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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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-state 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 climate-change predictions 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.[4] Using 35 years of weather and mortality data from the entire United States, my work is the first to provide extensive evidence that humidity is, in fact, an important determinant of mortality.

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 (2007) (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.[5] Using climate-change predictions from the Hadley CM3 climate model, DG project that mortality rates may

[3] See Deschênes and Greenstone (2007) for a comprehensive review of the epidemiological studies that examine the health effects of temperature.
[4] Braga *et al.* (2002) and Schwartz *et al.* (2004) both use data from only 12 metropolitan areas, for example.
[5] 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 (at most) in the coming century.[6] 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 but economically meaningful on aggregate for the United States. In addition, failing to account for humidity considerably biases estimates of the distributional impacts of climate change within the United States.

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 have mortality counts for the entire United States, and are available from 1968 through 2002. I construct state-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 state-month level using the state population within 50 miles of each weather station as weights. For my study, the key weather variables of interest are: daily mean temperature and daily specific humidity.[7]

There are three main empirical challenges with identifying the causal effects of temperature and humidity on mortality.[8] First, individuals select their area of residence based on a host of factors, which include their socioeconomic status, underlying health status, and their preferences 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

[6] 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.

[7] As I discuss below, I use "specific humidity", as opposed to "relative humidity", because the former is not mechanically determined by the temperature.

[8] These limitations are eloquently discussed in DG.

horizon. This could 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 state-by-calendar-month fixed effects to account for the possibility that individuals with unobservable predispositions to certain climates select into different states. I include state-by-calendar-month time trends and state-by-year fixed effects in order to address the possibility that there are unobservable state-level compositional changes that are also correlated with state-specific climatic trends. Second, my specification allows temperature and humidity to affect mortality rates for up to 30 days in order to account for potential inter-temporal effects. Third, I allow the mortality effects of temperature and humidity to vary by 10°F bins and 2 grams-of-water-vapor bins, respectively.[9]

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, excepting the fact that the energy data is at the state-year level (as opposed to state-month level). That is, I include year fixed effects, state fixed effects, and state-specific linear time trends. As such, the results from my energy consumption analysis can also be interpreted as causal since the identifying variation comes from plausibly exogenous within-state variation in temperature and humidity levels.

[9] In addition, I estimate a model with temperature-humidity interaction terms in order to test whether high-humidity levels exacerbate the adverse effects of hot temperatures via heat stress.

It is important to highlight the limitations with using my research design to measure 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 (DG).[10] On the other hand, like DG, I potentially understate the health impacts of climate change because I ignore morbidity and weather-related natural disasters (e.g., hurricanes).[11]

There are three 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.[12] Second, my results indicate that temperature and humidity have a large impact on cardiovascular-related mortalities and respiratory-related mortalities. Third, temperature and humidity mostly impact mortality rates for individuals over the age of 45.

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 1.3 percent, or an increase of 34 thousand deaths, in the United States by the end of the 21st century. Assuming the statistical value of one life is $7 million, my results suggest that the United States may have $235 billion added costs in terms of additional mortalities. I also find the per capita energy consumption is likely to increase by 4.8 percent, or 9.9 quads of BTU, which would raise

[10] 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).
[11] 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.
[12] 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.

the health-related costs of climate change an additional $75 billion to a total of $310 billion. Without controlling for humidity, I only estimate a 0.9 percent increase in mortality (or 24 thousand deaths) and a 2.4 percent increase in energy consumption (or 5.0 quads of BTU).[13] Although statistically insignificant, the bias is economically meaningful: without humidity the welfare costs of climate change are underestimated by $101 billion. Compared to DG, I find much larger effects of climate change on energy consumption, but qualitatively similar effects on mortality when accounting for humidity.

Importantly, omitting humidity causes significant 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 economically disadvantaged areas of the United States than previously anticipated. Consequently, incorporating the effects of humidity has important implications for devising both efficient and equitable climate-change policies. As a simple thought experiment, I also show that accounting for humidity is potentially even more important for understanding the distributional impacts of climate change worldwide.

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.

[13] Compared to DG, I find that climate change has a slightly smaller effect (i.e., around 0.9 percent increase) on mortality when I only control for temperature. This can be explained by the fact that I use monthly-level variation while DG rely on annual-level variation. Annual variation in temperature omits the impact of any winter weather that occurs in the previous calendar year or the possibility that the winter weather at the end of the calendar year may affect mortality rates into the next calendar year. In one robustness check, DG show that controlling for the previous year's weather diminishes their estimates of the impacts of climate change to 0.9 percent, which is identical to my estimate. Note that I favor monthly-level variation to mitigate mis-measuring exposure to adverse winter weather conditions. When I do not control for humidity, my energy-consumption projections are identical to DG (i.e., a 5 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.[14] 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).[15] 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 (or "g/kg").[16] For simplicity, I use "humidity" interchangeably with "specific humidity" for the remainder of the paper.

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[14] 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, specific humidity is the number of grams of water vapor in a one-kilogram parcel of 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).

[15] The saturation vapor pressure, which is the pressure at which water vapor in the air condenses, is an increasing function of temperature. Since the saturation vapor pressure is the denominator in the equation for determining relative humidity, any measurement error in temperature is negatively correlated with measurement error in relative humidity.

[16] These arguments for choosing specific humidity notwithstanding, my results are qualitatively similar when using dew point or water vapor pressure. I find no strong relationship between relative humidity and mortality after controlling for temperature. Results available upon request.

2.2 *Physical Determinants of Humidity*

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. In addition to warmer temperatures, humidity levels are higher when there is more surface water because the stock of potentially evaporable water molecules is greater.[17]

In sum, humidity is an increasing function of the temperature and the stock of surface water.[18] 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 differences in the temperature-humidity gradient across states and over time.

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-

[17] 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."
[18] Vegetation can also affect humidity levels through transpiration (Ahrens, 2009).

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) rely on mortality data from 12 metropolitan counties for the years 1986 through 1993.) Note that my study overcomes this challenge by using 35 years of weather and mortality data for every state in 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.[20] 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 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 airborne

[19] To ensure that the temperature-humidity gradient is not itself correlated with important omitted variables, I run estimate my model on the unemployment rate. Results not reported.
[20] In this section, I do not distinguish between specific humidity or relative humidity. After conditioning on temperature, changes in specific humidity and changes in relative humidity are conceptually equivalent.

diseases and pollutants (Lowen *et al.*, 2007; Xie *et al.*, 2007). 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 in several robustness checks 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 21,420 state-month cells (i.e., 50 states plus the District of Columbia 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.[21] I first construct all-cause and cause-specific mortality counts by state of residence and month of death.[22] I then calculate state-by-month mortality rates per 100,000 inhabitants using state-year population estimates from the National Cancer Institute.[23] For a separate set of analyses, I also construct state-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 aggregate the mortality data to the state level, as opposed to the county level, due to data constraints. Subsequent to 1989, counties with fewer than 100,000 inhabitants are not identified in the public-use MCOD data. Using state-level variation does not substantively affect my estimates since weather conditions are positively correlated within states.[24] Nonetheless, I present county-level estimates for the set of publicly identified counties as a check on my core identification strategy.[25]

4.2 *Global Summary of the Day*

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

[21] The 1972 MCOD file, which is a 50 percent sample, is the only exception.
[22] 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.
[23] The NCI population data is available from 1969 onwards. For simplicity, I assume that the state populations in 1968 are identical to 1969.
[24] Clustering the standard errors at the state level is arguably necessary because unobservable mortality shocks are likely positively correlated across counties that are within the same state. Clustering at the state level wipes out some of the potential gains in precision that county-level estimates might provide.
[25] These are the 389 most populated counties in the United States. These counties accounted for close to 70 percent of the entire United States population in 2000.

the GSOD files, I calculate specific humidity using a standard meteorological formula and information on dew point and air pressure.[26] 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.[27] From the GSOD station-day data, I construct aggregated state-month weather variables using inverse-distance weights of the state population within 50 miles of each weather station.[28]

4.3 Climate change predictions data

I use climate change predictions from the United Kingdom Meteorological Office's Hadley Centre. Following DG, I rely on the 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.[29] The A1F1 scenario assumes there is little or no additional effort (e.g., policy initiatives) to mitigate man-made pollution and is, therefore, a "business-as-usual" scenario. The Hadley CM3 model reports daily mean temperature, daily specific humidity, and total precipitation at several points across the United States that are separated by

[26] 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 a weather station, 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 annual-average daily precipitation (conditional on there being some precipitation) to those station-days that report having rainfall, but are missing the total amount of precipitation.
[27] For example, there were approximately 550 reporting stations in 1968, 1,130 in 1978, 1,330 in 1998, and 1,640 in 2002.
[28] The construction of the state-month weather variables is discussed more formally in the methodology section below.
[29] See IPCC (2007), Schlenker and Roberts (2008), and Stern (2008), for example.

2.5° latitude and 3.75° longitude grids. I create state-level variables from the Hadley CM3 A1F1 predictions using inverse-distance weights of the population (in 2000) within each grid section.[30]

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:

$$(1)\ \mathrm{MORT}_{kym} = \sum_{b} \beta_b\, \mathrm{TEMP}_{bkym} + \sum_{b'} \propto_{b'} \mathrm{HUMID}_{b'kym} + \partial \cdot \mathrm{X}_{kym} + \mu_{ym} + \varphi_{km} + \delta_{km} \cdot \mathrm{YEAR} + \rho_{ky} + e_{kym}\,,$$

where MORT is the monthly mortality rate (per 100,000 inhabitants) in state k, year y, and calendar month m; TEMP is the set of temperature variables that indicate the fraction of days state k is exposed to mean temperatures in a given 10°F bin b (e.g. 50-60°F); HUMID is the set of humidity variables that indicate the fraction of days state k is exposed to mean humidity levels in a given 2-grams-of-water-vapor bin b' (e.g. 2-4 g/kg); X is a vector of controls for

[30] The population data comes from the U.S. Census Bureau.

precipitation[31]; μ is a set of unrestricted time effects; YEAR is a set of unrestricted state by calendar month fixed effects; δ is a set of unrestricted state by calendar month fixed effects interacted with a linear time trend; ρ is a set of unrestricted state by year fixed effects; and, e is an error term.[32] I cluster the standard errors on state of residence to account for the possibility that e is correlated within states.[33]

The inclusion of the state-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 state-by-calendar-month linear time trends allows me to control for the possibility that within-state compositional changes (e.g., as a result of migration) are correlated with gradual climatic changes. Likewise, the state-by-year fixed effects control for unobservable compositional changes with more flexibility.

The TEMP and HUMID variables are derived by aggregating a station-day indicator variable to the state-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, as follows:

$$(2)\ \mathrm{TEMP}_{\mathrm{bkym}} = \sum_{\mathrm{d}} \left(\sum_{\mathrm{l}=0}^{29} \left(\sum_{\mathrm{i}} \mathrm{DUM}_{\mathrm{bikyd-l}} \cdot \omega_{\mathrm{iky}} \right) / 30 \right) / \mathrm{DAYS}_{\mathrm{ym}}\ ,$$

where DUM is an indicator variable set to one if the daily mean temperature on day d minus l of year y at station i is between 40 and 50°F; ω is the inverse-distance weight of the population in

[31] 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. In one specification, I also control for the heat index to account for dangerous temperature-humidity combinations.
[32] As a robustness check (not reported), I exclude the state-by-year fixed effects and the state-month linear time trends.
[33] For example, public health resources, which also affect mortality rates, are potentially correlated over time within states.

state k residing within 50 miles of station i in year y;[34] and DAYS is the number of days in calendar month m of year y (i.e. 28, 29, 30, or 31). The other temperature and humidity variables are constructed similarly to TEMP=40-50°F using equation (2).

Note that I control for temperature and humidity levels for 30 days prior to the month of death to mitigate any inter-temporal mortality effects. I use a 30-day lag 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, I vary the lag to 15 and 60 days in two separate specification checks (not reported).

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.

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.

[34] The weighting scheme follows the approach outlined in Hanigan *et al.* (2006). I use the county population and the geographic centroid of the county as of 2000 (U.S. Census Bureau).

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) $C_{ky} = \sum_b \beta_b \, TEMP_{bky} + \sum_{b'} \propto_{b'} \, HUMID_{b'ky} + \gamma \cdot X + \mu_y + \delta_k \cdot YEAR + e_{kym}$,

where C is the per capita energy consumption in the residential sector in state k and year y; TEMP, HUMID, and X are as in equation (2) except they are aggregated to the year level; year fixed effects (μ) control for macro-level shocks; and state-specific linear time trends ($\delta_k \cdot YEAR$) are included to account for the possibility that changes in energy consumption are spuriously correlated with state-specific climatic trends.[35]

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

[35] My results are robust to the inclusion of state-specific quadratic trends (not reported).

and the Midwest. Also, the South has significantly more high-humidity days than the other three regions. The Northeast, Midwest, and the South have qualitatively similar mortality rates (i.e., around 75 deaths per 100,000 inhabitants, while 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 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 state. Importantly, my model abstracts from any variation in the mortality rate that may be spuriously correlated with unobservable seasonal factors that are fixed within each state. 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 12.66 deaths per 100,000 inhabitants. Exposure to one month with temperatures above 90 ºF causes an additional 9.94 deaths per 100,000 inhabitants. These effects are large in relation to the average monthly mortality rate of 73.0. Importantly, my column (1) estimates are nearly identical 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 9.87 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 disentangle the 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 significantly 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. Thus, failure to control for humidity overstates the independent effect of temperature, and vice versa.

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 5.52 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 0.03 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.[36]

6.3 By Cause of Death

Figure 5 analyzes the effects of temperature and humidity on four of the most prominent causes of death: cardiovascular disease, respiratory illness, cancer, and motor vehicle accidents.[37] Except for temperatures below 30ºF, Figure 5 shows that the temperature-mortality relationship and the humidity-mortality relationship for cardiovascular deaths (Panel A) and respiratory deaths (Panel B) are both roughly U-shaped. In particular, low-humidity levels have a large effect on deaths from respiratory disease. I find that temperature and humidity have little effect

[36] Note that my research design produces local-average-treatment-effects. As such, my estimates provide only suggestive evidence regarding the benefits of being consistently (and expectedly) exposed to certain weather conditions.

[37] These four causes represent about 80 percent of all causes of death. Also, this analysis categorizes death by their "primary" cause so the categories are mutually exclusive.

on deaths from cancer (Panel C), which suggests that my identification strategy has effectively mitigated potential biases from inter-temporal displacement effects (Deschênes and Moretti, 2007). Also, I find that there is a positive relationship between temperature, but no discernable relationship between humidity, and deaths from motor vehicle accident (Panel D).

6.4 By Age Group

Table 3 estimates my core model on 11 separate age groups (see Appendix Table 1). In general, people over 45 years of age are most affected by temperature and humidity changes. One notable exception to this is that infant mortality rates increase significantly when the temperature is above 90°F. However, infant mortality rates are not particularly sensitive to changes in humidity levels. Nonetheless, the temperature-mortality and humidity-mortality relationships are consistent across most of the age groups. As such, my core model, which pools all age groups, is not affected by age-specific compositional changes across states.

6.5 Robustness Checks

As a check on my state-month model, I estimate the effects of exposure to temperature and humidity using data at the county-month level. Due to data constraints in the MCOD files, I restrict my county-month model to counties with over 100,000 inhabitants between 1968 and 2002. Figure 6 illustrates that both models produce nearly identical estimates except for the effects of temperatures above 90°F, which are smaller in magnitude in the county model. Also, I divide my sample into two groups of states based on the number of days per year with temperatures above 65°F. Figure 7 shows that the results are qualitatively similar for the group of "hot states" and the group of "cold states".

To account for the possibility that humidity exacerbates the effects of heat stress, I include controls for days with a heat index between 70 and 80, between 80 and 90, and above 90.[38] (See Appendix Table 1.) Also, I include controls for days with temperatures above 70°F and 80°F *interacted with* the day's humidity level, respectively.[39] (See Appendix Table 1.) In general, there is limited evidence to support the inclusion of these controls. As such, temperature and humidity enter as independent effects in my core model for simplicity.

I verify that temperature and humidity are not correlated with the state-month unemployment rate to ensure that my model is not spuriously identifying the effects of some omitted variable.[40] Also, my results are qualitatively similar when I use the log of the monthly mortality rate as my dependent variable. (Results are available upon request.)

I examine the sensitivity of my results to varying the set of fixed effects and the days-lag in equation (2) to 15 days and 60 days. Although there is loss of precision, my results are qualitatively similar when I use 5°F bins and one-gram-of-water-vapor bins. (Results are available upon request.)

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

My energy estimates, which are presented in Figure 8, 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

[38] The NOAA "cautions" people to monitor their health once the heat index is above 90. The heat index is equal to the temperature for all temperatures below 70°F (Steadman, 1979).
[39] In these specification checks, humidity enters in as a continuous variable. I have tried allowing for non-linearities in humidity; the results are qualitatively similar.
[40] These unemployment rates come from the BLS and are only available subsequent to 1977.

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 76 percent of all households posses (EIA, 2009).[41]

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

8 The Effects of Climate Change on Mortality and Energy Consumption

[41] 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 outside the scope of this paper.

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 9 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 example, the United States will experience approximately 5 fewer days between 30 and 40 ºF 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.

Panel A of Table 3 summarizes my welfare valuations of climate change's impact on mortality and energy consumption. Coupled with my core temperature-mortality and humidity-mortality estimates (Figure 4), I project that mortality rates are likely to increase approximately 1.3 percent (or 34,000 deaths) by the end of the 21st century (c. 2070-2099).[42] Using a statistical value of a life of $7 million (EPA (2000a), EPA (2000b)), my estimates imply that climate change will cost the United States approximately $235 billion dollars in terms of more fatalities. Ignoring the uncertainty with the climate-change predictions themselves, my estimate is statistically significant from zero at the five-percent level.

Furthermore, my estimates imply that there will be a 4.8 percent increase in energy consumption in the residential sector. (Or, an increase of 9.9 quadrillion BTUs.) Assuming a price per quadrillion BTU of $7.6 million (in 2006$), as done by DG, this translates into an additional $75 billion in energy expenditure per year. However, my energy estimate is not statistically significant from zero at conventional levels.

[42] I hold population constant at 300 million for simplicity.

Together, the health-related costs of climate change (in terms of mortality and energy consumption) are $310 billion dollars per year. Put another way, this translates into a loss of about $1,000 per capita per year ($310 billion divided by approximately 300 million inhabitants). This is a sizable cost relative to the United States' baseline income per capita of around $35 thousand (BEA).

8.2 Discussion: Importance of controlling for humidity

Excluding humidity biases estimates towards understating the costs of climate change. With my own model, excluding humidity causes me to estimate only a 0.9 percent increase in mortality rates and a 2.4 percent increase in energy consumption, as opposed to a 1.3 increase in mortality and 4.8 percent increase in energy consumption in my core model (see Panel B of Table 3). A model that omits humidity finds only a 2.5 percent increase, as opposed to 3.9 percent increase, in energy consumption. Although small and statistically insignificant at conventional levels, the bias is economically meaningful: omitting humidity underestimates the welfare costs of climate change by about $101 billion.

Incorporating humidity has particularly important implications for evaluating the distributional impacts of climate change. Table 4 shows that the adverse impacts of climate change, in terms of mortalities, are concentrated in the south of the United States, where the climate is hotter and more humid on average. Interestingly, northern areas of the United States are expected to see a decrease in mortality rates.[43] More importantly for the present discussion, omitting humidity causes me to considerably underestimate the costs of climate change in the

[43] This result suggests that the benefits of less-extreme winter weather will more than compensate for the more-extreme summer weather in the North.

South but overestimate the benefits of climate change in the North.[44] For example, the West South Central Division (e.g., Louisiana) is expected to see a 5.5 percent increase in mortality rates under my core model, but only a 3.8 percent increase when omitting humidity. Conversely, the New England Division (e.g., New York) has an estimated 1.9 percent decrease in mortality under my core model, as opposed to a 1.3 decrease without controlling for humidity. With respect to energy consumption, the bias from omitting humidity follows a similar pattern across states (results not reported). Given poverty is more concentrated in the South (Census Bureau, 2009), my results suggest that the omitting humidity underestimates the extent to which the poor will be impacted by climate change.

As an important aside, these estimates imply that accounting for humidity is even more important when evaluating the distributional effects of climate-change across countries. Generalizing my core estimates, Table 5 shows that tropical areas of the world might be expected to experience an increase in mortality in the coming century.[45] For example, my core model predicts that South-eastern Asia would experience an 8.3 percent increase in mortality rates. A model that omits humidity predicts only a 5.3 percent increase in mortality in South-eastern Asia. Conversely, temperate places are expected to have lower mortality rates in the future. For example, Western Europe is estimated to have a 2.0 percent decrease in mortality when controlling for humidity, but only a 0.9 percent decrease in mortality when humidity is excluded. As such, omitting humidity generally underestimates the burden of climate change on tropical (mostly developing) countries, but overestimates the burden on temperate (mostly developed) countries.

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[44] State-specific estimates are available upon request.

[45] Note that these estimates ignore the impacts of climate change on tropical diseases (e.g., malaria) among other things.

9 Conclusions

My research explores the impacts of temperature and humidity on mortality rates and energy consumption to help clarify the potential consequences of climate change for the United States. To my knowledge, this is the first study to 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 1.3 percent by the end of the 21st century. Also, there will be a 4.8 percent increase in energy expenditure in the residential sector. On the aggregate, omitting humidity causes me to underestimate the costs of climate change by a small but economically meaningful amount.

In particular, my research shows that controlling for humidity is important in the context of predicting the distributional effects of climate change. Omitting humidity underestimates the costs of climate change in areas with hot and humid climates, but overestimates the costs in areas with cold and dry climates. Given poverty rates are highest in places with hot and humid (or tropical) climates, my paper suggests that controlling for humidity has important implications for devising optimal climate-change policies that address 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

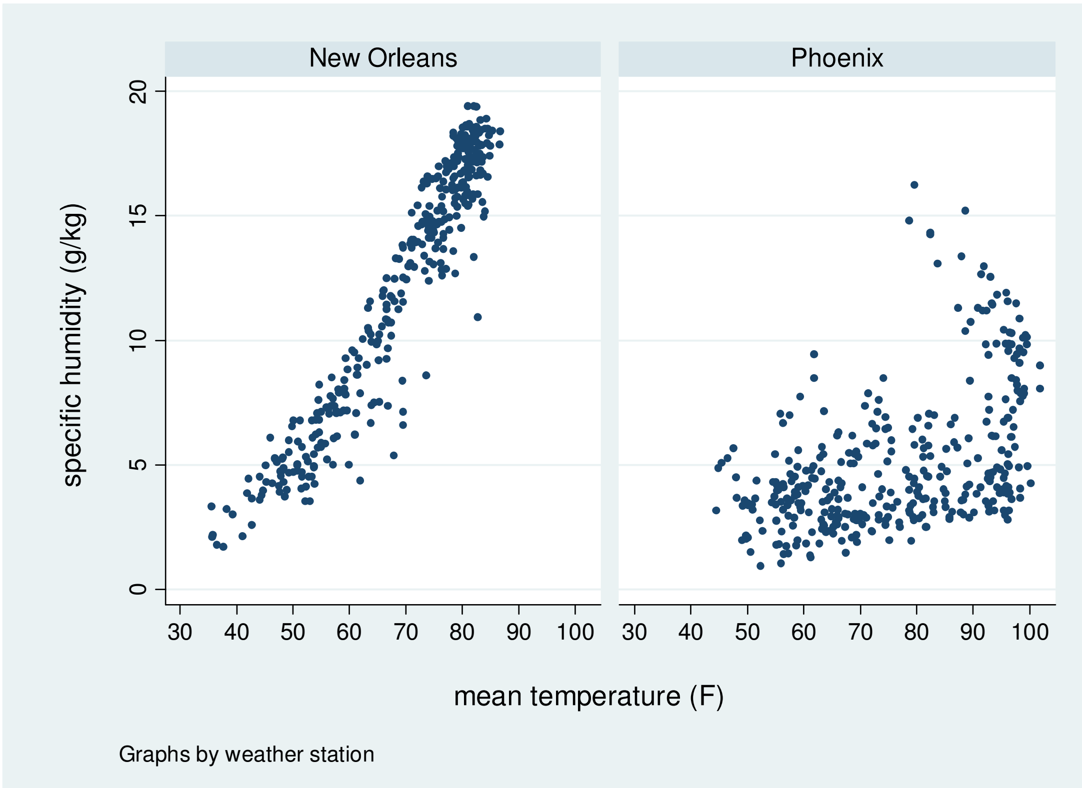
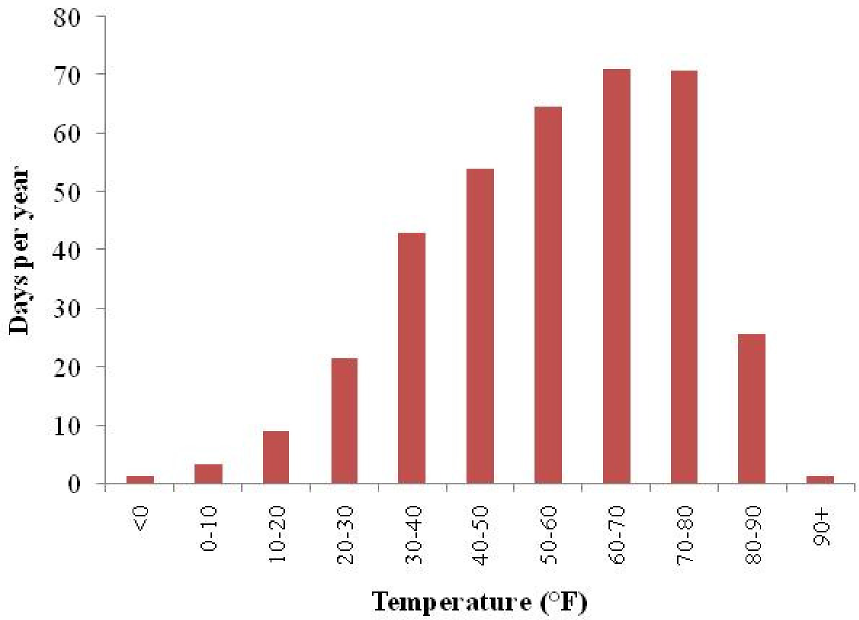
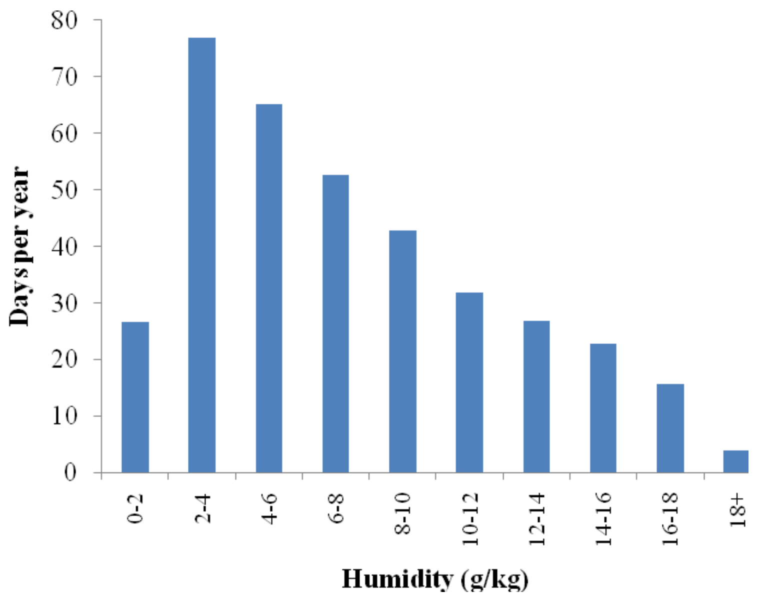


Figure 2

Daily distribution of temperature and humidity, 1968-2002
Panel A: Daily mean temperatures by 10ºF increments



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

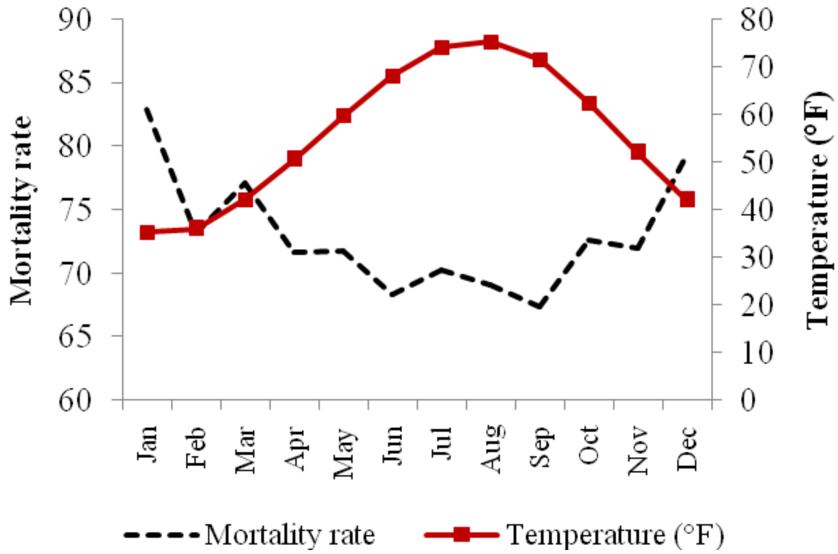


Notes: Frequencies were computed using state-year populations as weights.

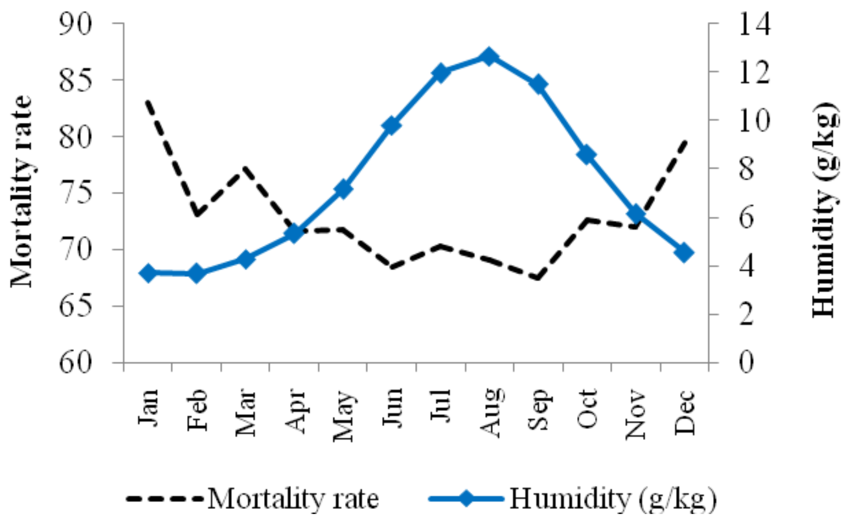
Figure 3

Mean monthly mortality rate, mean monthly temperature and mean monthly humidity, United States (1968-2002)

Panel A: Temperature



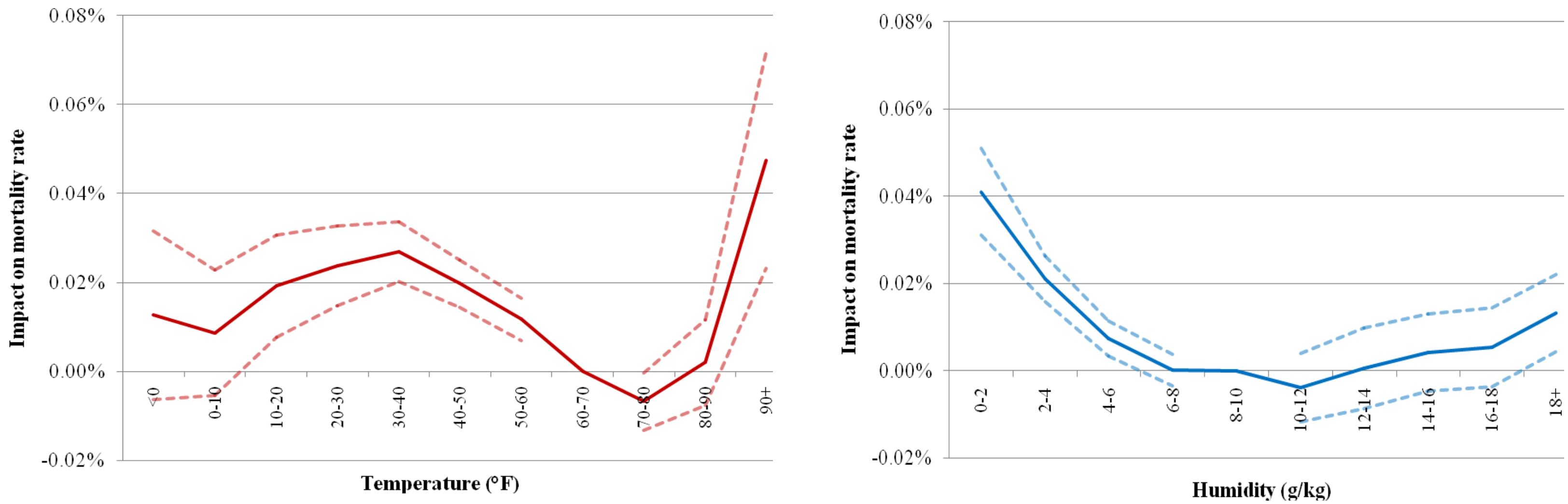
Panel B: Humidity



Notes: This figure was derived from population weighted state-month NCDC data, where the weights were fixed at the average population of each state between 1968 and 2002.

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

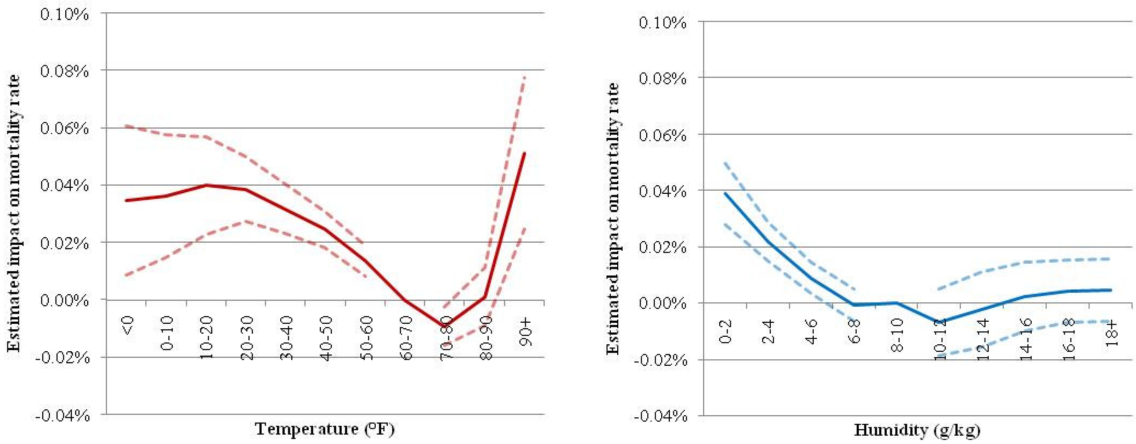


Notes: Regression coefficients from Table 1, column (3), are normalized based on the average annual mortality rate (per 100,000) for the United States, between 1968 and 2002. The dotted lines represent the 95% confidence interval.

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: Cardiovasular



Panel B: Respiratory

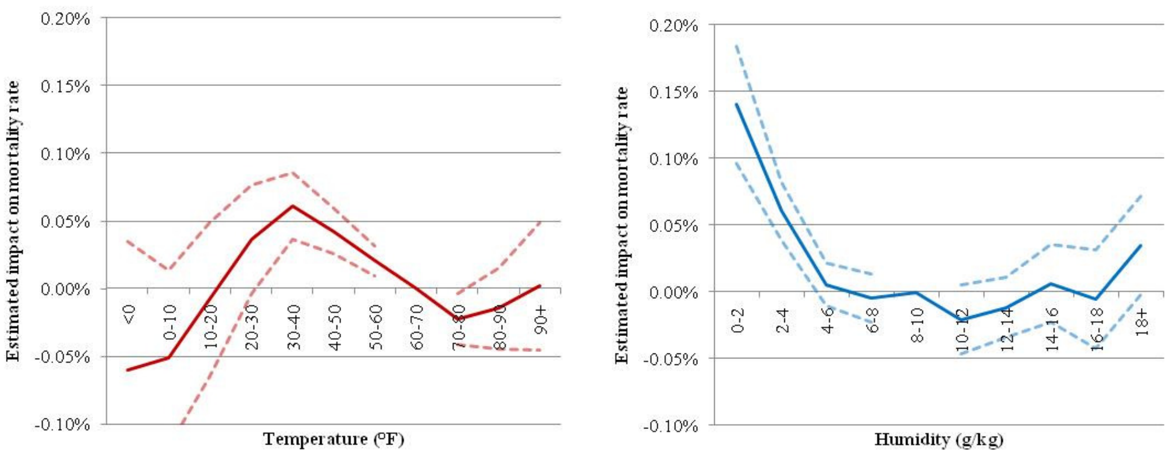
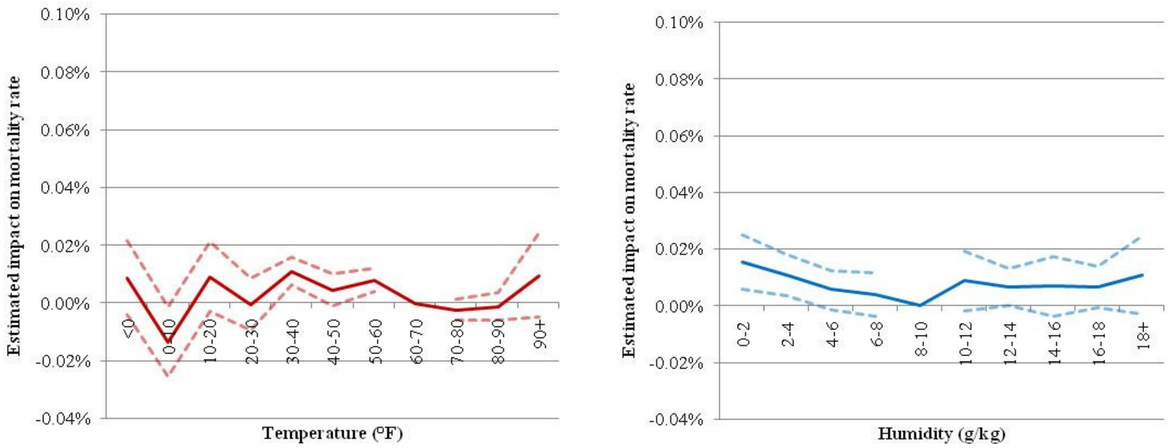
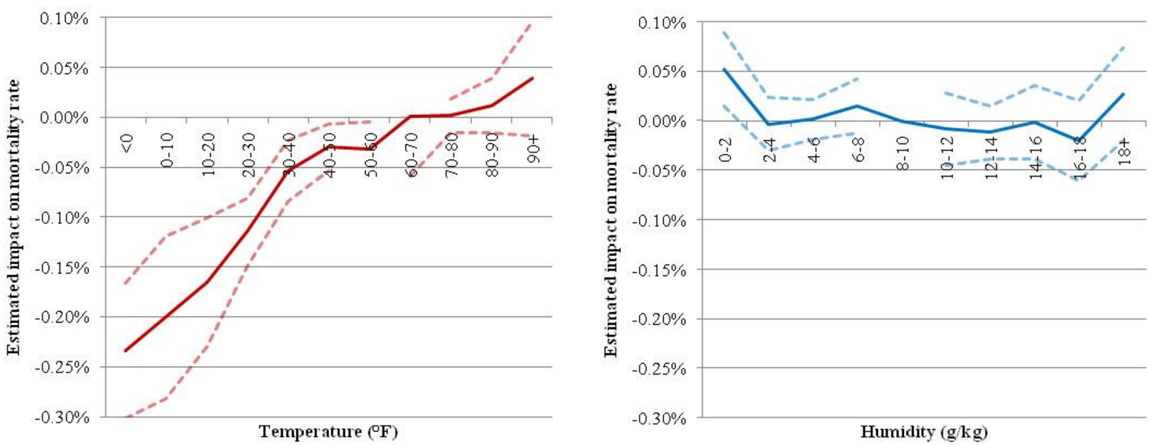


Figure 5 cont.

Panel C: Cancer



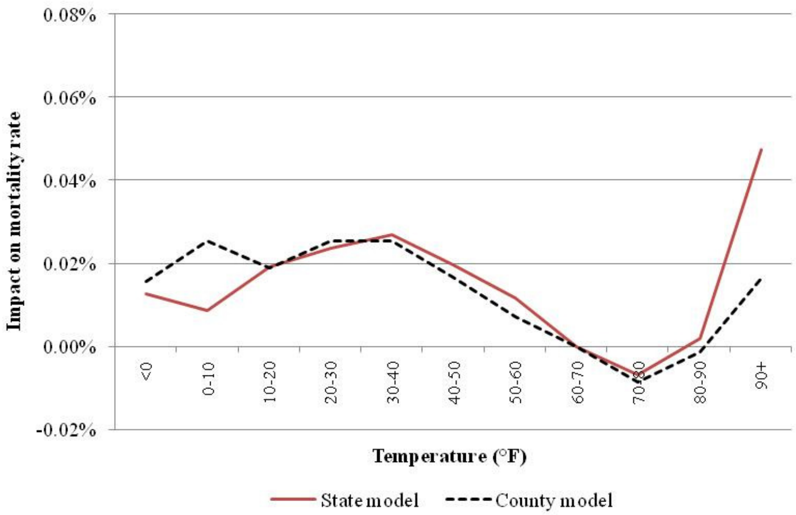
Panel D: Motor vehicle accidents

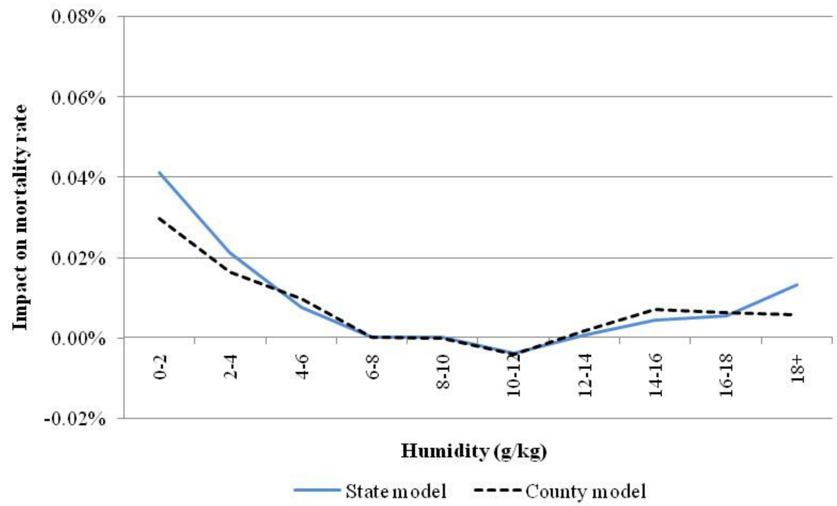


Notes: The axes vary across panels. See notes to Figure 4.

Figure 6

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, 1968-2002 for counties with over 100,000 inhabitants (N=389)



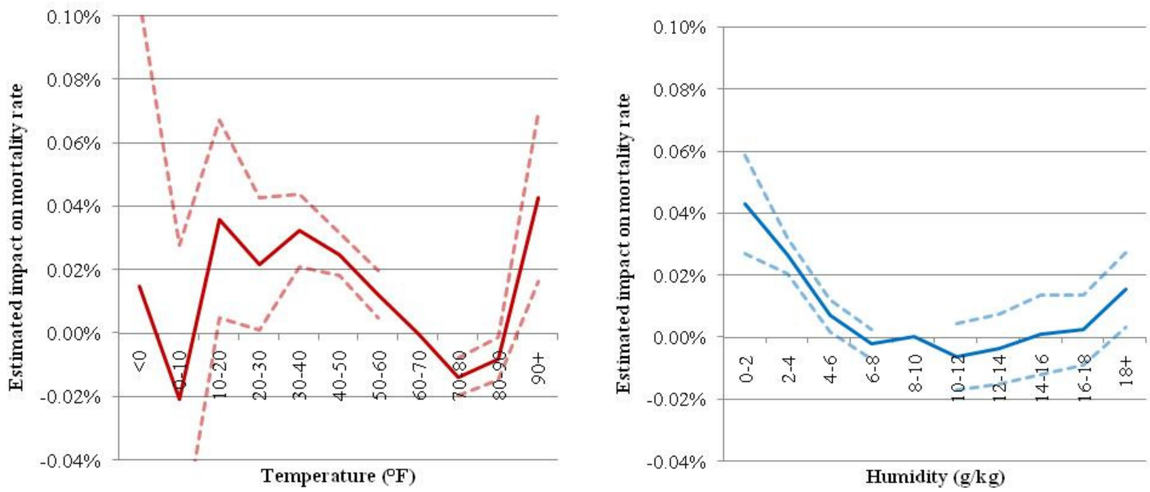


Notes: These estimates came from regressions that were weighted by county-year or state-year populations. Both models have controls for precipitation, unrestricted year-month fixed effects, state-by-calendar-month-specific linear time trends, and state-by-year fixed effects; the state model has state-by-calendar-month fixed effects, while the county model has county-by-calendar-month fixed effects and county-specific time trends.

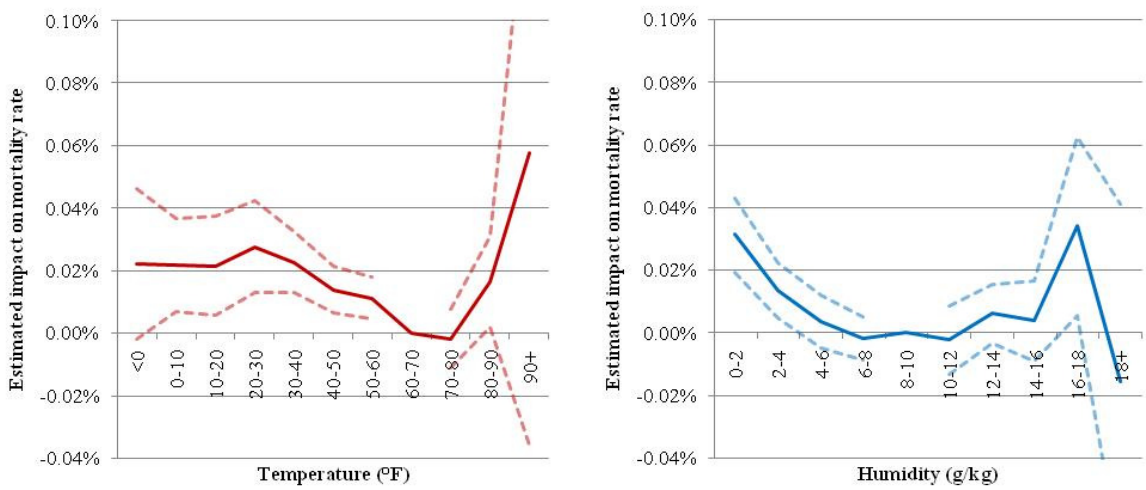
Figure 7

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: Hot states



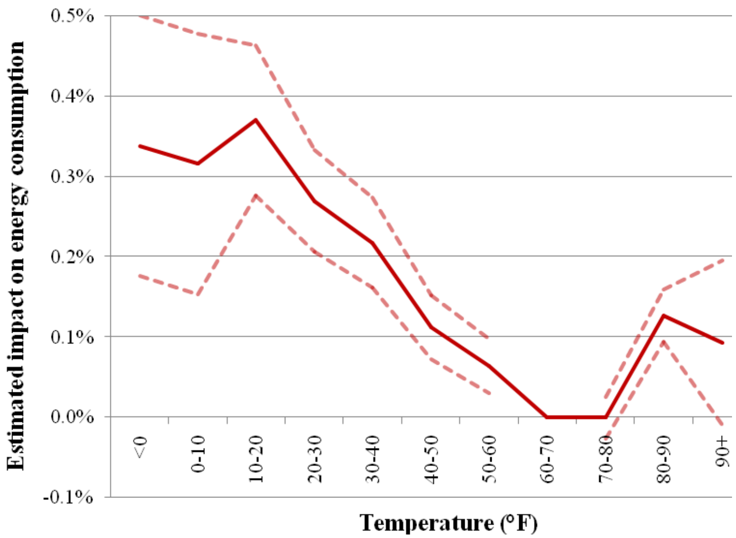
Panel B: Cold states

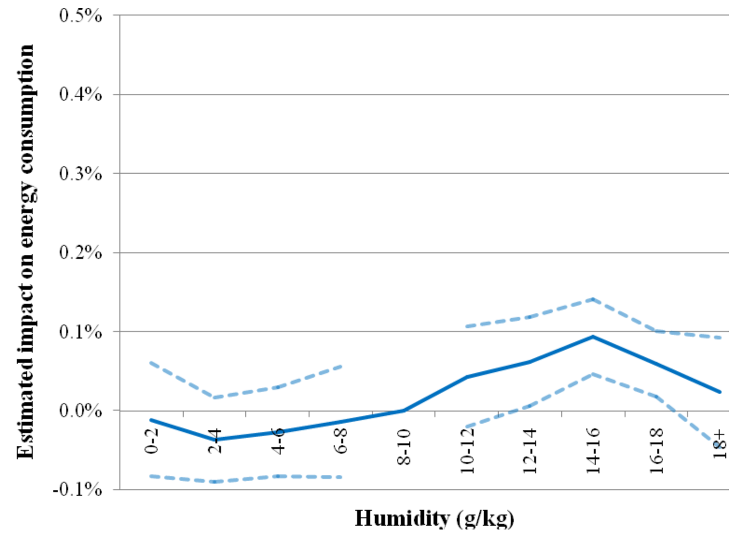


Notes: Hot states (cold states) are the 25 (26) states with the highest (lowest) frequency of days with temperatures above 65°F per year on average between 1968 and 2002.

Figure 8

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 9
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

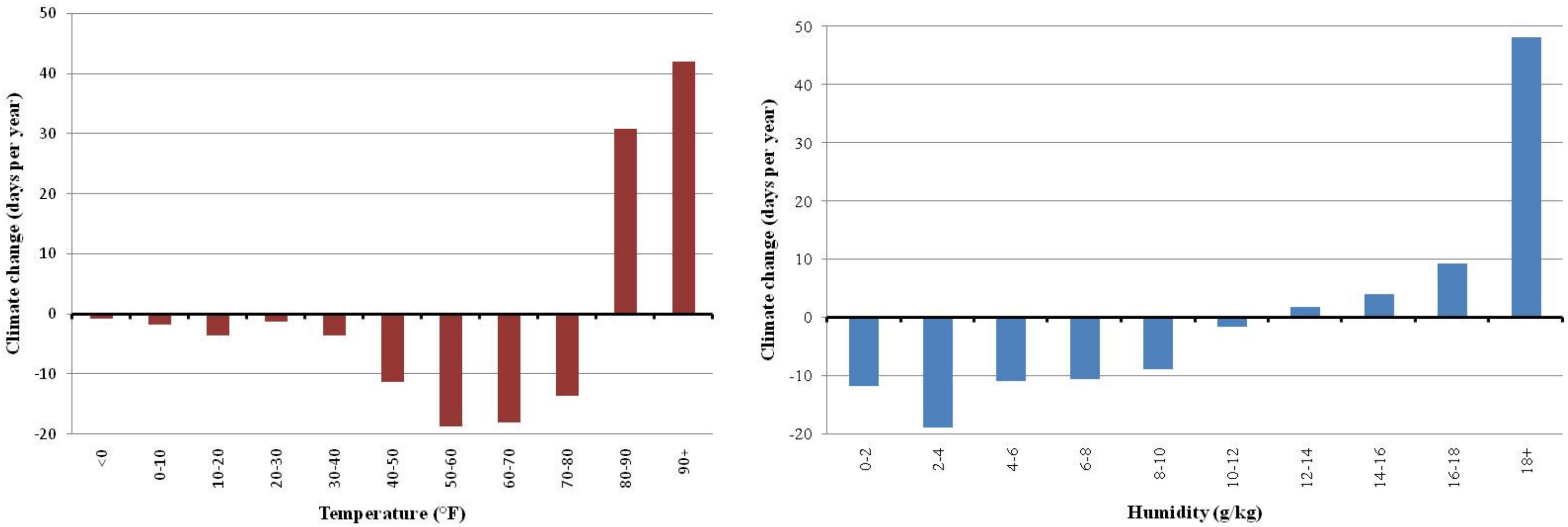


Table 1
Summary of monthly means
1968-2002

	Entire U.S.	Region: North-east	Mid-west	South	West
Mortality rate (per 100,000), by cause of death					
All causes	73.0	79.4	75.5	73.9	61.6
Cardiovascular	33.5	37.9	36.0	33.1	26.5
Cancer	15.9	17.9	16.3	15.8	13.5
Respiratory	5.0	5.1	5.0	4.8	4.9
Motor vehicle	1.7	1.2	1.6	2.0	1.7
Temperature (ºF) indicator variables					
TEMP = <0	0.00	0.003	0.009	0.000	0.002
TEMP = 0-10	0.01	0.012	0.022	0.001	0.004
TEMP = 10-20	0.02	0.042	0.048	0.005	0.010
TEMP = 20-30	0.06	0.097	0.096	0.022	0.034
TEMP = 30-40	0.12	0.168	0.158	0.075	0.088
TEMP = 40-50	0.15	0.162	0.138	0.130	0.175
TEMP = 50-60	0.18	0.162	0.145	0.160	0.260
TEMP = 70-80	0.19	0.145	0.169	0.269	0.148
TEMP = 80-90	0.07	0.018	0.039	0.136	0.054
TEMP = 90+	0.00	0.000	0.001	0.003	0.011
Humidity (g/kg) indicator variables					
HUMID = 0-2	0.07	0.127	0.116	0.032	0.033
HUMID = 2-4	0.21	0.260	0.261	0.150	0.199
HUMID = 4-6	0.18	0.164	0.161	0.142	0.277
HUMID = 6-8	0.14	0.122	0.113	0.114	0.256
HUMID = 10-12	0.09	0.093	0.089	0.107	0.046
HUMID = 12-14	0.07	0.070	0.072	0.109	0.019
HUMID = 14-16	0.06	0.040	0.053	0.115	0.008
HUMID = 16-18	0.04	0.012	0.025	0.099	0.001
HUMID = 18+	0.01	0.001	0.006	0.027	0.000

Notes: Means were calculated using the state-year population as weights.

Table 2
Main results, outcome = monthly mortality rate (per 100,000 inhabitants), 1968-2002

	(1)	(2)	(3)
	TEMP		TEMP +
Specification:	only	HUMID only	HUMID
Outcome mean:	73.0	73.0	73.0
TEMP = <0	15.27		3.34
	(2.52)***		(2.49)
TEMP = 0-10	12.95		2.29
	(1.74)***		(1.85)
TEMP = 10-20	15.93		5.06
	(1.12)***		(1.51)***
TEMP = 20-30	14.20		6.25
	(1.16)***		(1.18)***
TEMP = 30-40	12.66		7.08
	(0.98)***		(0.89)***
TEMP = 40-50	8.71		5.19
	(0.79)***		(0.69)***
TEMP = 50-60	4.28		3.09
	(0.78)***		(0.62)***
TEMP = 70-80	-1.28		-1.76
	(0.74)*		(0.85)**
TEMP = 80-90	1.15		0.53
	(1.04)		(1.26)
TEMP = 90+	9.94		12.46
	(3.48)***		(3.19)***
HUMID = 0-2		12.88	10.77
		(0.74)***	(1.31)***
HUMID = 2-4		9.87	5.52
		(0.62)***	(0.68)***
HUMID = 4-6		4.41	1.94
		(0.43)***	(0.53)***
HUMID = 6-8		1.13	0.03
		(0.39)***	(0.47)
HUMID = 10-12		-1.91	-1.03
		(1.03)*	(1.03)

Table 2 cont.

HUMID = 12-14		-1.53	0.15
		(1.28)	(1.21)
HUMID = 14-16		-0.12	1.11
		(0.91)	(1.16)
HUMID = 16-18		-0.14	1.41
		(1.00)	(1.20)
HUMID = 18+		4.24	3.47
		(1.23)***	(1.16)***
Precipitation	Yes	Yes	Yes
Year-by-month f.e.	Yes	Yes	Yes
State-by-month f.e.	Yes	Yes	Yes
State-by-calendar-month-specific linear time trends	Yes	Yes	Yes
State-by-year f.e.	Yes	Yes	Yes
R-squared	0.9720	0.9710	0.9720
F-statistic	41.63	53.74	82.79
Observations	21,420	21,420	21,420

Notes: *10%, **5%, ***1% significance levels. The unit of observation is state by year by calendar month (N=21,420). Standard errors (in parentheses) are clustered on decedent's state of residence. Regressions are weighted by the total state-year population. The F-test was conducted on the TEMP, HUMID, and precipitation variables. TEMP refers to daily mean temperature (ºF) and HUMID refers to daily specific humidity (g/kg). The controls in each regression include a vector of precipitation variables, unrestricted time effects, state-by-calendar month fixed effects, state-by-calendar-month linear time trends, and state-by-year fixed effects.

Table 3
Estimated impacts of climate change
A1F1 climate-change predictions from the Hadley CM3 model (c. 2070-2099)

	(1) Percentage change (std. error)	(2) Absolute change		(3) Welfare cost	
Panel A: Baseline estimates					
Change in mortality	1.3	34,000	deaths	$235	billion
	(0.6)				
Change in energy consumption (BTU)	4.8	9.9	quadrillion	$75	billion
	(3.4)				
Total cost				$310	billion
Panel B: Omitting humidity					
Change in mortality	0.9	24,000	deaths	$171	billion
	(0.6)				
Change in energy consumption (BTU)	2.4	5.0	quadrillion	$38	billion
	(2.9)				
Total cost				$209	billion

Table 4

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

	(1)	(2)	(1)-(2)
Specification:	Core (controls for humidity)	Omits humidity	Difference
New England	-1.9	-1.3	-0.6
	(1.10)	(0.88)	(1.41)
Middle Atlantic	-1.0	-0.7	-0.3
	(0.80)	(0.67)	(1.04)
East North Central	0.0	0.3	-0.3
	(1.27)	(1.20)	(1.75)
West North Central	1.1	0.9	0.2
	(2.02)	(2.06)	(2.88)
South Atlantic	2.3	1.3	1.1
	(2.57)	(2.05)	(3.29)
East South Central	3.2	2.3	0.9
	(1.80)	(1.80)	(2.55)
West South Central	5.5	3.8	1.8
	(3.01)	(3.17)	(4.37)
Mountain	-0.6	0.8	-1.4
	(1.44)	(1.32)	(1.95)
Pacific	1.6	1.1	0.5
	(1.43)	(1.40)	(2.00)

Notes: Standard errors are in parentheses.

Table 5
Percentage change in mortality rates worldwide,
by United Nations Division

Specification:	(1) Core (controls for humidity)	(2) Omits humidity	(1)-(2) Difference
Australia and New Zealand	-0.6	-0.6	0.0
Caribbean	7.4	5.4	2.0
Central America	3.2	1.7	1.4
Eastern Africa	4.1	2.3	1.8
Eastern Asia	0.6	0.7	-0.1
Eastern Europe	-1.3	-0.3	-0.9
Melanesia	5.1	3.3	1.9
Micronesia	3.2	3.3	-0.1
Middle Africa	6.4	3.6	2.8
Northern Africa	2.8	1.3	1.4
Northern America	2.5	2.2	0.3
Northern Europe	-2.4	-1.1	-1.3
Polynesia	3.4	2.3	1.1
South America	4.1	2.7	1.4
South-central Asia	6.6	4.3	2.4
South-eastern Asia	8.3	5.3	3.0
Southern Africa	0.5	-0.1	0.6
Southern Europe	0.2	0.2	0.0
Western Africa	8.3	5.0	3.2
Western Asia	2.1	1.2	0.9
Western Europe	-2.0	-0.9	-1.1

Notes: The global predictions use population estimates from the CIESIN and assume baseline mortality rates that are equal to the United States. These estimates use climate change predictions from the Hadley CM3 model and my core set of estimates (Figure 4). Standard errors not reported.

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:	98.94	4.62	2.38	8.59	10.89	19.26	44.26	106.5	236.1	527.43	1297.43
TEMP = <0	1.20	-3.98	-0.32	-4.13	-3.57	-2.53	4.72	2.73	17.07	24.04	175.16
	(11.61)	(1.13)	(0.61)	(1.20)	(1.15)	(1.66)	(3.38)	(4.97)	(10.06)	(25.42)	(93.45)
TEMP = 0-10	15.57	-0.89	-1.13	-3.53	-1.84	-2.09	3.69	7.14	15.56	1.96	67.11
	(15.09)	(1.03)	(0.52)	(1.10)	(1.04)	(1.47)	(3.10)	(5.56)	(8.49)	(24.20)	(65.30)
TEMP = 10-20	6.08	-2.85	-0.11	-2.49	-1.28	-3.42	1.12	3.99	24.21	34.21	158.01
	(9.70)	(0.89)	(0.55)	(0.68)	(1.02)	(1.13)	(2.15)	(4.48)	(6.33)	(20.47)	(62.48)
TEMP = 20-30	10.01	-0.92	-0.02	-1.44	-0.91	-1.16	2.42	6.71	20.19	48.95	205.20
	(6.37)	(0.58)	(0.31)	(0.57)	(0.57)	(0.62)	(1.00)	(2.75)	(4.98)	(15.30)	(43.20)
TEMP = 30-40	9.97	-0.29	0.13	-0.74	0.54	-0.19	3.21	5.90	20.73	61.20	201.20
	(5.36)	(0.40)	(0.26)	(0.43)	(0.48)	(0.65)	(0.75)	(2.56)	(3.91)	(7.49)	(25.83)
TEMP = 40-50	7.04	-0.23	0.10	-0.20	0.44	0.40	1.39	4.50	13.25	40.01	170.09
	(3.70)	(0.39)	(0.20)	(0.38)	(0.30)	(0.51)	(0.86)	(2.02)	(2.87)	(7.14)	(24.17)
TEMP = 50-60	6.23	0.08	0.12	-0.32	0.13	-0.27	1.23	3.52	9.37	23.65	103.16
	(2.99)	(0.33)	(0.16)	(0.36)	(0.28)	(0.57)	(0.89)	(1.47)	(3.03)	(5.60)	(15.70)
TEMP = 70-80	-1.63	0.11	0.12	0.12	0.61	-0.23	-0.34	-2.51	-5.45	-20.23	-38.37
	(2.46)	(0.34)	(0.14)	(0.33)	(0.30)	(0.47)	(0.77)	(1.56)	(3.12)	(6.47)	(30.29)
TEMP = 80-90	-1.34	0.03	0.26	0.77	1.05	0.93	1.24	0.73	1.35	-5.96	-13.31
	(2.80)	(0.29)	(0.19)	(0.47)	(0.42)	(0.75)	(0.99)	(2.52)	(3.80)	(9.23)	(42.25)
TEMP = 90+	22.77	-0.41	0.40	1.95	2.22	3.71	4.99	7.92	43.40	123.03	193.75
	(6.30)	(2.09)	(0.56)	(1.53)	(1.54)	(2.49)	(2.94)	(7.36)	(17.09)	(25.20)	(76.47)
HUMID = 0-2	-5.73	2.28	0.76	0.06	1.07	3.54	2.08	10.93	26.97	101.73	348.73
	(5.59)	(0.58)	(0.29)	(0.64)	(0.70)	(0.84)	(1.29)	(2.31)	(6.29)	(14.82)	(36.92)
HUMID = 2-4	-2.92	0.93	0.27	-0.74	-0.27	1.35	0.92	6.05	18.18	41.48	198.66
	(3.59)	(0.49)	(0.21)	(0.44)	(0.42)	(0.58)	(0.83)	(1.48)	(3.93)	(7.78)	(25.96)

Appendix Table 1 cont.

HUMID = 4-6	-5.72	0.45	0.07	-0.55	-0.01	0.33	0.67	3.65	10.60	14.16	46.90
	(3.06)	(0.39)	(0.16)	(0.35)	(0.33)	(0.49)	(0.87)	(1.48)	(3.30)	(6.77)	(19.46)
HUMID = 6-8	-4.34	0.34	0.27	-0.45	-0.02	0.08	-0.51	0.62	2.29	-8.91	-28.44
	(4.13)	(0.44)	(0.24)	(0.45)	(0.36)	(0.58)	(0.87)	(1.62)	(3.34)	(8.67)	(18.20)
HUMID = 10-12	-9.62	0.22	0.54	-0.90	-0.03	-0.07	-1.34	0.86	0.79	-14.52	-53.83
	(4.41)	(0.59)	(0.33)	(0.63)	(0.49)	(0.84)	(1.66)	(2.55)	(4.22)	(11.08)	(32.13)
HUMID = 12-14	0.11	-0.70	0.17	-0.44	-0.04	0.37	-0.83	1.35	3.96	0.08	4.46
	(5.00)	(0.41)	(0.26)	(0.41)	(0.50)	(0.60)	(1.09)	(2.44)	(4.04)	(8.33)	(33.88)
HUMID = 14-16	1.81	0.41	0.26	0.19	-0.50	0.38	-0.22	1.60	6.99	5.94	17.49
	(5.66)	(0.59)	(0.35)	(0.63)	(0.45)	(0.76)	(1.28)	(2.87)	(3.84)	(8.75)	(33.48)
HUMID = 16-18	6.43	-0.34	0.92	-1.11	0.32	0.36	-0.62	4.14	13.79	-2.46	6.66
	(5.59)	(0.67)	(0.32)	(0.64)	(0.57)	(0.94)	(1.60)	(2.81)	(5.79)	(10.37)	(44.05)
HUMID = 18+	1.83	0.70	0.72	0.50	0.23	0.85	2.17	4.01	5.74	21.22	91.62
	(7.41)	(0.74)	(0.42)	(0.61)	(0.87)	(0.79)	(3.29)	(3.51)	(4.75)	(11.56)	(38.25)
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
State-by-month f.e.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State-by-calendar-month-specific linear time trends	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State-by-year f.e.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F-test statistic	3.22	4.26	2.64	11.74	7.45	8.38	13.62	12.91	40.60	45.63	48.79
F-test p-value	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
R-squared	0.92	0.66	0.69	0.79	0.80	0.88	0.94	0.95	0.95	0.94	0.88

Notes: see notes to Table 1. Significance levels omitted.

Appendix Table 2
Controls for heat index, temperature-humidity interactions
Outcome = monthly mortality rate (per 100,000 inhabitants), 1968-2002

Specification:	(1)	(2)	(3)
TEMP = <0	3.30	2.70	3.12
	(2.49)	(2.36)	(2.48)
TEMP = 0-10	2.25	1.64	2.05
	(1.80)	(1.87)	(1.91)
TEMP = 10-20	5.00	4.44	4.82
	(1.46)***	(1.55)***	(1.58)***
TEMP = 20-30	6.22	5.66	6.06
	(1.24)***	(1.12)***	(1.20)***
TEMP = 30-40	7.03	6.48	6.88
	(1.04)***	(1.07)***	(0.93)***
TEMP = 40-50	5.16	4.65	5.02
	(0.73)***	(0.67)***	(0.72)***
TEMP = 50-60	3.10	2.62	3.00
	(0.89)***	(0.72)***	(0.62)***
TEMP = 70-80	-1.01	-5.10	-1.21
	(1.98)	(2.13)**	(0.99)
TEMP = 80-90	0.64	-2.71	-4.75
	(2.26)	(2.21)	(2.43)*
TEMP = 90+	8.49	9.19	9.08
	(3.76)**	(3.70)**	(2.95)***
HUMID = 0-2	10.84	11.23	11.02
	(1.34)***	(1.28)***	(1.36)***
HUMID = 2-4	5.57	5.94	5.72
	(0.69)***	(0.70)***	(0.69)***
HUMID = 4-6	1.98	2.29	2.10
	(0.53)***	(0.51)***	(0.54)***
HUMID = 6-8	0.04	0.28	0.12
	(0.45)	(0.47)	(0.46)
HUMID = 10-12	-1.07	-1.34	-1.17
	(1.11)	(1.11)	(1.08)
HUMID = 12-14	-0.14	-0.84	-0.20
	(1.26)	(1.31)	(1.17)
HUMID = 14-16	0.87	-0.86	0.56
	(1.23)	(1.72)	(1.22)
HUMID = 16-18	1.45	-1.18	0.51
	(1.26)	(1.92)	(1.38)
HUMID = 18+	1.25	0.09	1.09
	(1.79)	(2.45)	(1.88)

Appendix Table 1 cont.

HEAT INDEX=70-80	-0.33		
	(2.48)		
HEAT INDEX=80-90	-0.77		
	(2.79)		
HEAT INDEX=90+	3.23		
	(4.24)		
TEMP (70+) x HUMID		0.35	
		(0.21)*	
TEMP (80+) x HUMID			0.41
			(0.22)*
Precipitation	Yes	Yes	Yes
Year-by-month f.e.	Yes	Yes	Yes
State-by-month f.e.	Yes	Yes	Yes
State-by-calendar-month-specific linear time trends	Yes	Yes	Yes
State-by-year f.e.	Yes	Yes	Yes
R-squared	0.972	0.972	0.972
F-statistic	77.94	80.46	82.97
Observations	21,420	21,420	21,420

Notes: The heat index is a widely-cited measure of dangerously high temperature-humidity combinations (NOAA). TEMP (70+) x HUMID interacts a dummy for those days with temperatures above 70°F with humidity. TEMP (80+) x HUMID interacts a dummy for those days with temperatures above 80°F with humidity.