3.39)**		(3.21)
TEMP = 0-10	10.81		3.74
	(1.43)***		(1.48)**
TEMP = 10-20	9.59		2.42
	(1.19)***		(1.42)*
TEMP = 20-30	9.20		3.80
	(0.75)***		(0.78)***
TEMP = 30-40	8.73		5.02
	(0.76)***		(0.70)***
TEMP = 40-50	6.28		3.91
	(0.82)***		(0.52)***
TEMP = 50-60	2.93		2.18
	(0.53)***		(0.40)***
TEMP = 70-80	-1.34		-1.91
	(0.75)*		(0.46)***
TEMP = 80-90	1.78		1.01
	(0.73)**		(0.53)*
TEMP = 90+	4.98		5.18
	(1.31)***		(1.18)***
HUMID = 0-2		8.89	7.98
		(0.90)***	(0.99)***
HUMID = 2-4		6.60	4.30
		(0.65)***	(0.57)***
HUMID = 4-6		4.13	2.39
		(0.76)***	(0.63)***
HUMID = 6-8		1.27	0.34
		(0.43)***	(0.43)
HUMID = 10-12		-1.12	-0.38
		(0.40)***	(0.33)
HUMID = 12-14		0.07	1.25
		(1.47)	(1.14)

	(1)	(2)	(3)
Specification:	TEMP only	HUMID only	TEMP + HUMID
HUMID = 14-16		0.30	1.46
		(1.01)	(0.83)*
HUMID = 16-18		1.52	2.15
		(1.42)	(1.24)*
HUMID = 18+		3.20	3.14
		(1.02)***	(0.75)***
Precipitation controls	Yes	Yes	Yes
Year by month f.e.	Yes	Yes	Yes
County by calendar month f.e.	Yes	Yes	Yes
County by calendar month specific quadratic trends	Yes	Yes	Yes
R-squared	0.494	0.494	0.495
F-statistic (TEMP)	38.96	-	15.76
F-statistic (HUMID)	-	45.7	26.11
Observations	151,620	151,620	151,620

Notes: *10%, **5%, ***1% significance levels. The unit of observation is county by year by calendar month. Standard errors (in parentheses) are clustered on decedent's state of residence. Regressions are weighted by the county population in 2000. The F-test was conducted on the all the TEMP and the HUMID variables, respectively. TEMP refers to daily mean temperature (ºF) and HUMID refers to daily specific humidity (g/kg).

Table 3
Estimated impacts of climate change between 2070 and 2099
Projections incorporate my estimates and the climate-change predictions in the Hadley CM3 model (A1F1 scenario)

	(1) Percentage change	(2) Absolute change		(3) Welfare cost	
Panel A: Core model (incl. humidity)					
Change in mortality	0.88	22,967	additional deaths		
	(0.28)	574,180	life years lost	$57	billion
Change in energy consumption (BTU)	5.7	11.7	quadrillion	$89	billion
	(3.2)				
Total cost				$147	billion
Panel B: Model excluding humidity					
Change in mortality	0.78	20,294	additional deaths		
	(0.27)	507,339	life years lost	$51	billion
Change in energy consumption (BTU)	3.3	6.8	quadrillion	$51	billion
	(2.8)				
Total cost				$102	billion

Notes: Standard errors are in parentheses.

Table 4

By Census Division of the United States, projected percentage change in mortality rates (c. 2070-2099) using the A1F1 climate-change predictions from the Hadley CM3 model

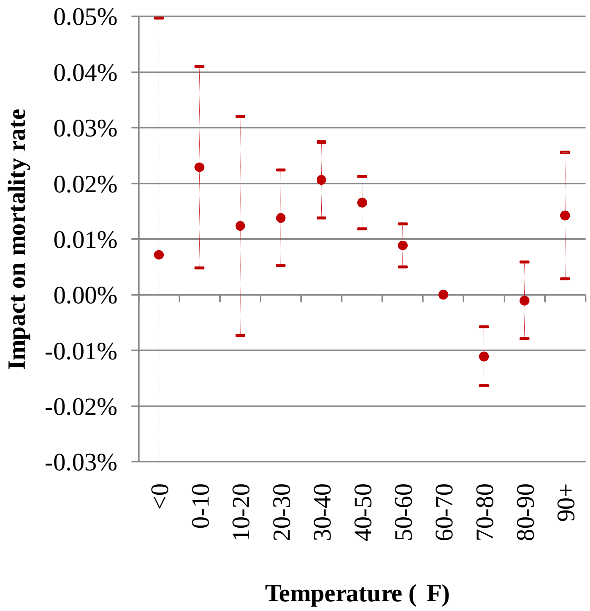
	Model specification			
	(1)	(2)	(3)	(4)
Division	Core model (incl. humidity)	No humidity controls	Diurnal temperatures	Temperature-humidity interactions
Entire U.S.	0.88	0.78	1.26	1.50
	(0.28)	(0.27)	(0.30)	(0.89)
New England	-1.05	-0.70	-0.94	-0.92
	(0.26)	(0.22)	(0.29)	(0.45)
Middle Atlantic	-0.24	-0.02	-0.06	0.01
	(0.24)	(0.21)	(0.26)	(0.51)
East North Central	0.00	0.19	0.35	0.45
	(0.28)	(0.25)	(0.31)	(0.72)
West North Central	0.47	0.59	1.04	1.21
	(0.32)	(0.31)	(0.35)	(1.03)
South Atlantic	1.59	0.96	1.80	2.92
	(0.42)	(0.31)	(0.44)	(1.26)
East South Central	1.71	1.26	2.27	2.98
	(0.38)	(0.37)	(0.41)	(1.35)
West South Central	2.64	1.98	3.77	4.67
	(0.57)	(0.60)	(0.57)	(2.17)
Mountain	-0.27	0.95	-0.07	-0.58
	(0.20)	(0.16)	(0.22)	(0.28)
Pacific	1.83	1.55	2.12	1.17
	(0.24)	(0.26)	(0.26)	(0.47)

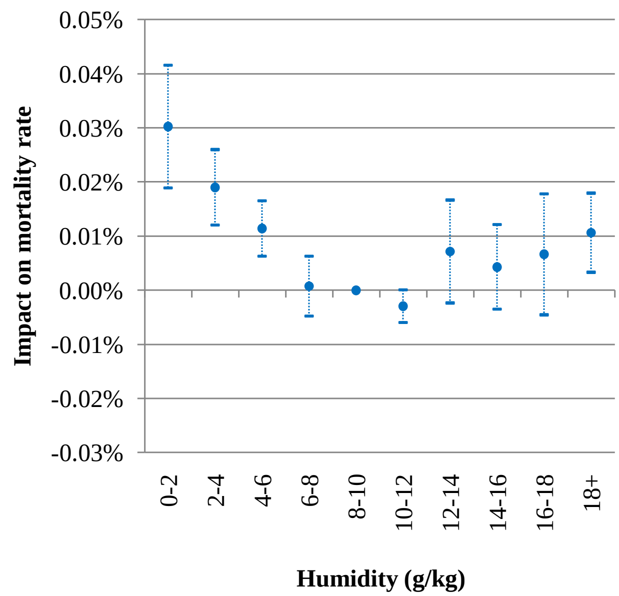
Notes: Standard errors are in parentheses. The diurnal temperatures model uses linearly-interpolated measures of the diurnal temperature in place of the mean temperature. The model with temperature-humidity interactions follows my core model except I also include a dummy for temperatures above 80°F and a dummy for temperatures above 90°F both interacted with the day's humidity level.

Appendix Figure 1

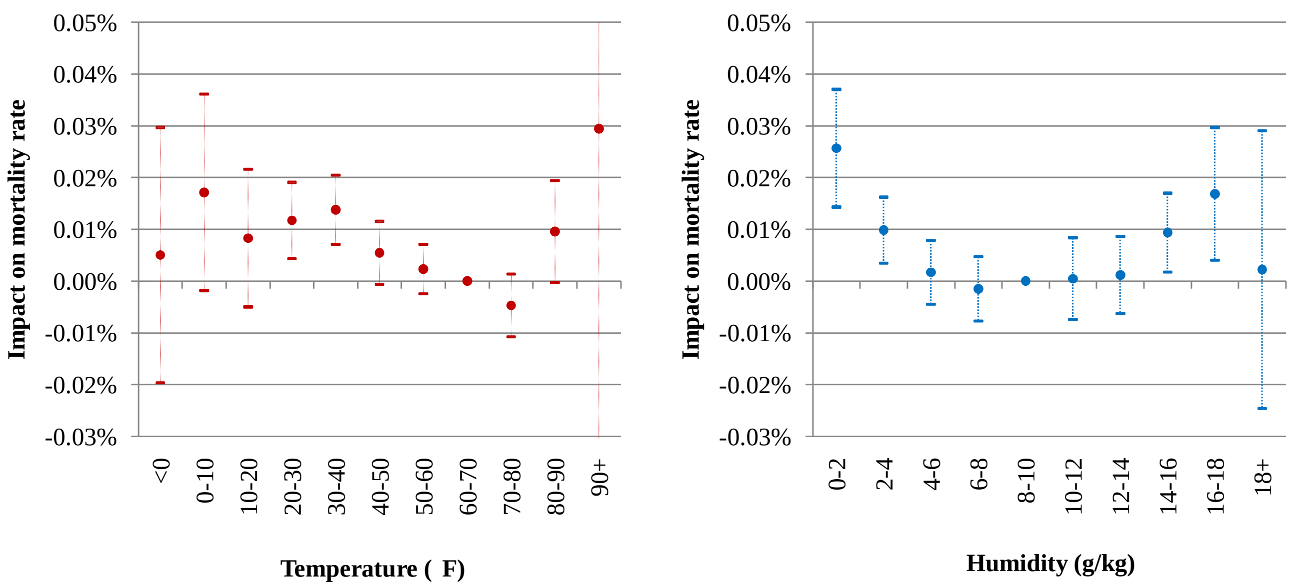
By climate of the state, the percentage change in the annual mortality rate from one additional day within a given temperature or humidity bin relative to 60-70ºF and 8-10 g/kg, respectively

Panel A: Counties in "hot" states





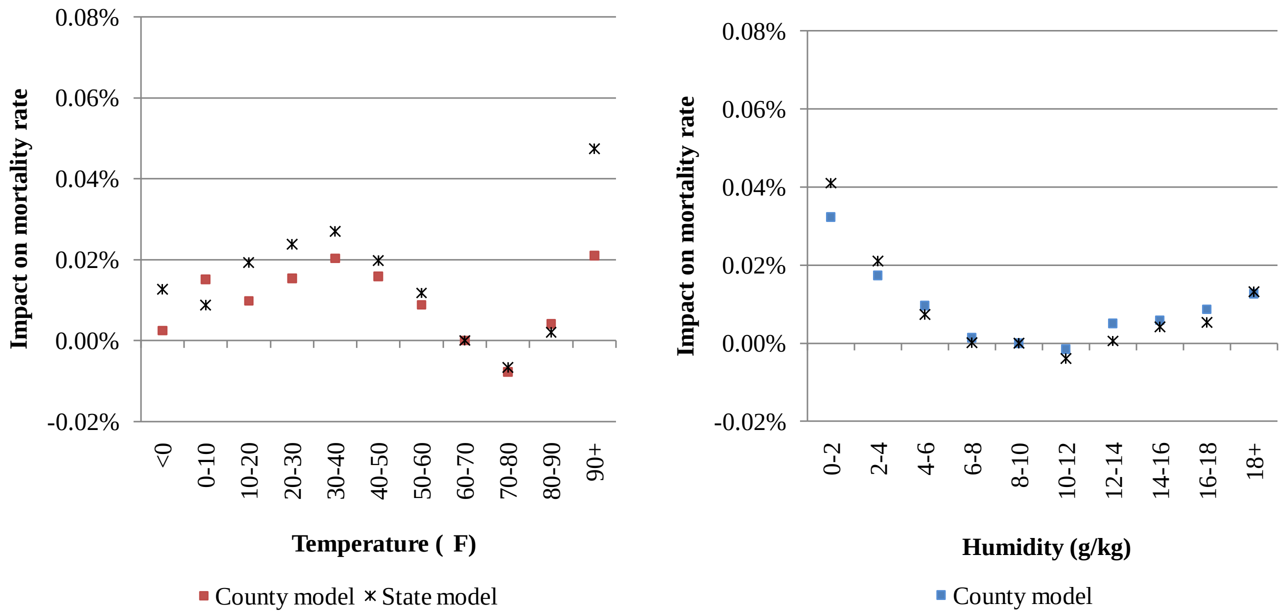
Panel B: Counties in "cold" states



Notes: Hot states (cold states) are the 25 (26) states with the highest (lowest) frequency of days with temperatures above 65°F per year on average. There are 184 and 177 counties in the hot states sample and in the cold states sample, respectively. Standard errors on temperatures below 0°F (hot states) and temperatures above 90°F (cold states) are too large to be presented here.

Appendix Figure 2

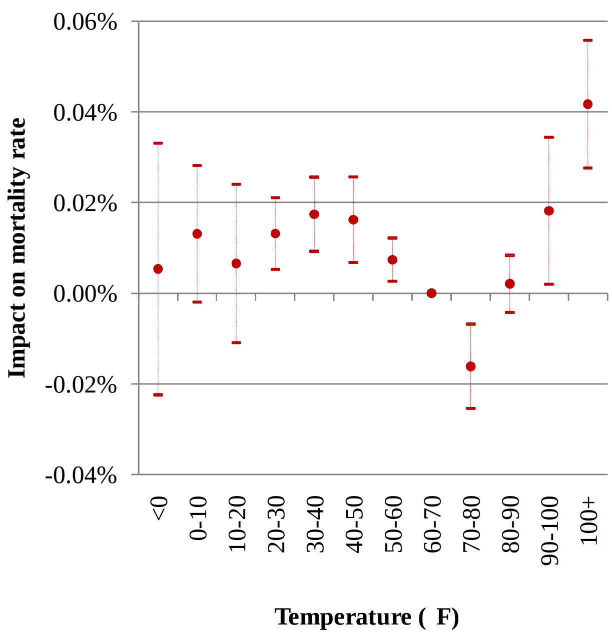
State model versus county model, the percentage change in the annual mortality rate from one additional day within a given temperature or humidity bin relative to 60-70ºF and 8-10 g/kg, respectively

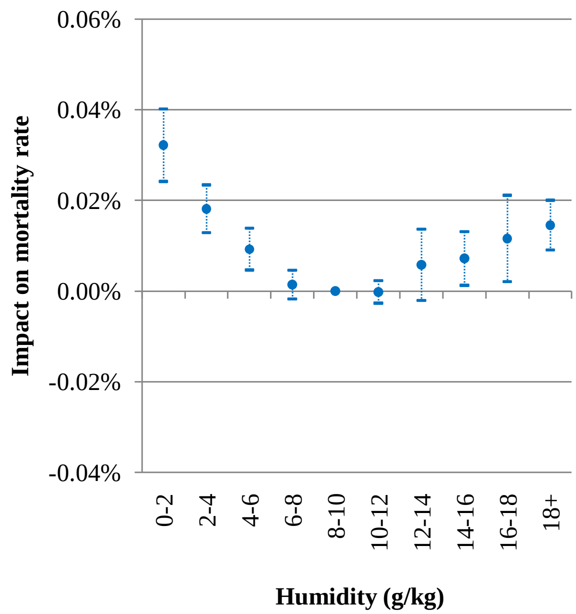


Notes: The state model has controls for precipitation, unrestricted year-month fixed effects, state-by-year fixed effects, state-by-calendar-month fixed effects, and state-by-calendar-month-specific linear time trends and weighted by state population.

Appendix Figure 3

Diurnal temperature model, the percentage change in the annual mortality rate from an additional 24 hours within a given temperature or humidity bin relative to 60-70ºF and 8-10 g/kg, respectively

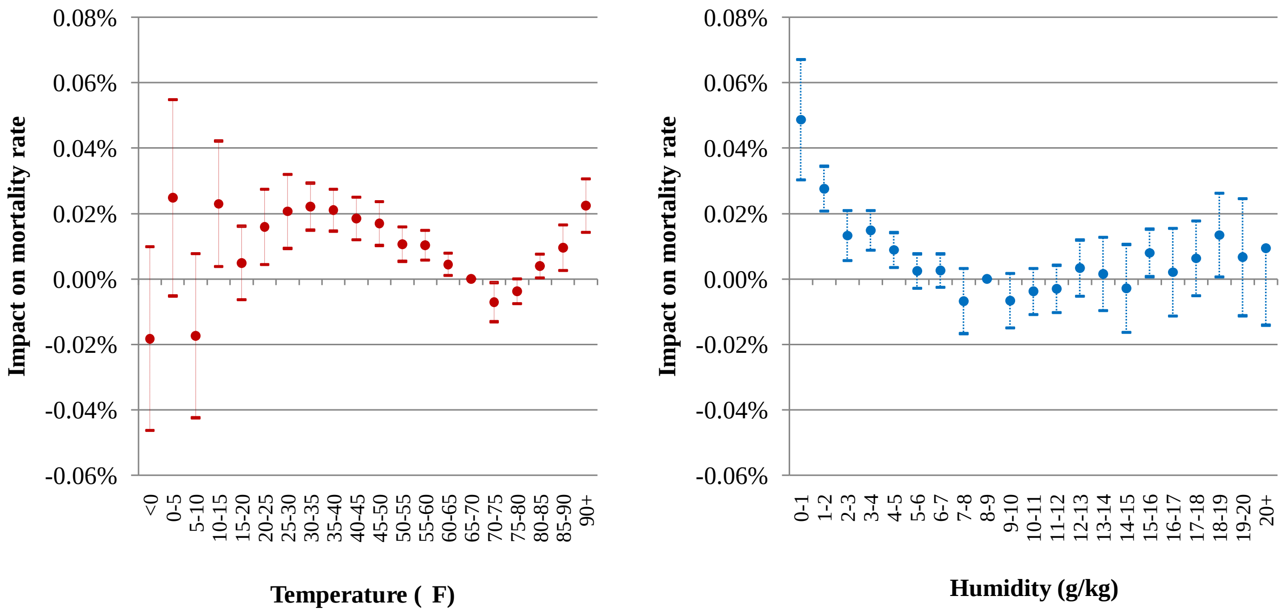




Notes: Diurnal temperatures were linearly interpoloated using information on the daily minimum and daily maximum temperatures.

Appendix Figure 4

Smaller bin size, the percentage change in the annual mortality rate from one additional day within a given temperature or humidity bin relative to 65-70ºF and 8-9 g/kg, respectively



Notes: See the notes to Figure 4.

Appendix Table 1
By age, outcome = monthly mortality rate (per 100,000 inhabitants), 1968-2002

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Age group:	< 1	1-4	5-14	15-24	25-34	35-44	45-54	55-64	65-74	75-84	85+
Outcome mean:	98.3	4.5	2.2	8.2	10.6	19.4	44.7	106.2	239.2	539.9	1,305.0
TEMP = <0	-13.70	-1.37	0.32	-4.67	-3.02	-2.90	5.64	-3.15	6.46	6.91	-34.12
	(13.93)	(1.87)	(0.73)	(1.09)***	(1.47)**	(1.87)	(3.35)*	(9.67)	(14.40)	(36.04)	(133.67)
TEMP = 0-10	6.34	0.30	-0.31	-1.87	-0.53	-1.63	3.20	14.91	23.31	42.04	203.86
	(13.06)	(1.16)	(0.48)	(1.28)	(1.39)	(1.51)	(3.60)	(5.94)**	(9.52)**	(20.88)**	(51.84)***
TEMP = 10-20	-11.07	-1.80	0.57	-2.17	-0.05	-1.55	1.11	2.29	24.18	34.40	119.02
	(8.93)	(0.89)**	(0.36)	(0.80)***	(0.98)	(1.30)	(2.28)	(3.73)	(8.19)***	(16.18)**	(50.90)**
TEMP = 20-30	7.12	0.31	-0.10	-1.55	-0.66	-1.88	2.30	5.74	16.39	33.15	122.01
	(5.34)	(0.69)	(0.25)	(0.54)***	(0.50)	(0.74)**	(1.63)	(2.51)**	(5.98)***	(12.79)**	(41.47)***
TEMP = 30-40	5.59	0.23	-0.03	-0.51	0.40	-0.44	0.72	2.80	19.36	53.91	158.08
	(3.82)	(0.54)	(0.18)	(0.46)	(0.55)	(0.86)	(1.38)	(2.19)	(5.10)***	(13.20)***	(29.52)***
TEMP = 40-50	3.46	0.63	-0.16	0.03	0.61	-0.36	0.70	1.70	12.74	31.39	106.99
	(2.67)	(0.61)	(0.18)	(0.34)	(0.31)*	(0.55)	(0.97)	(1.43)	(3.74)***	(8.45)***	(27.64)***
TEMP = 50-60	3.18	0.19	-0.08	-0.23	0.43	-0.81	-0.72	1.05	3.05	17.64	39.00
	(2.93)	(0.31)	(0.13)	(0.26)	(0.20)**	(0.48)*	(1.19)	(1.01)	(1.63)*	(7.66)**	(13.89)***
TEMP = 70-80	-4.68	-0.06	0.14	0.14	0.67	-0.19	-0.05	-3.70	-5.51	-10.05	-44.39
	(3.52)	(0.19)	(0.08)*	(0.34)	(0.28)**	(0.46)	(0.65)	(1.37)***	(1.59)***	(5.38)*	(12.20)***
TEMP = 80-90	-1.07	0.11	0.08	0.12	1.03	0.96	2.92	1.51	-1.58	9.62	1.49
	(2.86)	(0.28)	(0.12)	(0.35)	(0.38)***	(0.72)	(0.72)***	(1.19)	(2.86)	(5.32)*	(17.06)
TEMP = 90+	3.72	0.06	1.16	1.50	1.21	2.35	4.19	8.19	18.67	51.84	56.86
	(6.37)	(0.44)	(0.34)***	(1.14)	(0.75)	(0.78)***	(2.23)*	(1.42)***	(6.48)***	(8.96)***	(37.84)
HUMID = 0-2	-5.26	1.39	0.20	-0.32	-0.34	1.91	2.32	5.35	24.76	80.14	293.65
	(5.12)	(0.57)**	(0.24)	(0.52)	(0.68)	(0.93)**	(1.30)*	(2.72)*	(4.75)***	(12.42)***	(48.43)***
HUMID = 2-4	-8.46	0.51	0.17	-0.79	-0.37	0.11	2.27	4.35	16.66	38.97	181.19
	(3.52)**	(0.32)	(0.13)	(0.26)***	(0.34)	(0.60)	(0.60)***	(1.71)**	(3.50)***	(6.60)***	(19.81)***
HUMID = 4-6	-9.30	0.12	0.12	-0.47	-0.13	0.17	1.04	4.18	8.78	19.36	75.87
	(2.44)***	(0.36)	(0.16)	(0.23)**	(0.32)	(0.48)	(0.63)	(1.38)***	(2.97)***	(7.04)***	(26.98)***
HUMID = 6-8	-7.81	0.41	0.10	-0.61	-0.66	-1.27	1.14	2.11	3.04	-5.44	8.74
	(2.87)***	(0.25)	(0.13)	(0.26)**	(0.23)***	(0.47)***	(0.62)*	(1.04)**	(2.31)	(8.31)	(13.02)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Age group:	< 1	1-4	5-14	15-24	25-34	35-44	45-54	55-64	65-74	75-84	85+
Outcome mean:	98.3	4.5	2.2	8.2	10.6	19.4	44.7	106.2	239.2	539.9	1,305.0
HUMID = 10-12	-6.33	0.06	0.01	-0.17	-0.12	-0.96	-1.06	-0.13	-0.64	-20.13	-46.01
	(3.60)*	(0.32)	(0.12)	(0.29)	(0.24)	(0.57)*	(0.86)	(1.07)	(2.78)	(7.04)***	(11.74)***
HUMID = 12-14	0.90	0.21	0.11	0.16	-0.52	-0.49	-1.25	2.12	4.58	7.05	42.02
	(3.78)	(0.36)	(0.15)	(0.40)	(0.46)	(0.49)	(1.57)	(2.02)	(2.62)*	(6.42)	(23.18)*
HUMID = 14-16	1.06	0.24	0.06	0.41	-0.09	-0.64	0.37	3.80	8.73	-1.42	33.41
	(4.93)	(0.36)	(0.15)	(0.73)	(0.35)	(0.52)	(1.00)	(1.57)**	(2.97)***	(6.77)	(19.83)*
HUMID = 16-18	3.91	0.37	0.36	-0.06	0.11	0.13	1.06	2.10	11.38	-0.58	49.89
	(2.97)	(0.34)	(0.14)**	(0.37)	(0.59)	(0.80)	(1.29)	(1.37)	(3.61)***	(8.56)	(34.48)
HUMID = 18+	-0.43	1.29	0.21	1.16	0.51	0.75	2.62	4.92	10.10	0.41	75.66
	(4.33)	(0.55)**	(0.31)	(0.60)*	(0.72)	(0.86)	(0.94)***	(1.87)**	(3.61)***	(7.95)	(26.51)***
Precipitation	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year by month f.e.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County by calendar month f.e.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County by calendar month specific quadratic trends	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	151,620	151,620	151,620	151,620	151,620	151,620	151,620	151,620	151,620	151,620	151,620

Notes: see notes to Table 2

Appendix Table 2

Controlling for temperature-humidity interactions, outcome = monthly mortality rate (per 100,000 inhabitants), 1968-2002. Regression output abridged.

	(1)	(2)	(3)
Specification:	Core model	Added interaction terms	
TEMP = 80-90	1.01	-1.17	-1.95
	(0.53)*	(0.84)	(1.32)
TEMP = 90+	5.18	3.39	-3.79
	(1.18)***	(1.38)**	(1.95)*
HUMID = 10-12	-0.38	-0.60	-0.56
	(0.33)	(0.35)*	(0.34)
HUMID = 12-14	1.25	0.90	0.88
	(1.14)	(1.18)	(1.13)
HUMID = 14-16	1.46	0.60	1.03
	(0.83)*	(1.02)	(0.80)
HUMID = 16-18	2.15	3.07	1.42
	(1.24)*	(1.03)***	(1.19)
HUMID = 18+	3.14	-2.10	1.72
	(0.75)***	(2.32)	(0.76)**
TEMP > 80 x HUMID = 10-12		3.02	
		(1.28)**	
TEMP > 80 x HUMID = 12-14		2.83	
		(1.72)	
TEMP > 80 x HUMID = 14-16		4.14	
		(1.24)***	
TEMP > 80 x HUMID = 16-18		0.88	
		(0.97)	
TEMP > 80 x HUMID = 18+		8.30	
		(2.77)***	
TEMP > 80 x HUMID (linear)			0.24
			(0.10)**
TEMP > 90 x HUMID (linear)			0.64
			(0.26)**
R-squared	0.495	0.495	0.495
F-statistic (TEMP)	15.76	13.37	14.66
F-statistic (HUMID)	26.11	29.22	30.28
F-statistic (TEMPxHUMID)	-	6.62	9.08

Notes: See notes to Table 2. Controls and fixed effects are identical to Table 2 specification. Though included in my model, coefficient estimates on temperatures below 80°F and humidity levels below 10 g/kg are not reported here. These estimates are qualitatively similar to the estimates in Table 2.

Appendix Table 3

Robustness checks, outcome = monthly mortality rate (per 100,000 inhabitants), 1968-2002.

Specification	(1) Outcome = log mortality rate	(2) 3-month moving average	(3) 30-day moving average	(4) No moving average	(5) Linear county by calendar month trends only
TEMP = <0	-0.02	-2.71	2.00	6.25	0.71
	(0.04)	(3.55)	(2.38)	(2.41)**	(3.36)
TEMP = 0-10	0.06	1.48	4.96	6.31	3.95
	(0.02)***	(2.18)	(1.27)***	(1.68)***	(1.77)**
TEMP = 10-20	0.02	-0.56	2.40	4.76	3.17
	(0.02)	(1.61)	(0.92)**	(1.28)***	(1.62)*
TEMP = 20-30	0.05	3.53	4.51	2.70	4.02
	(0.01)***	(1.05)***	(0.64)***	(0.56)***	(1.03)***
TEMP = 30-40	0.06	4.46	5.09	2.79	5.09
	(0.01)***	(0.97)***	(0.52)***	(0.39)***	(0.97)***
TEMP = 40-50	0.05	3.81	3.74	2.65	3.73
	(0.01)***	(0.63)***	(0.43)***	(0.41)***	(0.84)***
TEMP = 50-60	0.03	2.33	2.36	1.08	1.52
	(0.00)***	(0.47)***	(0.30)***	(0.23)***	(0.65)**
TEMP = 70-80	-0.02	-1.88	-2.02	-0.51	-1.87
	(0.01)***	(0.51)***	(0.40)***	(0.37)	(0.76)**
TEMP = 80-90	0.01	0.96	0.45	2.44	0.36
	(0.01)*	(0.54)*	(0.46)	(0.51)***	(0.74)
TEMP = 90+	0.08	4.37	3.86	7.72	4.02
	(0.02)***	(1.29)***	(1.19)***	(1.20)***	(1.23)***
HUMID = 0-2	0.12	7.41	7.91	5.03	7.55
	(0.02)***	(1.03)***	(0.92)***	(0.63)***	(1.16)***
HUMID = 2-4	0.07	3.61	4.37	4.29	4.25
	(0.01)***	(0.69)***	(0.48)***	(0.38)***	(0.58)***
HUMID = 4-6	0.04	1.69	2.40	2.07	2.51
	(0.01)***	(0.59)***	(0.59)***	(0.36)***	(0.67)***
HUMID = 6-8	0.00	0.60	0.23	0.95	0.53
	(0.01)	(0.47)	(0.33)	(0.29)***	(0.40)
HUMID = 10-12	-0.01	-0.10	-0.29	-0.34	-0.32
	(0.01)**	(0.48)	(0.36)	(0.29)	(0.44)

Specification	(1) Outcome = log mortality rate	(2) 3-month moving average	(3) 30-day moving average	(4) No moving average	(5) Linear county by calendar month trends only
HUMID = 12-14	0.02	2.06	1.08	0.59	1.62
	(0.01)	(1.25)	(0.99)	(0.75)	(1.18)
HUMID = 14-16	0.02	1.50	1.15	-0.14	2.26
	(0.01)**	(0.94)	(0.74)	(0.64)	(0.82)***
HUMID = 16-18	0.03	2.45	2.00	1.11	2.77
	(0.02)**	(1.46)*	(1.05)*	(0.94)	(1.61)*
HUMID = 18+	0.04	2.88	2.65	1.64	3.44
	(0.01)***	(0.96)***	(0.73)***	(0.58)***	(1.22)***
Precipitation controls	Yes	Yes	Yes	Yes	Yes
Year by month f.e.	Yes	Yes	Yes	Yes	Yes
County by calendar month f.e.	Yes	Yes	Yes	Yes	Yes
County by calendar month linear trends only	No	No	No	No	Yes
County by calendar month specific quadratic trends	Yes	Yes	Yes	Yes	No
R-squared	0.494	0.493	0.497	0.496	0.451
F-statistic (TEMP)	12.99	15.73	20.46	21.38	15.17
F-statistic (HUMID)	26.41	24.64	23.9	27.68	30.8
Observations	151,620	151,620	151,620	151,620	151,620

Notes: See notes to Table 2.