Climate Change, Mortality, and Adaptation: Evidence from Annual Fluctuations in Weather in the US*

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ABSTRACT

This paper produces the first large-scale estimates of the US health related welfare costs due to climate change. Using the presumably random year-to-year variation in temperature and two state of the art climate models, the analysis suggests that under a 'business as usual' scenario climate change will lead to an increase in the overall US annual mortality rate ranging from 0.5% to 1.7% by the end of the 21st century. These overall estimates are statistically indistinguishable from zero, although there is evidence of statistically significant increases in mortality rates for some subpopulations, particularly infants. As the canonical Becker-Grossman health production function model highlights, the full welfare impact will be reflected in health outcomes and increased consumption of goods that preserve individuals' health. Individuals' likely first compensatory response is increased use of air conditioning; the analysis indicates that climate change would increase US annual residential energy consumption by a statistically significant 15% to 30% ($15 to $35 billion in 2006 dollars) at the end of the century. It seems reasonable to assume that the mortality impacts would be larger without the increased energy consumption. Further, the estimated mortality and energy impacts likely overstate the long-run impacts on these outcomes, since individuals can engage in a wider set of adaptations in the longer run to mitigate costs. Overall, the analysis suggests that the health related welfare costs of higher temperatures due to climate change are likely to be quite modest in the US.

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Introduction

The climate is a key ingredient in the earth's complex system that sustains human life and well being. There is a growing consensus that emissions of greenhouse gases due to human activity will alter the earth's climate, most notably by causing temperatures, precipitation levels, and weather variability to increase. According to the UN's Intergovernmental Panel on Climate Change (IPCC) Fourth Assessment Report, climate change is likely to affect human health directly through changes in temperature and precipitation and indirectly through changes in the ranges of disease vectors (e.g., mosquitoes) and other channels (IPCC Working Group II, 2007). The design of optimal climate change mitigation policies requires credible estimates of the health and other benefits of reductions in greenhouse gases; current evidence on the magnitudes of the direct and indirect impacts, however, is considered insufficient for reliable conclusions (WHO 2003).[1]

Conceptual and statistical problems have undermined previous efforts to develop estimates of the health related welfare costs of climate change. The conceptual problem is that the canonical economic models of health production predict that individuals will respond to climate changes that threaten their health by purchasing goods that mitigate the health damages (Grossman 2000). In the extreme, it is possible that individuals would fully "self-protect" such that climate change would not affect measured health outcomes. In this case, an analysis that solely focuses on health outcomes would incorrectly conclude that climate change had zero impact on welfare.

On the statistical side, there are at least three challenges. First, there is a complicated, dynamic relationship between temperature and mortality, which can cause the short-run relationship between temperature and mortality to differ substantially from the long-run (Huynen et al. 2001; Deschênes and Moretti 2007).[2] Second, individuals' locational choices---which determine exposure to a climate---are related to health and socioeconomic status, so this form of selection makes it difficult to uncover the

[1] See Tol (2002a and 2002b) for overall estimates of the costs of climate change, which are obtained by summing costs over multiple areas including human health, agriculture, forestry, species/ecosystems, and sea level rise. Deschenes and Greenstone (2007) provides evidence on the impacts on the US agricultures sector. Also, see Schlenker, Hanemann, and Fisher (2006).

[2] For example, Deschênes and Moretti (2007) document the importance of forward displacement or "harvesting" on hot days.

causal relationship between temperature and mortality. Third, the relationship between temperature and health is highly nonlinear and likely to vary across age groups and other demographic characteristics.

This paper develops measures of the welfare loss associated with the direct risks to health posed by climate change in the US that confront these conceptual and statistical challenges. Specifically, the paper reports on statistical models for demographic group by county mortality rates and for state-level residential energy consumption (perhaps the primary form of protection against high temperatures via air conditioning) that model temperature semi-parametrically. The mortality models include county and state by year fixed effects, while the energy ones include state and Census-division by year fixed effects. Consequently, the temperature variables are identified from the unpredictable and presumably random year-to-year variation in temperature, so concerns about omitted variables bias are unlikely to be important.

We combine the estimated impacts of temperature on mortality and energy consumption with predicted changes in climate from 'business as usual' scenarios to develop estimates of the health related welfare costs of climate change in the US. The preferred mortality estimates suggest an increase in the overall annual mortality rate ranging from 0.5% to 1.7% by the end of the century. These overall estimates are statistically indistinguishable from zero, although there is evidence of statistically significant increases in mortality rates for some subpopulations, particularly infants. The energy results suggest that by the end of the century climate change will cause total US residential energy consumption to increase by 15% - 30%. This estimated increase is statistically significant, and, when valued at the average energy prices from 1991-2000, it implies that there will be an additional $15 - $35 billion (2006$) per year of US residential energy consumption.

Overall, the analysis suggests that the health related welfare costs of higher temperatures due to climate change will be quite modest in the US. The small magnitude of the mortality effects is evident when they are compared to the approximately 1% per year decline in the overall mortality rate that has prevailed over the last 35 years. Further, it seems likely that the mortality impacts would be larger without the compensatory increase in energy consumption. Finally, it is evident that an exclusive analysis of mortality would substantially understate the health related welfare costs of climate change.

There are a few important caveats to these calculations and, more generally, to the analysis. The estimated impacts likely overstate the mortality and adaptation costs, because the analysis relies on inter-annual variation in weather, and less expensive adaptations (e.g., migration) will be available in response to permanent climate change. On the other hand, the estimated welfare losses fail to include the impacts on other health-related determinants of welfare (e.g., morbidities) that may be affected by climate change, so in this sense they are an underestimate. Additionally, the effort to project outcomes at the end of the century requires a number of strong assumptions, including that the climate change predictions are correct, relative prices (e.g., for energy and medical services) will remain constant, the same energy and medical technologies will prevail, and the demographics of the US population (e.g., age structure) and their geographical distribution will remain unchanged. These are strong assumptions, but their benefit is that they allow for a transparent analysis based on data rather than on unverifiable assumptions.

The analysis is conducted with the most detailed and comprehensive data available on mortality, energy consumption, weather, and climate change predictions for fine US geographic units. The mortality data come from the 1968-2002 Compressed Mortality Files, the energy data are from the Energy Information Administration, and the weather data are from the thousands of weather stations located throughout the US. We focus on two sets of end of century (i.e., 2070-2099) climate change predictions that represent "business-as-usual" or no carbon tax cases. The first is from the Hadley Centre's 3rd Ocean-Atmosphere General Circulation Model using the Intergovernmental Panel on Climate Change's (IPCC) A1F1 emissions scenario and the second is from the National Center for Atmospheric Research's Community Climate System Model (CCSM) 3 using IPCC's A2 emissions scenario.

Finally, it is notable that the paper's approach mitigates or solves the conceptual and statistical problems that have plagued previous research. First, the availability of data on energy consumption means that we can measure the impact on mortality <u>and</u> self-protection expenditures. Second, we demonstrate that the estimation of annual mortality equations, rather than daily ones, mitigates concerns about failing to capture the full mortality impacts of temperature shocks. Third, the county fixed effects adjust for any differences in unobserved health across locations due to sorting. Fourth, we model daily temperature semi-parametrically by using 20 separate variables, so we do not rely on functional form

assumptions to infer the impacts of the hottest and coldest days on mortality. Fifth, we estimate separate models for 16 demographic groups, which allows for substantial heterogeneity in the impacts of temperature.

The paper proceeds as follows. Section I briefly reviews the patho-physiological and statistical evidence on the relationship between weather and mortality. Section II provides the conceptual framework for our approach. Section III describes the data sources and reports summary statistics. Section IV presents the econometric approach, and Section V describes the results. Section VI assesses the magnitude of our estimates of the effect of climate change and discusses a number of important caveats to the analysis. Section VII concludes the paper.

I. Background on the Relationship between Weather and Mortality

Individuals' heat regulation systems enable them to cope with high and low temperatures. Specifically, high and low temperatures generally trigger an increase in the heart rate in order to increase blood flow from the body to the skin, leading to the common thermoregulatory responses of sweating in hot temperatures and shivering in cold temperatures. These responses allow individuals to pursue physical and mental activities without endangering their health within certain ranges of temperature. Temperatures outside of these ranges pose dangers to human health and can result in premature mortality. This section provides a brief review of the mechanisms and the challenges for estimation.

Hot Days. An extensive literature documents a relationship between extreme temperatures (usually during heat waves) and mortality (e.g., Klineberg 2002; Huynen 2001; Rooney et al. 1998). These excess deaths are generally concentrated among causes related to cardiovascular, respiratory, and cerebrovascular diseases. The need for body temperature regulation imposes additional stress on the cardiovascular and respiratory systems. In terms of specific indicators of body operations, elevated temperatures are associated with increases in blood viscosity and blood cholesterol levels. It is not surprising that previous research has shown that access to air conditioning greatly reduces mortality on hot days (Semenza et al. 1996).

An important feature of the relationship between heat and mortality is that the number of deaths

immediately caused by a period of very high temperatures is at least partially compensated for by a reduction in the number of deaths in the period immediately subsequent to the hot day or days (Basu and Samet 2002; Deschênes and Moretti 2007). This pattern is called forward displacement or "harvesting," and it appears to occur because heat affects individuals that were already very sick and would have died in the near term. Since underlying health varies with age, these near-term displacements are more prevalent among the elderly.

Cold Days. Cold days are also a risk factor for mortality. Exposure to very cold temperatures causes cardiovascular stress due to changes in blood pressure, vasoconstriction, and an increase in blood viscosity (which can lead to clots), as well as levels of red blood cell counts, plasma cholesterol, and plasma fibrinogen (Huynen et al. 2001). Further, susceptibility to pulmonary infections may increase because breathing cold air can lead to bronchoconstriction.

Deschênes and Moretti (2007) provide the most comprehensive evidence on the impacts of cold days on mortality. They find "evidence of a large and statistically significant effect on mortality within a month of the cold wave. This effect appears to be larger than the immediate effect, possibly because it takes time for health conditions associated with extreme cold to manifest themselves and to spread" (Deschênes and Moretti 2005). Thus, in the case of cold weather, it may be that there are delayed impacts and that the full effect of a cold day takes a few weeks to manifest itself. Further, they find that the impact is most pronounced among the young and elderly and concentrated among cardiovascular and respiratory diseases.

Implications. The challenge for this study and any study focused on substantive changes in life expectancy is to develop estimates of the impact of temperature on mortality that are based on the full long-run impact on life expectancy. In the case of hot days, the previous literature suggests that this task requires purging the temperature effects of the influence of harvesting or forward displacement. In the case of cold days, the mortality impact may accumulate over time. In both cases, the key point is that the full impact of a given day's temperature may take numerous days to manifest fully.

Our review of the literature suggests that the full mortality impacts of cold and hot days are evident within 30 days (Huynen et al. 2001; Deschênes and Moretti 2007). The below econometrics

section outlines a method that allows the mortality impacts of temperature to manifest themselves over long periods of time. Further, the immediate and longer run effects of hot and cold days are likely to vary across the populations, with larger impacts among relatively unhealthy subpopulations. One important determinant of healthiness is age, with the old and young being especially sensitive to environmental insults. Consequently, we conduct separate analyses for 16 demographic groups defined by the interaction of gender and 8 age categories.

II. Conceptual Framework

In principle, it is possible to capture the full welfare effects of climate change through observations on the land market. Since land is a fixed factor, it will capture all the differences in rents associated with differences in climate (Rosen 1974).[3] The advantage of this approach is that in principle the full impact of climate change can be summarized in a single market. Despite the theoretical and practical appeal of this approach, it is unlikely to provide reliable estimates of the welfare impacts of climate change. We base this conclusion on a series of recent papers that suggest that the results from the estimation of cross-sectional hedonic equations for land prices are quite sensitive to seemingly minor decisions about the appropriate control variables, sample, and weighting and generally appear prone to misspecification (Black 1999; Chay and Greenstone 2005; Deschenes and Greenstone 2007; Greenstone and Gallagher 2007). An alternative approach is to develop estimates of the impact of climate change in a series of sectors, which could then be summed.

This paper's goal is to develop a partial estimate of the health related welfare impact of climate change. This section begins by reviewing a Becker-Grossman style 1-period model of health production (Grossman 2000). It then uses the results to derive a practical expression for the health related welfare impacts of climate change (Harrington and Portney 1987). This expression guides the subsequent empirical analysis. The section then discusses the implications of our estimation strategy that relies on inter-annual fluctuations in weather for the development of these welfare estimates.

A Practical Expression for Willingness to Pay/Accept (WTP/WTA) for an Increase in

[3] It is also possible that climate differences are reflected in wages (Roback 1982).

Temperature. We assume a representative individual consumes a jointly aggregated consumption good, x_C. Their other consumption good is their mortality risk, which leads to a utility function of

(1) $U = U[x_C, s]$,

where s is the survival rate. The production function for survival is expressed as:

(2) $s = s(x_H, T)$,

so survival is a function of x_H, which is a private good that increases the probability of survival, and ambient temperature, T. Energy consumption is an example of x_H, since energy is used to run air conditioners, which affect survival on hot days. We define x_H such that $\partial s/\partial x_H > 0$. For expositional purposes, we assume that climate change leads to an increase in temperatures in the summer only when higher temperatures are harmful for health so $\partial s/\partial T < 0$.

The individual faces a budget constraint of the form:

(3) $I - x_C - px_H = 0$,

where I is exogenous earnings or income and prices of x_C and x_H are 1 and p, respectively.

The individual's problem is to maximize (1) through her choices of x_C and x_H, subject to (2) and (3). In equilibrium, the ratio of the marginal utilities of consumption of the two must be equal to the ratio of the prices: $[(\partial U/\partial s)\cdot(\partial s/\partial x_H)]/[\partial U/\partial x_C] = p$. Solution of the maximization problem reveals that the input demand equations for x_C and x_H are functions of prices, income, and temperature. Further, it reveals the indirect utility function, V, which is the maximum utility obtainable given p, I, and T.

We utilize V(p, I, T) to derive an expression for the welfare impact of climate change, holding constant utility (and prices). Specifically, we consider changes in T as are predicted to occur under climate change. In this case, it is evident that the consumer must be compensated for changes in T with changes in I when utility is held constant. The point is that in this setting income is a function of T, which we denote as I*(T). Consequently, for a given level of utility and fixed p, there is an associated V(I*(T),T).

Now, consider the total derivative of V with respect to T along an indifference curve:

$dV/dT = V_I(dI^*(T)/dT) + \partial V/\partial T = 0$ or $dI^*(T)/dT = -(\partial V/\partial T)/(\partial V/\partial I)$.

The term $dI^*(T)/dT$ is the change in income necessary to hold utility constant for a change in T. In other

words, it measures willingness to pay (accept) for a decrease (increase) in summer temperatures. Thus, it is the theoretically correct measure of the health-related welfare impact of climate change.

Since the indirect utility function isn't observable, it is useful to express $dI^*(T)/dT$ in terms that can be measured with available data sets. By using the derivatives of V and the first order conditions from the above maximization problem, it can be rewritten as $dI^*(T)/dT = -p\ [(\partial s/\partial T)/(\partial s/\partial x_H)]$. In principle, it is possible to measure these partial derivatives, but it is likely infeasible since data files containing measures of the complete set of x_H are unavailable generally. Put another way, data limitations prevent the estimation of the production function specified in equation (2). However, a few algebraic manipulations based on the first order conditions and that $\partial s/\partial T = ds/dT - (\partial s/\partial x_H)(\partial x_H/\partial T)$ (because $ds/dT = (\partial s/\partial x_H)(\partial x_H/\partial T) + \partial s/\partial T$) yields:

(4) $dI^*(T)/dT = -ds/dT\ (\partial U/\partial s)/\lambda + p\ \partial x_H/\partial T$,

where λ is the Lagrangian multiplier from the maximization problem or the marginal utility of income.

As equation (4) makes apparent, willingness to pay/accept for a change in temperature can be inferred from changes in s and x_H. Since temperature increases raise the effective price of survival, theory would predict that $ds/dT \leq 0$ and $\partial x_H/\partial T \geq 0$. Depending on the exogenous factors, it is possible that there will be a large change in the consumption of x_H (at the expense of consumption of x_C) and little change in s. The key point for this paper's purposes is that the full welfare effect of the exogenous change in temperature is reflected in changes in the survival rate <u>and</u> the consumption of x_H.

It is of tremendous practical value that all of the components of equation (4) can be measured. The total derivative of the survival function with respect to temperature (ds/dT), or the dose-response function, is obtained through the estimation of epidemiological-style equations that don't control for x_H. We estimate such an equation below.[4] The term $(\partial U/\partial s)/\lambda$ is the dollar value of the disutility of a change in the survival rate. This is known as the value of a statistical life (Thaler and Rosen 1976) and empirical estimates are available (e.g., Ashenfelter and Greenstone 2004). The last term is the partial derivative of x_H with respect to temperature multiplied by the price of x_H. We estimate how energy consumption

[4] Previous research on the health impacts of air pollution almost exclusively estimate these dose-response functions, rather than the production functions specified in equation (2) (e.g., Chay and Greenstone 2003a and 2003b).

changes with temperature (i.e., $\partial x_H/\partial T$) below and information on energy prices is readily available.

It is appealing that the paper's empirical strategy can be directly connected to an expression for WTP/WTA, but this connection has some limitations worth highlighting from the outset. The empirical estimates will only be a partial measure of the health-related welfare loss, because climate change may affect other health outcomes (e.g., morbidity rates). Further, although energy consumption likely captures a substantial component of health preserving (or defensive) expenditures, climate change may induce other forms of adaptation (e.g., substituting indoor exercise for outdoor exercise or changing the time of day when one is outside).[5] These other outcomes are unobservable in our data files, so the resulting welfare estimates will be incomplete and understate the costs of climate change.

Adaptation in the Short and Long Runs. The one-period model sketched in the previous subsection obscures an issue that may be especially relevant in light of our empirical strategy relying on inter-annual fluctuations in weather to learn about the welfare consequences of permanent climate change. It is easy to turn the thermostat down and use more air conditioning on hot days, and it is even possible to purchase an air conditioner in response to a single year's heat wave. A number of adaptations, however, cannot be undertaken in response to a single year's weather realization. For example, permanent climate change is likely to lead individuals to make their homes more energy efficient or perhaps even to migrate (presumably to the North). Our approach fails to capture these adaptations.

Figure 1 illustrates this issue in the context of alternative technologies to achieve a given indoor temperature. Household annual energy related expenditures are on the y-axis and the ambient temperature is on the x-axis. For simplicity, we assume that an annual realization of temperature can be summarized in a single number, T. The figure depicts the cost functions associated with three different technologies. These cost functions all have the form $C_j = rF_j + f_j(T)$, where C is annual energy related expenditures, F is the capital cost of the technology, r is the cost of capital, and f(T) is the marginal cost

[5] Energy consumption may affect utility through other channels in addition to its role in self-protection. For example, high temperatures are uncomfortable. It would be straightforward to add comfort to the utility function and make comfort a function of temperature and energy consumption. In this case, this paper's empirical exercise would fail to capture the impact of temperature on heat but the observed change in energy consumption would reflect its role in self-protection <u>and</u> comfort.

which is a function of temperature, T. The j subscripts index the technology.[6] As the figure demonstrates, the cost functions differ in their fixed costs, which determine where they intersect the y-axis, and their marginal cost functions or how costs rise with temperature.

The cost minimizing technology varies with expectations about temperature. For example, Technology 1 minimizes costs between T_1 and T_2 and the costs associated with Technologies 1 and 2 are identical at T_2 where the cost functions cross (i.e., point B), and Technology 2 is optimal at temperatures between T_2 and T_4. The outer envelope of least cost technology choices is depicted as the broken line and this is where households will choose to locate.[7] Notably, there aren't any theoretical restrictions on the outer envelope as it is determined by technologies so it could be convex, linear, or concave.

The available data sets provide information on annual energy consumption quantities but not on annual energy expenditures. This means that existing data sources can only identify the part of the cost function associated with the marginal costs of ambient temperatures or f(T). Further, it highlights that the estimation of the outer envelope with data on quantities can reveal the equilibrium relationship between energy consumption and temperature. However, it is not informative about how total energy related expenditures vary with temperature, precisely because the fixed costs associated different technologies are unobserved. One clear implication is that it is infeasible to determine the impact of climate change on total energy expenditures with cross-sectional data as is claimed by Mansur, Mendelsohn, and Morrison (2007).

We now discuss what can be learned from inter-annual variation in temperature and a panel data file on residential energy consumption quantities. Consider, an unexpected increase in temperatures from T_1 to T_3 for a single year, assuming that it is infeasible for households to switch technologies in response. The representative household's annual energy related expenditures would increase from A to C' and with fixed prices this is entirely captured by the increase in energy consumption quantities. If the change in

[6] For illustrative purposes, consider the technologies to be central air conditioning without the use of insulation in the construction of the house (Technology 1), central air conditioning with insulation (Technology 2), and zonal air conditioning with insulation (Technology 3).

[7] To keep this example simple, we assume that there isn't any variation in temperature across years (i.e., the expected standard deviation of temperature at a location is zero) and households base their technology choice on this information. In reality, technology choice depends on the full probability distribution function of ambient temperatures at a house's location.

temperature were permanent as would be the case with climate change, then the household would switch to Technology 2 and their annual energy related expenditures would increase from A to C (again this cannot be inferred from data on energy consumption quantities alone). Thus, the change in energy related costs in response to a single year's temperature realization overstates the increase in energy costs, relative to the change associated with a permanent temperature increase. It is noteworthy that the changes in costs associated with a new temperature $\geq T_1$ and $\leq T_2$ are equal regardless of whether it is transitory or permanent, because the outer envelope and Technology 1 cost curve are identical over this range.

To summarize, this section has derived an expression for WTP/WTA for climate change that can be estimated with available data sets. The first subsection pointed out that due to data limitations, we can only examine a subset of the outcomes likely to be affected by climate change, so this will cause the subsequent analysis to underestimate the health-related welfare costs. On the other hand, the second subsection highlighted that our empirical strategy of utilizing inter-annual variation in weather will overestimate the measurable health-related welfare costs, relative to the costs due to permanent changes in temperature (unless the degree of climate change is "small"). This is because the available set of adaptations in response to a year's weather realization is constrained.

III. Data Sources and Summary Statistics

To implement the analysis, we collected the most detailed and comprehensive data available on mortality, energy consumption, weather, and predicted climate change. This section describes these data and reports some summary statistics.

A. Data Sources

Mortality and Population Data. The mortality data is taken from the Compressed Mortality Files (CMF) compiled by the National Center for Health Statistics. The CMF contains the universe of the 72.3 million deaths in the US from 1968 to 2002. Importantly, the CMF reports death counts by race, sex, age group, county of residence, cause of death, and year of death. In addition, the CMF files also contain population totals for each cell, which we use to calculate all-cause and cause-specific mortality rates. Our

sample consists of all deaths occurring in the continental 48 states plus the District of Columbia.

Energy Data. The energy consumption data comes directly from the Energy Information Administration (EIA) State Energy Data System. These data provide state-level information about energy price, expenditures, and consumption from 1968 to 2002. The data is disaggregated by energy source and end use sector. All energy data is given in British Thermal Units, or BTU.

We used the database to create an annual state-level panel data file for total energy consumption by the residential sector, which is defined as "living quarters for private households." The database also reports on energy consumption by the commercial, industrial, and transportation sectors. These sectors are not a focus of the analysis, because they don't map well into the health production function model outlined in Section II. Further, factors besides temperature are likely to be the primary determinant of consumption in these sectors.

The measure of total residential energy consumption is comprised of two pieces: "primary" consumption, which is the actual energy consumed by households, and "electrical system energy losses." The latter accounts for about 2/3 of total residential energy consumption; it is largely due to losses in the conversion of heat energy into mechanical energy to turn electric generators, but transmission and distribution and the operation of plants also account for part of the loss. In the 1968-2002 period, total residential energy consumption increased from 7.3 quadrillion (quads) British thermal units to 21.2 quads, and the mean over the entire period was 16.6 quads.

Weather Data. The weather data are drawn from the National Climatic Data Center (NCDC) Summary of the Day Data (File TD-3200). The key variables for our analysis are the daily maximum and minimum temperature as well as the total daily precipitation.[8] To ensure the accuracy of the weather readings, we developed a weather station selection rule. Specifically, we dropped all weather stations at elevations above 7,000 feet since they were unlikely to reflect the weather experienced by the majority of the population within a county. Among the remaining stations, we considered a year's readings valid if

[8] Other aspects of daily weather such as humidity and wind speed could influence mortality, both individually and in conjunction with temperature. Importantly for our purposes, there is little evidence that wind chill factors (a non-linear combination of temperature and wind speed) perform better than simple temperature levels in explaining daily mortality rates (Kunst et al. 1994).

the station operated at least 363 days. The average annual number of stations with valid data in this period was 3,879 and a total of 7,380 stations \met our sample selection rule for at least one year during the 1968-2002 period. The acceptable station-level data is then aggregated at the county level by taking the simple average of the measurements from all stations within a county. The county by years with acceptable weather data accounted for 53.4 of the 72.3 million deaths in the US from 1968 to 2002.

Climate Change Prediction Data. Climate predictions are based on two state of the art global climate models. The first is the Hadley Centre's 3rd Coupled Ocean-Atmosphere General Circulation Model, which we refer to as Hadley 3 (T. C. Johns et al. 1997, Pope et al. 2000). This is the most complex and recent model in use by the Hadley Centre. It is a coupled atmospheric-ocean general circulation model, so it considers the interplay of several earth systems and is therefore considered the most appropriate for climate predictions. We also use predictions from the National Center for Atmospheric Research's Community Climate System Model (CCSM) 3, which is another coupled atmospheric-ocean general circulation model (NCAR 2007). The results from both models were used in the 4th IPCC report (IPCC 2007).

Predictions of climate change from both of these models are available for several emission scenarios, corresponding to 'storylines' describing the way the world (population, economies, etc.) may develop over the next 100 years. We focus on two "business-as-usual" scenarios, which are the proper scenarios to consider when judging policies to restrict greenhouse gas emissions.

We emphasize the results based on predictions from the application of the A1F1 scenario to the Hadley 3 model. This scenario assumes rapid economic growth (including convergence between rich and poor countries) and a continued heavy reliance on fossil fuels. Given the abundant supply of inexpensive coal and other fossil fuels, a switch to alternative sources is unlikely without greenhouse gas taxes or the equivalent, so this is a reasonable benchmark scenario. This scenario assumes the highest rate of greenhouse gas emissions, and we emphasize it to explore a worst case outcome.

We also present results from the application of the A2 scenario to the CCSM 3. This scenario assumes slower per capita income growth but larger population growth. Here, there is less trade among nations and the fuel mix is determined primarily by local resource availability. This scenario is

characterized as emphasizing regionalism over globalization and economic development over environmentalism. It is "middle of the road" in terms of greenhouse gas emissions, but it would still be considered business as usual, because it doesn't appear to reflect policies to restrict emissions.[9]

We use the results of the application of A1F1 scenario to the Hadley 3 model and the A2 scenario to the CCSM 3 model to obtain daily temperature predictions for the period 2070-2099 at grid points throughout the US. Each set of predictions is based on a single run of the relevant model. The Hadley 3 predictions are available for grid points spaced at 2.5° (latitude) x 3.75° (longitude), and we use the 89 (of the 153) grid points located on land to develop the regional estimates. Six states do not have a grid point, so we developed daily Census division-level predictions for the 9 US Census divisions.

The CCSM 3 predictions are available at a finer level with separate predictions available for grid points spaced at roughly 1.4° (latitude) x 1.4° (longitude). There are a total of 416 grid points on land in the US, and we use them to develop state-specific estimates of climate change for the years 2070-2099. The daily mean temperature was available for these predictions, whereas the minimum and maximum are available for the Hadley 3 predictions. The Data Appendix provides more details on the climate change predictions.

B. Summary Statistics

Mortality Statistics. Table 1 reports the average annual mortality rates per 100,000 by age group and gender using the 1968-2002 CMF data. It is reported separately for all causes of death and for deaths due to cardiovascular disease, neoplasms (i.e., cancers), respiratory disease, and motor-vehicle accidents (since it is the leading cause of death for individuals aged 15-24).[10] These four categories account for roughly 72% of all fatalities, though the relative importance of each cause varies by sex and age.

The all cause and all age mortality rates for women and men are 804.4 and 939.2 per 100,000, respectively, but there is tremendous heterogeneity in mortality rates across age and gender groups. For

[9] We planned to have A1F1 and A2 predictions for both Hadley 3 and NCAR CCSM 3, but we were unable to obtain A1F1 predictions for NCAR CCSM 3 and A2 predictions for Hadley 3.

[10] In terms of ICD-9 Codes, the causes of deaths are defined as follows: Neoplasms = 140-239, Cardiovascular Diseases = 390-459, Respiratory Diseases = 460-519, and Motor Vehicle Accidents = E810-E819.

all-cause mortality, the female and male infant mortality rates are 1,031.1 and 1,292.1. After the first year of life, mortality rates don't approach this level again until the 55-64 category. The annual mortality rate starts to increase dramatically at older ages, and in the 75-99 age category it is 8.0% for women and 9.4% for men. The higher annual fatality rates for men at all ages are striking and explain their shorter life expectancy.

As is well-known, mortality due to cardiovascular disease is the single most important cause of death in the population as a whole. The entries indicate that cardiovascular disease is responsible for 48.4% and 43.6% of overall female and male mortality. It is noteworthy that the importance of the different causes of death varies dramatically across age categories. For example, motor vehicle accidents account for 22.1% (23.8%) of all mortality for women (men) in the 15-24 age group. In contrast, cardiovascular disease accounts for 59.6% (53.7%) of all mortality for women (men) in the 75-99 category, while motor vehicle accidents are a negligible fraction. More generally, for the population aged 55 and above---where mortality rates are highest---cardiovascular disease and neoplasms are the two primary causes of mortality.

Weather and Climate Change Statistics. We take advantage of the richness of daily weather data and climate change predictions data by using the information on daily minimum and maximum temperatures. Specifically, we calculate the daily mean temperatures at each weather station as the average of each day's minimum and maximum temperature. The county-wide mean is then calculated as the unweighted average across all stations within a county. The climate change predictions are calculated analogously, except that we take the average of the daily predicted mean temperature across the grid points within the Census Division (Hadley 3) and state (CCSM 3).

Table 2 reports on national and regional measures of observed temperatures from 1968-2002 and predicted temperatures from 2070-2099. For the observed temperatures, this is calculated across all county by year observations with nonmissing weather data, where the weight is the population between ages 0 and 99. The predicted temperatures under climate change are calculated across the 2070-2099, where the weight is the population of individuals 0 to 99 residing in counties with nonmissing weather data in the relevant geographic unit summed over the years 1968-2002. It is important to emphasize that

these calculations of actual and predicted temperatures depend on the distribution of the population across the US, so systematic migration (e.g., from South to North) would change these numbers even without any change in the underlying climate.

The "Actual" column of Table 2 reports that the average daily mean is 56.6° F.[11] The entries for the four Census regions confirm that the South is the hottest part of the country and the Midwest and Northeast are the coldest ones.[12] Since people are more familiar with daily highs and lows from newscasts, the table also documents the average daily maximum and minimums.[13] The average daily spread in temperatures is 21.2° F, indicating that highs and lows can differ substantially from the mean.

Figure 2 depicts the variation in the measures of temperature across 20 temperature bins in the 1968-2002 period. The leftmost bin measures the number of days with a mean temperature less than 0° F and the rightmost bin is the number of days where the mean exceeds 90° F. The intervening 18 bins are all 5° F wide. These 20 bins are used throughout the remainder of the paper, as they form the basis for our semi-parametric modeling of temperature in equations for mortality rates and energy consumption. This binning of the data preserves the daily variation in temperatures. The preservation of this variation is an improvement over the previous research on the mortality impacts of climate change that obscures much of the variation in temperature.[14] This is important because there are substantial nonlinearities in the daily temperature-mortality and daily temperature–energy demand relationships.

The figure depicts the mean number of days that the typical person experiences in each bin; this is calculated as the weighted average across county by year realizations, where the county by year's population is the weight. The average number of days in the modal bin of 70° - 75° F is 38.2. The mean

[11] The average daily mean and all other entries in the table (as well as in the remainder of the paper) are calculated across counties that meet the weather station sample selection rule described above.

[12] The states in each of the Census regions are: Northeast-- Connecticut, Maine, Massachusetts, New Hampshire, Vermont, Rhode Island, New Jersey, New York, and Pennsylvania; Midwest-- Illinois, Indiana, Michigan, Ohio, Wisconsin, Iowa, Kansas, Minnesota, Missouri, Nebraska, North Dakota, and South Dakota; South-- Delaware, District of Columbia, Florida, Georgia, Maryland, North Carolina, South Carolina, Virginia, West Virginia, Alabama, Kentucky, Mississippi, Tennessee, Arkansas, Louisiana, Oklahoma, and Texas; and West-- Arizona, Colorado, Idaho, Montana, Nevada, New Mexico, Utah, Wyoming, Alaska, California, Hawaii, Oregon, and Washington.

[13] For counties with multiple weather stations, the daily maximum and minimum are calculated as the average across the maximums and minimums, respectively, from each station.

[14] For example, Martens (1998) and Tol (2002a) use the maximum and the minimum of monthly mean temperatures over the course of the year.

number of days at the endpoints is 0.8 for the less than 0° F bin and 1.6 for the greater than 90° F bin.

The remaining columns of Table 2 report on the predicted changes in temperature from the two sets of climate change predictions for the 2070-2099 period.[15] The CCSM 3 model and A2 scenario predict a change in mean temperature of 5.6° F or 4.1° Celsius (C). Interestingly, there is substantial heterogeneity, with mean temperatures expected to increase by 9.8° F in the Midwest and by 3.0° F in the West. The A1F1 scenario predicts a gain in mean temperature of 6.0 ° F or 4.3° C. The increases in the Midwest and South exceed 9° F, while there is virtually no predicted change in the West.[16]

Figure 3 provides an opportunity to understand how the full distributions of mean temperatures are expected to change. One's eye is naturally drawn to the last two bins. The Hadley 3 A1F1 (CCSM 3 A2) predictions indicate that typical person will experience 18.9 (12.4) additional days per year where the mean daily temperature is between 85° F and 90° F. Even more amazing, the mean daily temperature is predicted to exceed 90° F 43.8 (20.7) extra days per year.[17] To put this in perspective, the average person currently experiences just 1.6 days per year where the mean exceeds 90° F and 7.1 in the 85° - 90° F bin.

An examination of the rest of the figure highlights that the increase in these very hot days is not being drawn from the entire year. For example, the number of days where the maximum is expected to be between 50° F and 80° F declines by 62.6 (30.4) days under Hadley 3 A1F1 (CCSM A2). Further, the mean number of days where the minimum temperature will be below 30° F is predicted to fall by just 3.8 (10.4) days. Thus, these predictions indicate that the reduction in extreme cold days is much smaller than the increase in extreme hot days. As will become evident, this will have a profound effect on the estimated impacts of climate change on mortality and energy consumption.

Returning to Table 2, the bottom panel reports on temperatures for days when the mean exceeds 90° F, which, as was evident in Figure 3, is an especially important bin. The paper's econometric model

[15] For comparability, we follow much of the previous literature on climate change and focus on the temperatures predicted to prevail at the end of the century.

[16] The fourth and most recent IPCC report summarizes the current state of climate change predictions. This report says that the a doubling of carbon dioxide concentrations is "likely" (defined as P > 66%) to lead to an increase of average surface temperatures in the range of 2° to 4.5° C with a best estimate of 3° C (IPCC 4 2007). Thus, the predictions in Table 2 are at the high end of the likely temperature range associated with a doubling of carbon dioxide concentrations.

[17] At the risk of insulting the reader, we emphasize that a mean daily temperature of 90° F is very hot. For example, a day with a high of 100° F would need a minimum temperature greater than 80° F to qualify.

assumes that the impact of all days in this bin on mortality and energy consumption are constant. This assumption may be unattractive if climate change causes a large increase in temperature among days in this bin. On the whole, the increase in mean temperatures among days in this bin is relatively modest, with predicted increases of 2.4° F (CCSM 3 A2) and 4.3° F (Hadley 3 A1FI). Consequently, we conclude that historical temperatures can be informative about the impacts of the additional days predicted to occur in the > 90° F bin.

IV. Econometric Strategy

This section describes the econometric models that we employ to learn about the impact of temperature on mortality rates and residential energy consumption.

A. Mortality Rates.

We fit the following equations for county-level mortality rates of various demographic groups:

$$(5)\ Y_{ctd} = \sum_j \theta_{dj}^{TMEAN} TMEAN_{ctj} + \sum_l \delta_{dl}^{PREC} PREC_{ctl} + X_{ct}\beta_d + \alpha_{cd} + \gamma_{std} + \varepsilon_{ctd}.$$

Y_{ctd} is the mortality rate for demographic group d in county c in year t. In the subsequent analysis, we use 16 separate demographic groups, which are defined by the interaction of 8 age categories (0-1, 1-14, 15-24, 25-44, 45-54, 55-64, 65-74, and 75+) and gender. X_{ct} is a vector of observable time varying determinants of fatalities measured at the county level. The last term in equation (5) is the stochastic error term, ε_{ctd} .

The variables of interest are the measures of temperature and precipitation, and we have tried to model these variables with as few parametric assumptions as possible while still being able to make precise inferences. Specifically, they are constructed to capture the full distribution of annual fluctuations in weather. The variables $TMEAN_{ctj}$ denote the number of days in county c and year t where the daily mean temperature is in one of the 20 bins used in Figures 1 and 2. Thus, the only functional form restriction is that the impact of the daily mean temperature is constant within 5F degree intervals.[18] This

[18] Schlenker and Roberts (2006) also consider a model that emphasizes the importance of nonlinearities in the relationship between crop yields and temperature.

degree of flexibility and freedom from parametric assumptions is only feasible because we are using 35 years of data from the entire US. Since extreme high and low temperatures drive most of the health impacts of temperature, we tried to balance the dual and conflicting goals of allowing the impact of temperature to vary at the extremes and estimating the impacts precisely enough so that they have empirical content. The variables $PREC_{ctl}$ are simple indicator variables denoting annual precipitation equal to "l" in county c in year. These intervals correspond to 2 inch bins.

The equation includes a full set of county by demographic group fixed effects, α_{cd}. The appeal of including the county fixed effects is that they absorb all unobserved county-specific time invariant determinants of the mortality rate for each demographic group. So, for example, differences in permanent hospital quality or the overall healthiness of the local age-specific population will not confound the weather variables. The equation also includes state by year indicators, γ_{std}, that are allowed to vary across the demographic groups. These fixed effects control for time-varying differences in the dependent variable that are common within a demographic group in a state (e.g., changes in state Medicare policies).

The validity of any estimate of the impact of climate change based on equation (5) rests crucially on the assumption that its estimation will produce unbiased estimates of the θ_{dj}^{TMEAN} and δ_{dl}^{PREC} vectors. The consistency of the components of each θ_{dj} requires that after adjustment for the other covariates the unobserved determinants of mortality do not covary with the weather variables. In the case of the mean temperatures, this can be expressed formally as $E[TMEAN_{ctj}\ \varepsilon_{ctd} \mid X_{ct}, \alpha_{cd}, \gamma_{std}] = 0$. By conditioning on the county and state by year fixed effects, the θ_{dj}'s are identified from county-specific deviations in weather about the county averages after controlling for shocks common to all counties in a state. Due to the unpredictability of weather fluctuations, it seems reasonable to presume that this variation is orthogonal to unobserved determinants of mortality rates. The point is that there is reason to believe that the identification assumption is valid.

A primary motivation for this paper's approach is that it may offer an opportunity to identify weather-induced changes in the fatality rate that represent the full impact on the underlying population's life expectancy. Our review of the literature suggests that the full effect of particularly hot and cold days is evident within approximately 30 days (Huynen et al. 2001; Deschênes and Moretti 2007).

Consequently, the results from the estimation of equation (5) that use the distribution of the year's daily temperatures should largely be free of concerns about forward displacement and delayed impacts. This is because a given day's temperature is allowed to impact fatalities for a minimum of 30 days for fatalities that occur from February through December. An appealing feature of this set-up is that the θ_{dj}^{TMEAN} coefficients can be interpreted as reflecting the full long-run impact of a day with a mean temperature in that range.

The obvious limitation is that the weather in the prior December (and perhaps earlier parts of the year if the time frame for harvesting and delayed impacts is longer than 30 days) may affect current year's mortality. To assess the importance of this possibility, we also estimate models that include a full set of temperature variables for the current year (as in equation (5)) and the prior year. As we demonstrate below, our approach appears to purge the estimates of fatalities of people with relatively short life expectancies.[19]

There are two further issues about equation (5) that bear noting. First, it is likely that the error terms are correlated within county by demographic groups over time. Consequently, the paper reports standard errors that allow for heteroskedasticiy of an unspecified form and that are clustered at the county by demographic group level.

Second, it may be appropriate to weight equation (5). Since the dependent variable is demographic group-specific mortality rates, we think there are two complementary reasons to weight by the square root of demographic group's population (i.e., the denominator). First, the estimates of mortality rates with large populations will be more precise than the estimates from counties with small populations, and this weight corrects for the heteroskedasticity associated with the differences in precision. Second, the results can then be interpreted as revealing the impact on the average person, rather than on the average county.

[19] A daily version of equation (5) is very demanding of the data. In particular, there is a tension between our flexibility in modeling temperature and the number of previous days of temperature to include in the model. Equation (5) models temperature with 20 variables, so a model that includes 30 previous days would use 600 variables for temperature, while one with 365 days would require 7300 temperature variables. Further, daily mortality data for the entire US is only available from 1972-1988, and there may be insufficient variation in temperature within this relatively short period of time to precisely identify some of the very high and very low temperature categories.

Residential Energy Consumption. We fit the following equation for state-level residential energy consumption:

$$(6)\ \ln(C_{st}) = \sum_j \theta_j^{TMEAN} TMEAN_j + \sum_l \delta_l^{PREC} PREC_l + X_{st}\beta + \alpha_s + \gamma_{dt} + \varepsilon_{st}.$$

C_{st} is residential energy consumption in state s in year t and d indexes Census Division. The modeling of temperature and precipitation is identical to the approach in equation (5). The only difference is that these variables are measured at the state by year level—they are calculated as the weighted average of the county-level versions of the variables, where the weight is the county's population in the relevant year. The equation also includes state fixed effects (α_s) and census division by year fixed effects (γ_{dt}) and a stochastic error term, ε_{st}.

A challenge for the successful estimation of this equation is that there has been a dramatic shift in the population from the North to the South over the last 35 years. If the population shifts were equal within Census divisions, this wouldn't pose a problem for estimation but this hasn't been the case. For example, Arizona's population has increased by 223% between 1968 and 2002 compared to just 124% for the other states in its Census Division, and due to its high temperatures it plays a disproportionate role in the identification of the θ_j 's associated with the highest temperature bins.[20] The point is that unless we correctly adjust for these population shifts, the estimated θ_j 's may confound the impact of higher temperatures with the population shifts.

As a potential solution to this issue, the vector X_{st} includes the ln of population and gross domestic product by state as covariates. The latter is included since energy consumption is also a function of income. Adjustment for these covariates is important to avoid confounding associated with the population shifts out of the Rust Belt and to warmer states.

Finally, we will also report the results from versions of equation (6) that model temperature with heating and cooling degree days. We follow the consensus approach and use a base of 65° F to calculate

[20] For example, we estimated state by year regressions for the number of days where the mean temperature was in the > 90° F bin that adjusted for state fixed effects and census division by year fixed effects. The mean of the annual sum of the absolute value of the residuals for Arizona is 3.6 but only 0.6 in the other states in its Census Division. The other states in Arizona's Census Division are Colorado, Idaho, New Mexico, Montana, Utah, Nevada, and Wyoming.

both variables.[21] Specifically, on a given day, the number of cooling degree days equals the day's mean temperature (i.e., the average of the minimum and maximum) minus 65° F for days where the mean is above 65° F and zero for days when the mean is below 65° F. Analogously, a day's heating degree days is equal to 65° F minus its mean for days where the mean is below 65° F and zero otherwise. So, a day with a mean temperature of 72° F would contribute 7 cooling degree days and 0 heating degree days, while a day with a mean of 51° F would contribute 0 cooling degree days and 14 heating degree days.

To implement this alternative method for modeling a year's temperature, we sum the number of heating and cooling degree days separately over the year. We then include the number of heating and cooling degree days and their squares in equation (6) instead of the $TMEAN_{ctj}$ variables.

V. Results

This section is divided into three subsections. The first explores the extent of variation in the temperature variables in the context of the rich statistical models that we employ. The second provides estimates of the impact of predicted climate change on the mortality rates of specific demographic groups and the general population. The third examines the impact of predicted climate change on residential energy consumption.

A. How Much Variation is there in Temperature?

As we discussed above, our preferred specifications model temperature with 20 separate variables. For this method to be successful, it is important that there is substantial inter-annual variation in county temperature after adjustment for these county and state by year fixed effects in the mortality equations. If this is the case, the predicted health impacts of climate change will be identified from the data rather than by extrapolation due to functional form assumptions.

[21] Electrical, natural gas, power, heating, and air conditioning industries utilize heating and cooling degree calculations to predict demand (http://www.fedstats.gov/qf/meta/long_242362.htm). Further, the National Oceanic and Atmospheric Administration recommends using a base of 65° F for both heating and cooling degree days (http://www.cpc.ncep.noaa.gov/products/analysis_monitoring/cdus/degree_days/ddayexp.shtml). Further, an examination of the figures in Engle et al.'s seminal paper on relationship between temperature and electricity sales suggests that 65° F is a reasonable base for both cooling and heating degree days (Engle et al. 1986).

Figure 4 depicts the extent of inter-annual variation in temperature. For each daily mean temperature bin, we create a data file where the observations are from all county by year observations with valid weather data between 1968 and 2002. We then regress the annual realization of the number of days that the relevant county had a daily mean in the temperature bin against state-by-year and county fixed effects. For each county by year, we sum the absolute value of the residuals. The figure reports the mean of this number across all county by year observations. The resulting figures can be interpreted as the average number of days in a county by year that are available to identify the parameter associated with that temperature bin after adjustment for the fixed effects.

An inspection of the figure demonstrates that there is substantial variation in temperatures, so it should be possible to obtain relatively precise estimates of the impacts of most of the temperature bins. Notably, due to the large data file, there are still many days available to estimate the impact of even the extreme bins. For example, the mean of the absolute value of the residuals for the bin for the > 90° F bin is 0.7 days. Although this may seem small, the size of our data file helps greatly. Since there are 57,531 county by year observations (and thus a total of 20,998,815 county by days observations), this means that there are roughly 40,272 county by days to help identify the impact of a day in this bin. The analogous figure for the 85° - 90° F bin is 149,005 days.

B. Estimates of the Impact of Climate Change on Mortality

All Cause Mortality Results. Figure 5 provides an opportunity to better understand the paper's approach. It plots the estimated θ_j's from the estimation of equation (5) for male infants. In this version of the equation, we dropped the $TMEAN_j$ variable associated with the 65° - 70° F bin so each θ_j reports the estimated impact of an additional day in bin j on the infant mortality rate (i.e., deaths per 100,000) relative to the mortality rate associated with a day where the temperature is between 65° - 70° F. The figure also plots the estimated θ_j's plus and minus one standard error of the estimates so that the precision of each of these estimates is evident.

The most striking feature of this graph is that the response function is generally flat, meaning that temperature has little influence on male infant mortality rates except at the hottest and coldest

temperatures. Recall, the climate change models predict that the changes in the distribution of temperature will be concentrated among days where the mean temperatures exceeds 50° F, so the estimated θ_j's in this range are most relevant for this paper's exercise. If the estimates are taken literally, it is evident that the predicted shift of days into the last bin will lead to an increase in infant mortality. For example, the results suggest that the shift of a day from the 70° - 75° F bin (estimated θ = -0.78) to the > 90° F bin (estimated θ = 0.92) would lead to 1.7 more infant deaths per 100,000 births.

It is also important to highlight that the estimated θ_j's have associated sampling errors. Among the most relevant θ_j's, the largest standard error is in the highest bin due to the relatively small number of days with a mean temperature exceeding 90° F. The imprecision of the estimated impact of this bin poses a challenge for making precise inferences about the impact of the predicted changes in temperature on mortality rates. The estimated θ_j's at the lowest temperatures are even more imprecise, but they play little role in this exercise due to the distribution of the predicted changes in temperature.

We now turn to Table 3, which summarizes the results from the estimation of separate versions of equation (5) for the 16 gender by age groups using the Hadley 3 A1F1 scenario. These versions include all twenty TMEAN_j variables. Estimates for females and males are reported in the left and right panels, respectively. Columns (1a) and (2a) report the predicted change in annual mortality for each demographic group and its estimated standard error. For a given county and demographic groups, these impacts are calculated as follow:

$$(7)\ \ M_{cd} = POP_{cd} \times \sum_j \hat{\theta}_{dj}^{TMEAN} \Delta TMEAN_{cj}$$

That is, we multiply the predicted change in the number of days in each temperature cell from the Hadley 3 A1F1 predictions ($\Delta TMEAN_{cj}$) by the corresponding demographic-group specific impact on mortality ($\hat{\theta}_{dj}^{TMEAN}$) and then sum these products. This sum is then multiplied by the average population for that demographic in that county (POP_{cd}) over the sample period. Finally, the impacts for a given demographic group are summed over all counties. This sum is the national demographic group-specific estimate of the change in annual mortality. It is straightforward to calculate the standard error, since the estimated mortality change is a linear function of the estimated parameters.

Columns (1b) and (2b) report the estimated percentage change in the annual mortality rate and its standard error. The percentage change is calculated as the ratio of the change in the demographic group's mortality rate due to predicted climate change to the group's overall mortality rate. Columns (1c) and (2c) report the change in life years due to predicted climate change for each age category. This entry is the product of the predicted increase in annual fatalities and the residual life estimate for each age group (evaluated in the middle of the age range) and sex, taken from the 1980 Vital Statistics.[22] Negative values correspond to losses of life-years, while positive entries correspond to gains in life-years. We note that this calculation may overstate the change in life years, because affected individuals are likely to have shorter life expectancies than the average person. Nevertheless, these entries provide a way to capture that fatalities at young ages may have greater losses of life expectancy than those at older ages.

The entries in columns (1d) and (2d) report p-values from F-tests of the hypothesis that the twenty estimated θ_j's are equal. This test is not directly informative about the mortality impacts of predicted climate change, but it provides a summary of the impact of temperature on mortality in the US. A failure to reject the null is consistent with the view that in the US individuals are able to easily adapt to changes in temperature that pose potential risks to mortality.

We begin by returning to infant mortality, which is reported in the first row. These entries indicate that predicted climate change will increase the number of female and male infant deaths by roughly 1,000 and 1,800 per year, respectively. The female estimate borders on statistical significance at conventional levels, while the male estimate is substantially more precise. These estimates are equivalent to increases of 5.5% (female) and 7.8% (male) in the infant mortality rates. The life-years calculation suggests that these extra fatalities would lead to a loss of about 200,000 life years of life expectancy every year. This finding of higher temperatures leading to increased rates of infant mortality is consistent with the medical evidence that infants' thermoregulatory systems are not fully developed (Knobel and Holditch-Davis 2007).

In the remainder of the table, there is mixed evidence of mortality impacts from the Hadley 3

[22] Starting with infants and progressing towards the oldest age category, the residual life estimates for females are 78.1, 72.1, 59.4, 45.8, 30.9, 22.4, 14.8, and 6.3. The corresponding estimates for males are 70.7, 64.8, 52.4, 39.5, 25.2, 17.5, 11.3, and 5.0.

A1FI scenario for the other demographic groups. The most substantial impacts are concentrated among 75-99 females. The entries suggest that there would be an additional 11,500 fatalities per year in this demographic group and that their annual mortality rate would increase by roughly 2.0%. Due to their age, the total loss of life years is comparable to the loss for infants even though the increase in fatalities is 11 times larger. There is also evidence of increased mortality rates for 1-14 year olds and for men in the 45-54 and 55-64 age categories.

The evidence in favor of an increase in the mortality rate is weak for many of the demographic groups, however. For example, the null of a zero increase in fatalities cannot be rejected at even the 10% level for 9 of the 16 demographic groups. Similarly, the null that twenty estimated θ_j 's are equal cannot be rejected at the 10% level in 9 of the 16 cases. Overall, these differences in the results across demographic groups underscore the value of estimating separate models for each group.

The bottom row of Table 3 reports the aggregate impacts, which are the sum of the impacts for each demographic group, from the Hadley 3 A1FI scenario. For both females and males, annual mortality is predicted to increase by approximately 17,500 deaths per year. This excess mortality corresponds to increases in the annual mortality rate of 1.8% for women and 1.6% for men.[23] It is important to note, however, that these aggregate impacts are statistically indistinguishable from zero for both genders.[24] The 95% confidence intervals for the estimated impact on the overall female and male mortality rates are [4.3%, -0.7%] and [4.7%, -1.5%], respectively.

To understand the source of these aggregate estimates, it is instructive to examine the regression coefficients (i.e., $\hat{\theta}_{dj}^{TMEAN}$) that drive the overall estimates. Figures 6A and 6B plot the weighted sums of these parameters across age groups for female and males, respectively, where the weights are the population shares in each age category.

[23] We examined the variability in the estimated impact on mortality rates when predictions for individual years from the 2070-2099 period are used, rather than the average over the entire period. The smallest annual impact implies increases in the annual mortality rates (standard error) of 1.0% (0.9%) and 0.9% (2.0%) for women and men, respectively. The largest annual impacts are 2.9% (1.6%) and 2.7% (2.2%) for men and women.

[24] We also investigated the impacts of predicted climate change on deaths due to cardiovascular diseases, neoplasms, respiratory diseases, and motor-vehicle accidents. This exercise is very demanding of the data and generally led to imprecise estimates. Nevertheless, a few findings of note emerged. Specifically, the largest increases in mortality occur among cardiovascular and respiratory diseases. Further, there is a substantial decline in motor vehicle fatalities among 15-24 year olds (especially males), which is likely related to a reduction in dangerous driving days.

Each data point represents the impact on the annual mortality rate (per 100,000) of an additional day in the relevant temperature bin, relative to the 65° - 70° F bin. The figure also plots the estimated θ_j's plus and minus one standard error of the estimates. The y-axes are scaled identically so that the response functions can be compared easily.

Both figures suggest that mortality risk is highest at the colder and hotter temperatures, so the response functions have U-shapes, loosely defined. It is evident that trading days in the 50° - 80° F range for hotter days as is predicted in the Hadley 3 A1F1 scenario will lead to mortality increases. Further, the mortality rate is higher below 50° F than in the 50° - 80° F range. It is also apparent that the colder days (e.g., < 50° F) are generally more harmful than the hotter days (e.g., > 80° F). These figures demonstrate that an alternative climate change scenario where the warming was concentrated in the coldest months and regions would lead to a substantial reduction in mortality.

The approach of modeling temperature with 20 separate variables and allowing their impact to vary by demographic group allows for important nonlinearities and heterogeneity across demographic groups and nonlinearities), but the cost is that this is demanding of the data. We assessed whether making some restrictions would help to allow for more precise inferences and generally concluded that the answer is no. For example, we estimated models that restricted the θj's to be the same for males and females of the same age group. In addition, we also estimated models for age-adjusted mortality rates that pool together all age groups. None of these alternative specifications helped to reduce the standard errors substantially.

Robustness Analysis. Table 4 reports on the estimated impacts on female and male fatality rates from a series of alternative models and approaches. Columns (1a) and (1b) of the first row ("Baseline Estimates") repeats the overall estimate from Table 3 and is intended as a basis for comparisons.

The validity of the paper's estimates of the impact of climate change depends on the validity of the climate change predictions. The state of climate modeling has advanced dramatically over the last several years, but there is still much to learn, especially about the role of greenhouse gases on climate (Karl and Trenberth 2003). Thus, the Hadley 3 A1F1 predictions should be conceived of as a single realization from a superpopulation of models and modeling choices. Put another way, in addition to the

sampling errors associated with the statistical models, the "true" standard error should reflect the uncertainty associated with climate modelers' decisions. It isn't feasible to directly incorporate this source of uncertainty into our estimates.

To shed light on how modeling choices can affect the range of estimates, this table supplements the Hadley 3 A1F1 results with ones that utilize the CCSM 3 A2 predictions in columns (2a) and (2b). Recall, these predictions are for a similar increase in mean temperatures but one that is more evenly spread throughout the temperature distribution.[25] The predicted increases in the annual mortality rate of 0.5% (females) and 0.4(males) have associate t-statistics less than 0.7 and are substantially smaller than the predictions from the Hadley 3 A1F1 scenario. The 95% confidence intervals for the estimated impact on the overall female and male mortality rates are [2.1%, -1.1%] and [1.8%, -1.0%]. Further, infants are the only demographic group predicted to have a statistically significant increase.[26] [27]

Panel B reports on several changes in the basic specification in equation (5). In row 1, the state by year fixed effects are replaced by year fixed effects. In rows 2 and 3, the specifications include 40 separate temperature variables: 1 uses two separate sets of the same 20 temperature bins for the daily maximum and minimum temperatures, respectively, while 2 uses separate sets of the 20 temperature bins for the current year's daily mean temperature and the previous year's daily mean temperature to allow for the possibility that equation (5) inadequately accounts for the dynamics of the mortality-temperature relationship. There is some evidence that individuals acclimate to higher temperatures over time, so consecutive days with high temperatures (i.e., heatwaves) may have a different impact on annual mortality than an equal number of hot days that don't occur consecutively.[28] The specification in row 4 of this panel adds a variable for the number of instances of 5 consecutive days of mean daily temperature

[25] Our intention was to provide estimates from a wider range of models. However, once we focused on daily predictions, we found that the Hadley 3 A1FI and NCAR CCSM 2 A2 predictions are the only "business as usual" ones available through the internet or from requests to climate researchers.

[26] The predicted increases (standard errors) in the mortality rates for female and male infants are 4.1 (1.7) and 4.0 (1.6), respectively.

[27] We also experimented with a completely arbitrary climate change scenario of an increase of 5° F every day. In light of the response functions in Figures 6A and 6B, it isn't surprising that this scenario predicts declines in annual mortality rates (standard error) of -0.6% (0.8%) and -0.7% (1.2%) for females and males.

[28] For example Hajat et al. (2002) find that heat waves later in the summer have a smaller impact on mortality and morbidity than earlier heat waves. Further, according to medical convention, exercising adults acclimate to heat within 3-12 days (Armstrong 1986).

above 90° F and its associated parameter is used in the calculations for the mortality impacts of climate change.[29]

None of these alterations to the basic specification has a meaningful impact on the qualitative findings. Some of them modestly increase the point estimates, while others decrease them. Overall, they suggest a small and statistically insignificant increase in the annual mortality rate. Further, the generally poorer precision of the estimates underscores that these specifications are very demanding of the data.

Climate change may affect relative prices and individuals' choices in ways that will change the response functions. As an alternative to a full-blown general equilibrium model that necessarily involves numerous unverifiable assumptions, Panel C uses the available data to see if such changes are likely to alter the paper's findings. Specifically, row 1 estimates the response function using data after 1980 only. The intuition is that in these years medical technologies are more advanced, air conditioning is more pervasive, and the oil shocks have raised the relative price of energy as climate change might. In row 2, the response function is estimated with data from the half of counties where the average number of days per year with a mean temperature above 80° F exceeds the national median (14 days). The idea is that individuals are likely to have undertaken a series of adaptations to protect themselves against high temperatures in these counties and these adaptations may resemble what climate change will cause individuals throughout the US to do. In this respect, the resulting response functions may better approximate the long-run impacts of climate change on mortality. The entries in both rows reflect the application of the relevant response function to our full sample.

In the context of the sampling errors, neither approach alters the predicted impact on mortality rates, so the qualitative findings are largely unchanged. We expected the point estimates based on the response function from the hotter half of the country to decline; the results may indicate that individuals throughout the country have implemented the full set of adaptations available for reducing mortality. An alternative possibility, which would undermine the meaning of this test, is that these counties are also

[29] We also estimated the mortality impacts of climate change using the Hadley 3 A1FI and CCSM 3 A2 predictions on temperature and precipitation. These estimated impacts are virtually identical to the baseline estimates, highlighting that the predicted increase in precipitation is unlikely to have an important independent influence on mortality rates.

poorer and that this test confounds the impacts of adaptation and income.

A natural approach to assess this possibility is to restrict the analysis sample to counties from the lower parts of the per-capita income distribution. In particular, we consider estimating the impacts using only counties where per capita income is less than the national median. Unfortunately, this analysis revealed little meaningful information. In particular, the standard errors from the estimates based on the poorest half of the counties in our sample were 7-10 times larger than the standard errors from the baseline model. This lack of statistical precision is attributable to the fact that poorer counties have lower population on average and that consequently the regression estimates were very poorly determined.

In summary, the results in Tables 3 and 4 suggest that climate change will increase the annual mortality rate by roughly 1.7% with the Hadley 3 A1FI predictions and 0.5% with the CCSM A2 predictions. However, these overall impacts are statistically indistinguishable from zero.

The Importance of Accounting for the Dynamic Relationship Between Temperature and Mortality. Figure 7 provides an opportunity to assess the paper's success at modeling the unknown dynamic relationship between temperature and mortality to address the issues of harvesting/forward displacement and delayed impacts. The figure replicates the daily analysis of Deschênes and Moretti (2007) and was constructed with the Multiple Cause of Death Files (MCOD) for the 1972-1988 period. The key difference with the CMF is that the MCOD files contain the exact date of death between 1972 and 1988.

We use these MCOD data to estimate daily and annual versions of equation (5). In the daily regressions, the unit of observation is a county by day and the dependent variable is the county-level mortality rate for an age group. This equation includes county fixed effects, state by year fixed effects, state by month fixed effects, and the 20 temperature variables. The estimation of this equation is very expensive in computing power and time, so we have combined genders within each age category. The annual version is identical to equation (5), except that for comparability reasons we combine genders. For both the daily and annual approaches, the figure reports the weighted sums of the $\hat{\theta}_{dj}^{TMEAN}$'s across the 8 age categories, where the weights are the population share in each age category (just as in Figures 6A and 6B, except here the population shares are based on both genders).

The figure reveals the shortcomings of the daily model. This is most evident at the coolest temperatures. Specifically, the estimated mortality rate from the annual approach greatly exceeds the mortality rate from the daily approach for almost all bins representing temperatures below 50° F. For example, the average of the estimated $\hat{\theta}_j^{TMEAN}$ for the 11 bins representing temperatures below 50° F is .003, which suggests that an extra day in that temperature range is associated with .003 additional deaths per 100,000 population. The analogous calculation from the annual approach is 0.197, which is about 65 times larger! These results support the validity of the delayed impacts hypothesis and reveal that cold days are associated with fatalities due to diseases like pneumonia that do not immediately lead to death.

The paper's primary purpose is to learn about the likely impacts of climate change, and there are important differences between the estimated $\hat{\theta}_{dj}^{TMEAN}$ at the higher temperatures too. Here, the estimated coefficients from the daily model overstate the mortality impact of a hot day; for example the estimated impact of days in the 85° - 90° F, 85° - 90° F and > 90° F bins are 0.15, 0.12 and 0.10 larger, respectively, in the daily model. The result is that the predicted increase in the mortality rate from the Hadley 3 A1F1 (CCSM 3 A2) predictions is 2.5% (1.6%) with the daily approach but just 1.7% (0.5%) with the annual one. Thus, a failure to account for forward displacement and delayed impacts would lead one to overstate the direct mortality impacts by roughly 47% (202%).[30]

Geographic Variation in the Estimated Impacts. Table 6 explores the distributional consequences of climate change across states. It lists the predicted impact of the two sets of climate change predictions on state-level mortality rates. The states are ordered from largest to smallest with the Hadley 3 A1F1 predictions in columns (1a) and (1b) and the CCSM A2 ones in (2a) and (2b). The entries are based on the estimation of equation (5), and then the resulting response function is applied to each state. In interpreting the results, it is important to recall that due to the greater number of CCSM grid points, the CCSM predictions on climate change are at the state-level whereas the Hadley predictions are at the

[30]Furthermore, these results suggest that the reports of the extremely elevated risk of mortality associated with hot days overstate the mortality impacts of these episodes (Whitman et al. 1997; Vandentorren et al. 2003). This is because the individuals that die on these days appear to have had little life expectancy remaining, just as is predicted by the harvesting/forward displacement hypothesis. In this respect, the results confirm the Deschênes and Moretti (2005) findings, although we have done so with a much more blunt approach; their paper traces out the precise dynamics of the mortality-temperature relationship on hot days.

Census Division-level.

The entries indicate that the currently hot states will experience the largest increases in mortality rates. For example, the Hadley (CCSM) predictions suggest increases in Arizona's, California's, and Texas' mortality rates of 4.1% (1.8%), 4.0% (2.3%), and 3.4% (1.4%), respectively. Interestingly, the estimates suggest that 12 (19) states will have declines in their mortality rates with the Hadley (CCSM) predictions. It is evident that the reduction in cold days in Wyoming and Montana drive those states' reductions in mortality rates under the Hadley scenario.

Overall, the table reveals substantial heterogeneity in the estimated impacts of climate change on mortality rates. However, it would be remiss to fail to point out that this exercise is demanding of the data and, these state-specific predictions are generally imprecise. For example, the null of zero is rejected at the 10% level or better for only five states under Hadley 3 A1FI (i.e., Arizona, California, Kansas, Missouri, and New Mexico) and just three states with CCSM A2 (California, Nevada, and Arizona). Furthermore, only 1 of the 98 estimates would be judged statistically significant at the 5% level.

C. Estimates of Adaptation from Energy Consumption

We now turn to an analysis of the effect of inter-annual fluctuations in temperature on residential energy consumption. Specifically, this subsection fits versions of equation (6) to the state by year data on residential energy consumption from the EIA. Recall, the annual mean of residential energy consumption is 16.6 quads in this period.

Figure 8 plots the estimated θ_j's from the specification that includes the familiar 20 temperature variables. The coefficients report the estimated impact of an additional day in bin j on annual energy consumption, relative to energy consumption on a day where the temperature is between 65° - 70° F. The estimates are adjusted for the ln of population and state gross domestic product, their squares and interaction. The figure also plots the estimated θ_j's plus and minus one standard error of the estimates, so their precision is evident.

The response function has a U-shape, indicating that that energy consumption is highest on cold and hot days. Notably, the function turns up sharply at the three highest temperature bins. So, for

example, an additional day in the > 90° F bin is associated with an extra 0.11 quads of energy consumption. The response function is very flat and precisely estimated for temperatures between 45 – 80° F; these seven estimated θ_j 's all range between -0.013 and 0.007. In fact, the shape of this function undermines the convention in the literature of modeling heating and cooling degree days linearly with a base of 65 because fitting a line through these points will overstate consumption in the flat range and understate it at the extremes of the temperature distribution.

Table 6 reports the predictions of the impact of climate change on annual residential energy consumption from the estimation of several versions of equation (6). The table is laid out similarly to Table 4. All specifications include state and census division by year fixed effects, as well as quadratics in ln population, ln state GDP, their interactions, and a set of 50 indicator variables capturing the full distribution of annual precipitation. For both sets of climate change predictions, we reports results from modeling temperature with the 20 separate variables and with cooling and heating degree days and their squares.

The baseline specification in the first row reports compelling evidence that predicted climate change will cause a sharp increase in energy consumption. Specifically, the estimates suggest an increase in residential energy consumption in the range of 5-6 quads or 30%-35% with the Hadley 3 A1FI predictions and about 2.5 quads or 15% with the CCSM A2 predictions. All of these estimates would be judged to be statistically different from zero at conventional significance levels.

The specification checks in Panel B support the validity of the findings in the baseline specification. Some of the estimated impacts are larger and some are smaller, but they are almost all within one standard error of the baseline estimates.[31]

Panel C reports on the estimated impacts when the response function is estimated on subsamples of the data. In rows 1. and 2., the underlying response functions are estimated with observations from after 1980 and states with an average number of days with temperatures above 80° F that exceeds the

[31] We also estimated the mortality impacts of climate change using the predictions on temperature and precipitation. When temperature is modeled with the 20 bins, the resulting estimated increases (standard errors) in energy consumption are 4.7 (1.9) with Hadley 3 A1FI and 2.7 (0.9) with CCSM 3 A2. Just as with the mortality results, the findings suggest that the predicted increase in precipitation is unlikely to have an important independent influence.

national median. The idea is that in both subsamples individuals may have undertaken some of the adaptations that resemble those that will be taken in response to permanent climate change. In the former, this is because these observations occur after the oil shocks, and in the latter, this is due to the warmer climates. In the context of the model outlined in Section II, we expect the response in energy consumption to be smaller when these response functions are used.

The entries in this panel confirm this prediction. The response function obtained from the 1980 data implies an increase in energy consumption that is roughly 40% smaller than the baseline estimates. In the second row, the results are less stable across the alternative methods for modeling temperature, but these results also point to a decline, relative to the baseline results.

These results underscore the central role of adaptation in responding to climate change and that the sum of the baseline mortality and energy consumption impacts from this approach overstate its costs. As Section II highlighted, however, the costs implied in Panel C are likely to understate the total costs. This is because this approach fails to account for the fixed costs associated with switching technologies that allow for the smaller increases in energy consumption. For example, it fails to account for the extra construction costs associated with more energy efficient homes and the greater upfront costs of energy efficient appliances.[32]

Overall, these results imply that predicted climate change will lead to substantial increases in energy consumption in the residential sector. This finding is consistent with predicted increases in energy consumption from a study of California (Franco and Sanstad 2006). To the best of our knowledge, these estimates on energy consumption are the first ones based on data from the entire country. In addition to being useful for policy purposes, they should help climate modelers who have not yet incorporated feedback effects from higher energy consumption into their models.

VI. Interpretation

[32] Mansur, Mendelsohn, and Morrison (2007) and Mendelsohn (2006) estimate the relationship between energy consumption and temperatures in the cross-section. As the discussion in Section II highlighted, this approach will reveal the equilibrium relationship between energy consumption and temperature (in the absence of specification error). Consequently, this cross-sectional approach is useful in predicting equilibrium energy demand, but in the presence of fixed costs it isn't informative about the impact of climate change on energy related costs.

Optimal decisions about climate change policies require estimates of individuals' willingness to pay to avoid climate change over the long run. Previous research has suggested that human health is likely to be a big part of these costs. This section places the estimates in context and also discusses some caveats to this exercise.

The central tendency of the baseline mortality estimates are that the overall mortality rate will increase by about 1.7% with the Hadley 3 A1FI predictions and 0.5% with the CCSM A2 ones. To put these numbers in some context, the US age adjusted death rate for both genders has dropped from 1304.5 to 832.7 per 100,000 between 1968 and 2003, which is a decline of approximately 1% per year. Thus, even if the point estimates are taken literally, the climate change induced increase in mortality is roughly equivalent to losing just 0.5 to 1.7 years of typical improvement in longevity. It is important to note though that these estimates have associated sampling errors and that the 95% confidence intervals include reductions in mortality rates so that a zero impact cannot be rejected.

An alternative approach to putting the numbers in context is to develop a measure of the health related welfare impacts of the expected temperature increases due to climate change and we now do this. When the Hadley 3 A1FI results in Table 3 are scaled by fraction of the population in our sample (72%), they suggest that climate change would lead to a loss of roughly 1,100,000 life years annually. The analogous calculation from the CCSM A2 prediction is for a loss of about 400,000 life years annually. A valuation of a life year at about $100,000 is roughly consistent with Ashenfelter and Greenstone's (2004) estimate of the value of a statistical life. So when the sampling variability is ignored, the results suggest that the direct impacts of climate change on mortality will lead to annual losses of roughly $110 billion and $40 billion, respectively, in the 2070-2099 period.[33]

As equation (4) highlights, the cost of the additional energy consumption should be added to the monetized mortality impact to develop a complete measure of the welfare loss due to climate change. The baseline estimates from Table 6 imply an increase in consumption of 5 quads with the Hadley 3 A1FI predictions and 2.3 quads with the CCSM 3 A2 predictions. The average cost of a quad in 2006$ between

[33] It is also possible to make a similar calculation using estimates of how the value of a statistical life varies over the life cycle (Murphy and Topel 2006).

1990 and 2000 is $7.6 billion; this implies an additional $35 billion (Hadley) and $15 billion (CCSM) of energy consumption at the end of the century.

Thus the analysis suggests that by the end of the 21st century, annual willingness to pay to avoid climate change will be about $145 billion with the Hadley 3 A1FI predictions and $55 billion with the CCSM 3 A2 predictions. These estimates are just 1.1% and 0.4%, respectively, of 2006 GDP. If GDP grows at 2% real per year between now and the end of the century, then per capita GDP would be about 6.4 times its current levels by 2100 and these welfare losses would appear even smaller if this is used to normalize them. Further, a major limitation of these calculations is that they ignore the associated sampling variability and this is especially relevant for the mortality estimates that drive these calculations.

There are a number of other caveats to these calculations and to the analysis more generally that bear noting. First, the effort to project outcomes at the end of the century requires a number of strong assumptions, including that the climate change predictions are correct, relative prices (e.g., for energy and medical services) will remain constant, the same energy and medical technologies will prevail, and the demographics of the US population (e.g., age structure) and their geographical distribution will remain unchanged. These assumptions are strong, but their benefit is that they allow for a transparent analysis that is based on the available data rather than on unverifiable assumptions.

Second, the life-years calculation assumes that the individuals whose lives are affected by the temperature changes had a life expectancy of 78.6 for women and 71.2 for men. It is certainly possible that our efforts to purge the influence of harvesting and delayed impacts were not entirely successful and, in this case, the estimated impact on life years would be smaller.

Third, it is likely that these calculations do not reflect the full impact of climate change on health. In particular, there may be increases in the incidence of morbidities due to the temperature increases. Additionally, there are a series of indirect channels through which climate change could affect human health, including greater incidence of vector borne infectious diseases (e.g., increased incidence of malaria and dengue fever). Further, it is possible that the incidence of extreme events would increase, and these could affect human health (Emanuel 2005). This study is not equipped to shed light on these issues.

Fourth, the theoretical section highlighted that our estimates likely overstate the increase in

mortality and energy consumption due to climate change. This is because the higher temperatures will cause individuals to increase expenditures on goods that protect themselves from the changes in temperature. Our identification strategy relies on inter-annual fluctuations in weather, rather than a permanent change. There are a number of adaptations that cannot be undertaken in response to a single year's weather realization. For example, permanent climate change is likely to lead to some migration (presumably to the North), and this will be missed with our approach. Although these adaptations may be costly, individuals will only undertake them if they are less costly than the alternative. For this reason, our approach is likely to overstate the part of the health costs of climate change that we can estimate.

VII. Conclusions

This study has produced the first large-scale estimates of the health related welfare costs due to climate change. Using the presumably random year-to-year variation in temperature and two state of the art climate models, the analysis suggests that under a 'business as usual' scenario climate change will lead to a small and statistically indistinguishable from zero increase in the overall US mortality rate by the end of the 21st century. There is, however, evidence of a meaningful increase in mortality rates for some subpopulations, especially infants. We also find that climate change will lead to a statistically significant increase in residential energy consumption of 15%-30% or $15 to $35 billion (2006$) by the end of the century. In the context of a model of health production, it seems reasonable to assume that the mortality impacts would be larger without the increase in energy consumption. Further, the estimated mortality and energy impacts likely overstate the long-run impacts on these outcomes, since individuals can engage in a wider set of adaptations in the longer run to mitigate the costs. Overall, the analysis suggests that the health related welfare costs of climate change are likely to be quite modest in the US.

There are several broader implications of this research. First, the demographic group-specific mortality and residential energy consumption response functions are not specific to any climate model. In fact, as global climate models advance and new climate change predictions emerge, the resulting predictions can be applied to this paper's response functions to obtain updated estimates of the mortality and energy impacts of climate change.

Second, the production of many types of energy involves the release of greenhouse gases. Thus, the finding of increased residential energy consumption suggests that climate modelers should account for this feedback between higher temperatures and greater greenhouse gas emissions that lead to yet higher temperatures. It is our understanding that current climate models fail to account for this feedback loop.

Third, this paper has demonstrated that it is possible to develop harvesting and delayed-impact resistant estimates of the impacts of weather on mortality by combining annual mortality data and daily weather data. In principle, this approach can be applied to other settings where there is an unknown dynamic relationship between environmental exposure and human health. For example, a number of commentators have questioned whether the documented relationship between daily air pollution concentrations and daily mortality rates largely reflects harvesting. This paper's approach can be applied to that setting.

Finally, the impacts of climate change will be felt throughout the planet. This paper's approach can be applied to data from other countries to develop estimates of the health related welfare costs of climate change elsewhere. In fact, it may be reasonable to assume that the welfare costs will be larger in countries where current temperatures are higher than in the US and adaptations like air conditioning constitute a larger share of income. Ultimately, the development of rational climate policy requires knowledge of the health and other costs of climate change from around the world.

Data Appendix

I. Hadley 3 Census Division-Level Predictions

We downloaded the Hadley Climate Model 3 (HadCM3) data from the British Atmospheric Data Centre (http://badc.nerc.ac.uk/home/), which provides a wealth of atmospheric data for scientists and researchers. Hadley Centre data appears on BADC thanks to the Climate Impacts LINK Project, a distributor of archived climate model output to researchers. Daily climate predictions generated by the Hadley 3 model are available for all future years from the present to 2099 and for several climate variables – we downloaded the predicted maximum and minimum temperatures and precipitation levels for each day during the years 2070-2099.

The HadCM3 grid spans the entire globe; latitude points are separated by 2.5°, and longitude points are separated by 3.75°. We use the 89 gridpoints that fall on land in the contiguous United States to develop climate predictions for the 9 US Census Divisions. At the Census Division level, each day's mean temperature is calculated as the simple average across all grid points within the Division. The data used in this paper was originally generated by the Hadley Centre for the International Panel on Climate Change's (IPCC) Special Report on Emissions Scenarios (SRES).

II. National Center for Atmospheric Research's Community Climate System Model 3

We downloaded the NCAR Community Climate System Model (CCSM) 3 data from the World Climate Research Programme's Coupled Model Intercomparison Project's data portal (https://esg.llnl.gov:8443/index.jsp), which aims to organize a variety of past, present, and future climate data from models developed across the world for use by researchers. Daily climate predictions generated by the CCSM3 model are available for all future years from the present to 2099 and for several climate variables – we downloaded the predicted mean temperatures and precipitation levels for each day during the years 2010-2099.

The CCSM3 grid spans the entire globe; latitude and longitude points are both separated by 1.4°. We use the 416 gridpoints that fall on land in the contiguous United States to develop climate predictions for the contiguous United States. At the state level, each day's mean temperature is calculated as the simple average across all grid points within the state. The data used in this paper was originally generated by the National Center for Atmospheric Research for the International Panel on Climate Change's (IPCC) Special Report on Emissions Scenarios (SRES).

III. EIA Energy Consumption Data

The consumption data is derived from several different reports and forms depending on energy source. Coal consumption data for most sectors comes from the EIA's Annual Coal Report; electric power sector coal use is the exception, coming instead from forms EIA-906 "Power Plant Report" and EIA-920 "Combined Heat and Power Plant Report". Natural gas consumption data comes from the EIA's Natural Gas Annual. Most petroleum data is the "product supplied" data found in EIA's Petroleum Supply Annual, with the exception again of electric power sector use, which is reported on EIA-906 and EIA-920. Solar, wind, geothermal, and most biomass energy use data is also reported on those forms. Residential and commercial use of biomass is reported on forms EIA-457 "Residential Energy Consumption Survey" and "Commercial Buildings Energy Consumption Survey". Nuclear electric power and other electricity data comes from the EIA Electric Power Annual. Finally, system energy losses and interstate flow are estimated in the State Energy Data System.

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Figure 1: Theoretical Relationship Between Household Annual Energy Expenditures and Ambient Temperature for a Given Level of Indoor Temperature

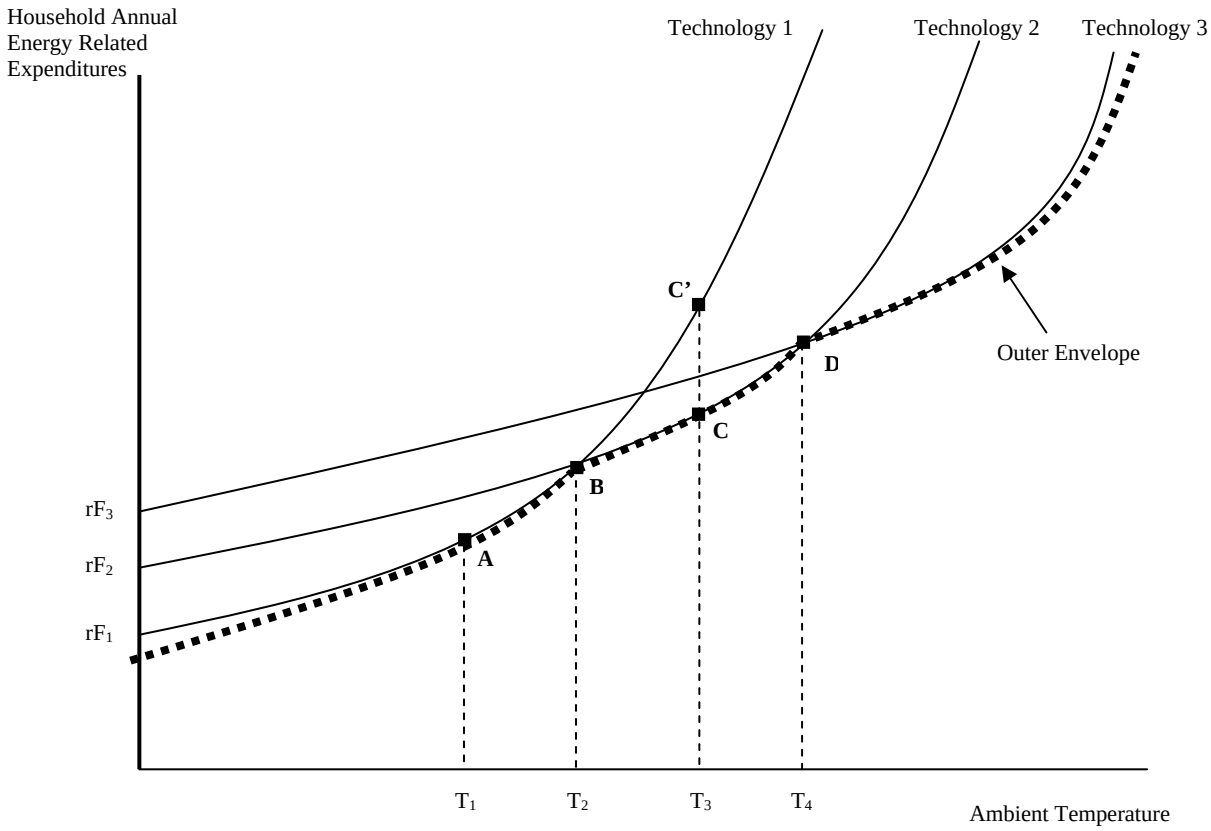
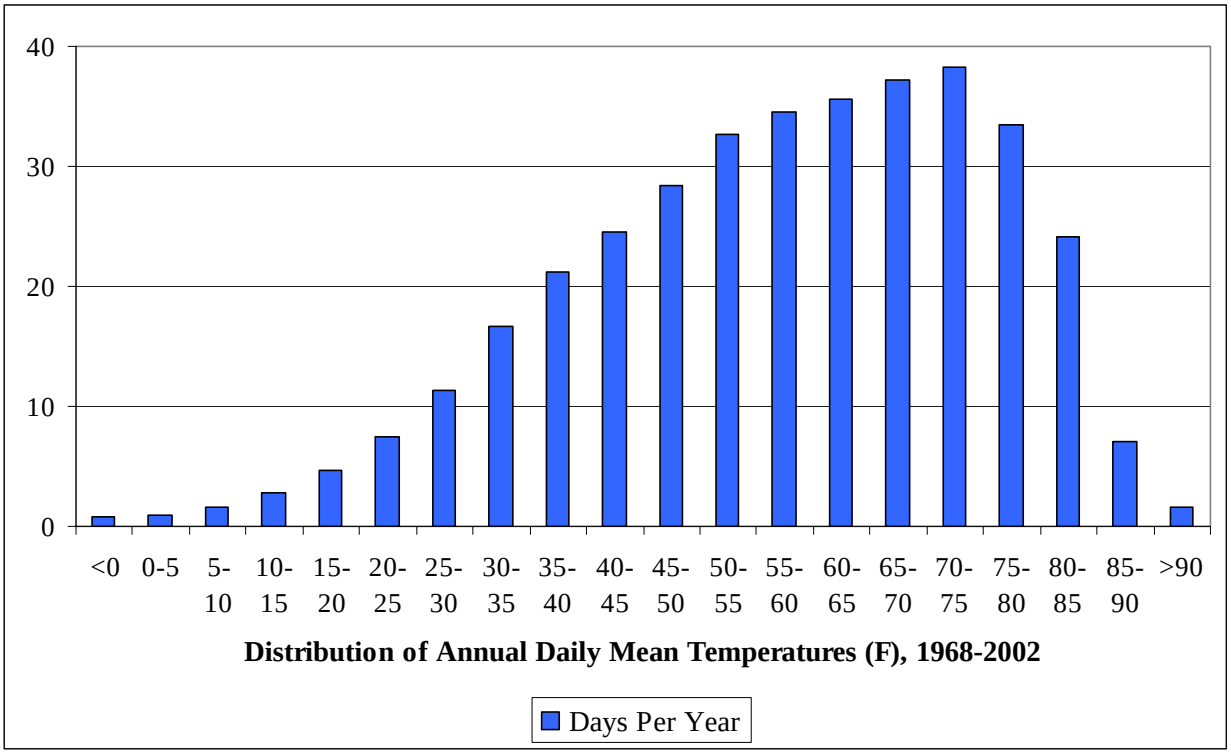
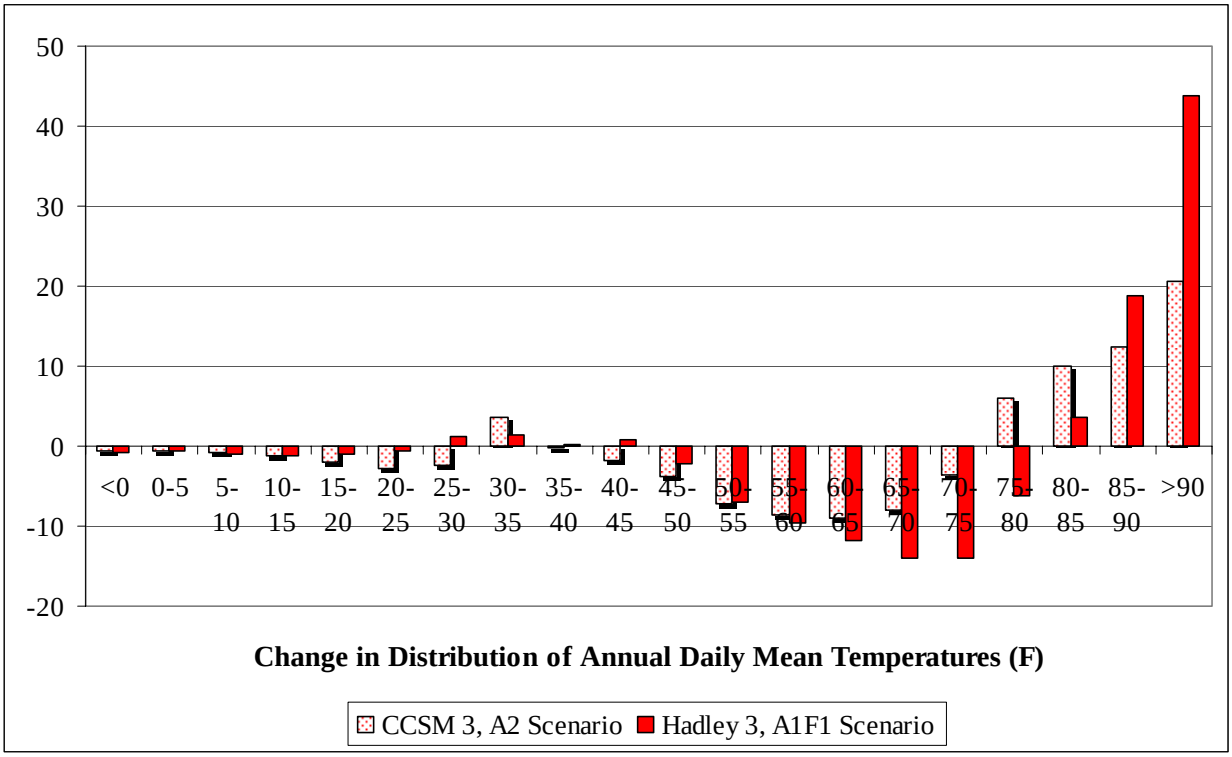


Figure 2: Distribution of Annual Daily Mean Temperatures (F), 1968-2002



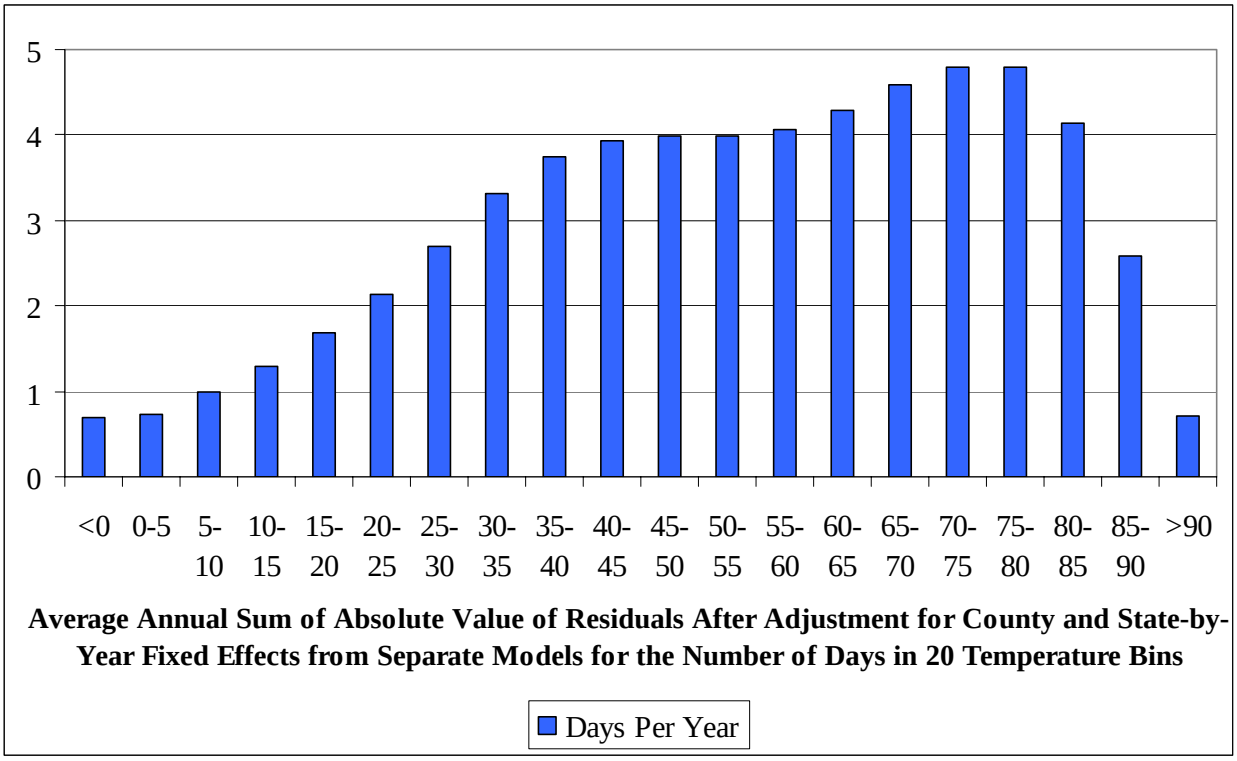
Notes: Figure 2 depicts the distribution of daily mean temperatures across 20 temperature bins between 1968 and 2002. More specifically, each bar represents the average number of days per year in each temperature category for the 57,531 county-year observations in the sample, weighted by the total population in a county-year. The leftmost bin measures the number of days with a mean temperature less than 0° F and the rightmost bin is the number of days where the mean exceeds 90° F. The intervening 18 bins are all 5° F wide.

Figure 3: Changes in Distribution of Annual Daily Mean Temperatures (F) Under Hadley 3, A1F1 and CCSM 3, A2



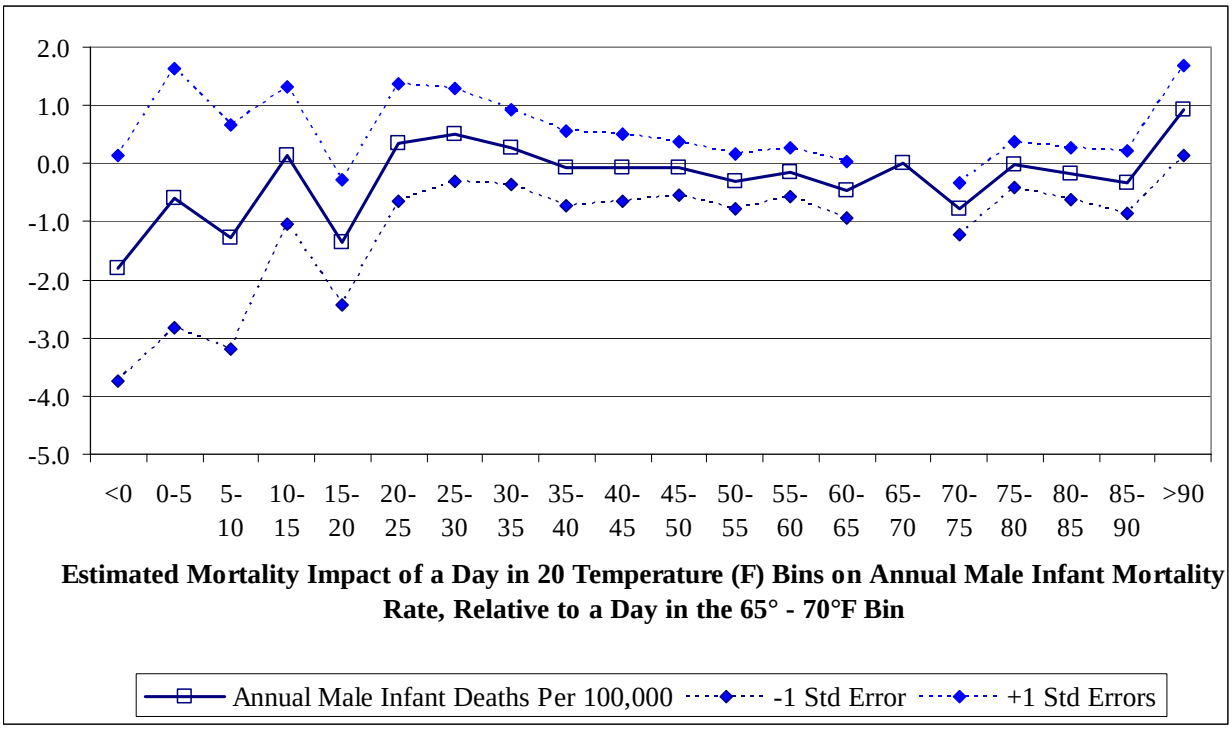
Notes: Figure 3 depicts the distribution of predicted changes in daily mean temperatures across the 20 temperature bins. More specifically, each bar represents the change in the average number of days per year in each temperature category. "Changes" are defined as the difference between the 1968-2002 average in each category and the 2070-2099 predicted average number of days in each category. Both averages are weighted by the average total population over 1968-2002 in a county. The temperature categories are defined as in Figure 2.

Figure 4: Residual Variation in Annual Daily Mean Temperatures (F), 1968-2002



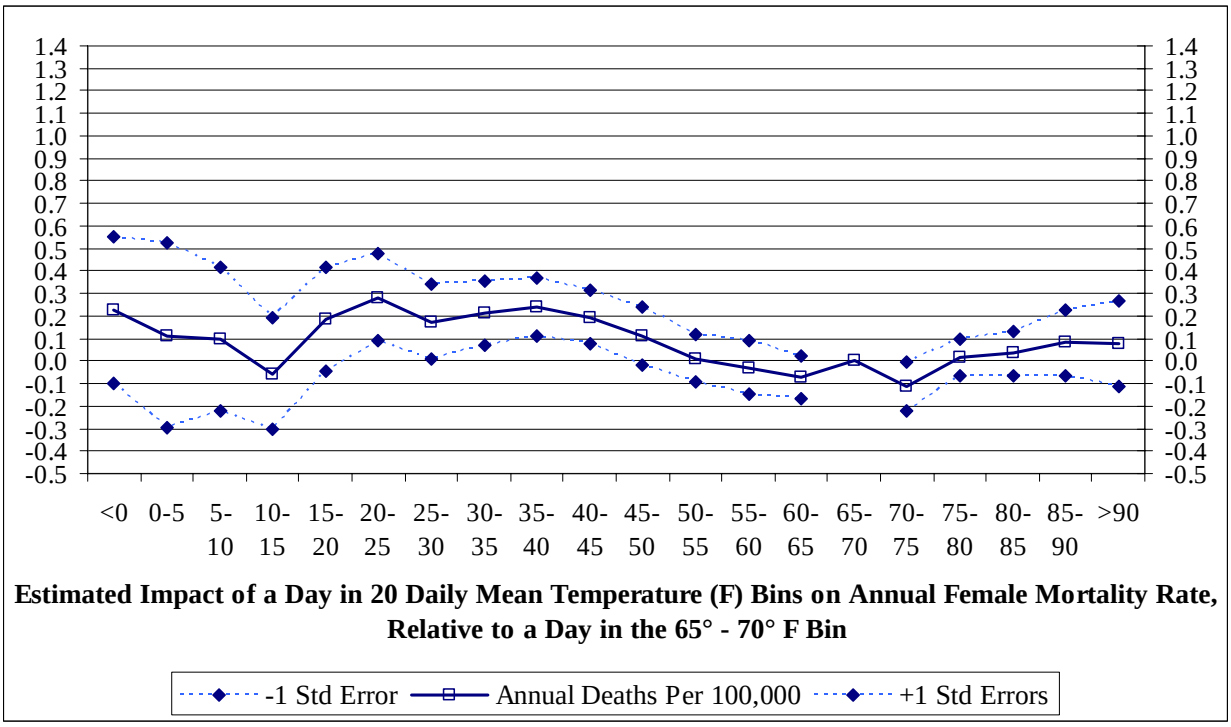
Notes: Figure 4 shows the extent of residual inter-annual variation in temperature. Each bar is obtained by first estimating a regression of the number of days in the relevant temperature category on unrestricted county effects and state-by-year effects, weighting by the total population in a county-year. For each county-year, we sum the absolute value of the residuals from the regression. The figure reports the mean of this number across all county by year observations. The resulting figures can be interpreted as the average number of days in a county by year that are available to identify the parameter associated with that temperature bin after adjustment for the fixed effects.

Figure 5: Estimated Regression Coefficients, Male Infants (relative to temperature cell 65-70)



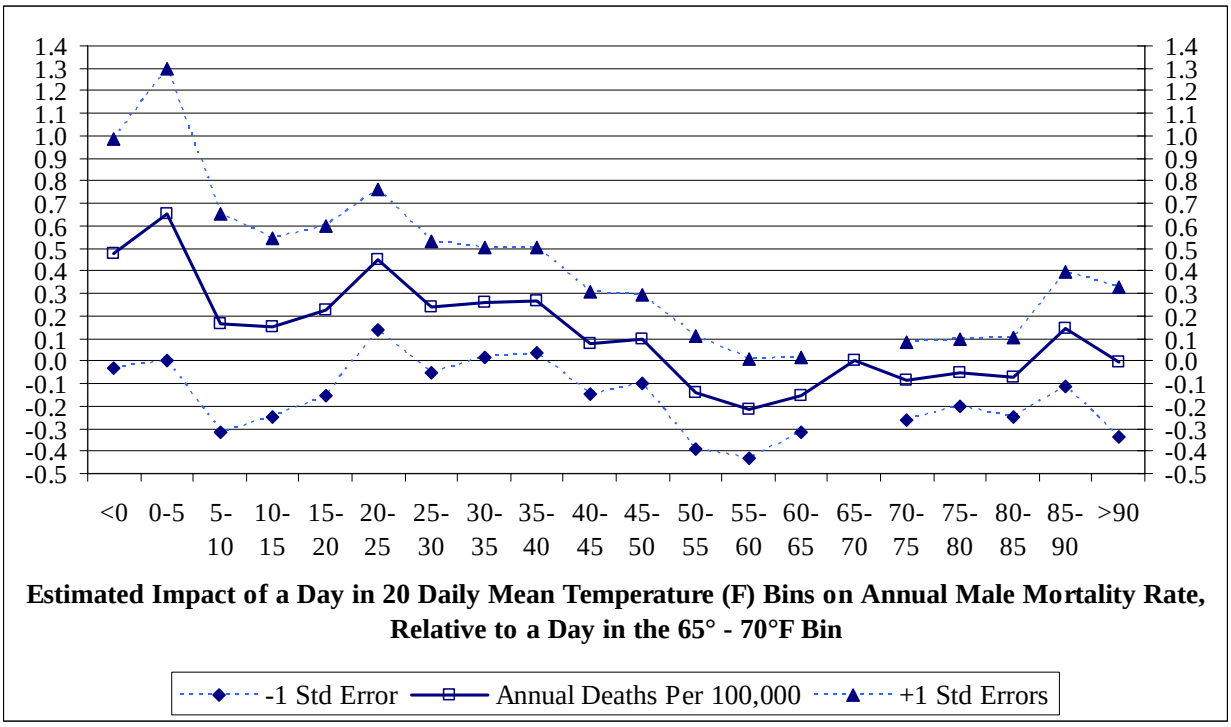
Notes: Figure 5 plots the estimated response function between male infant annual mortality rate (per 100,000) and daily mean temperatures. This is obtained by fitting equation (5) for the male infant group. The response function is normalized with the 65° - 70° F category so each θ_j corresponds to the estimated impact of an additional day in bin j on the male infant mortality rate (i.e., deaths per 100,000) relative to the mortality rate associated with a day where the temperature is between 65° - 70° F. The figure also plots the estimated θ_j's plus and minus one standard error of the estimates.

Figure 6A: Population-Weighted Sum of Regression Estimates Across Age Groups, Females (relative to temperature cell 65-70)



Notes: Figure 6A plots aggregate female response function between annual mortality rate (per 100,000) and daily mean temperatures. This is obtained by fitting equation (4) for the female mortality rate in each age group. The age-group specific estimates are then combined into a single "aggregate" estimate by taking a weighted sum of the age-specific estimates, where the weight is the average population size in each age group. The response function is normalized with the 65° - 70° F category so each θ_j corresponds to the estimated impact of an additional day in bin j on the aggregate female mortality rate (i.e., deaths per 100,000) relative to the mortality rate associated with a day where the temperature is between 65° - 70° F. The figure also plots the estimated θ_j's plus and minus one standard error of the estimates.

Figure 6B: Population-Weighted Sum of Regression Estimates Across Age Groups, Males (relative to temperature cell 65-70)



Notes: Figure 6B plots aggregate male response function between annual mortality rate (per 100,000) and daily mean temperature. This is obtained by fitting equation (5) for the male mortality rate in each age group. The age-group specific estimates are then combined into a single "aggregate" estimate by taking a weighted sum of the age-specific estimates, where the weight is the average population size in each age group. The response function is normalized with the 65° - 70° F category so each θ_j corresponds to the estimated impact of an additional day in bin j on the aggregate male mortality rate (i.e., deaths per 100,000) relative to the mortality rate associated with a day where the temperature is between 65° - 70° F. The figure also plots the estimated θ_j's plus and minus one standard error of the estimates.

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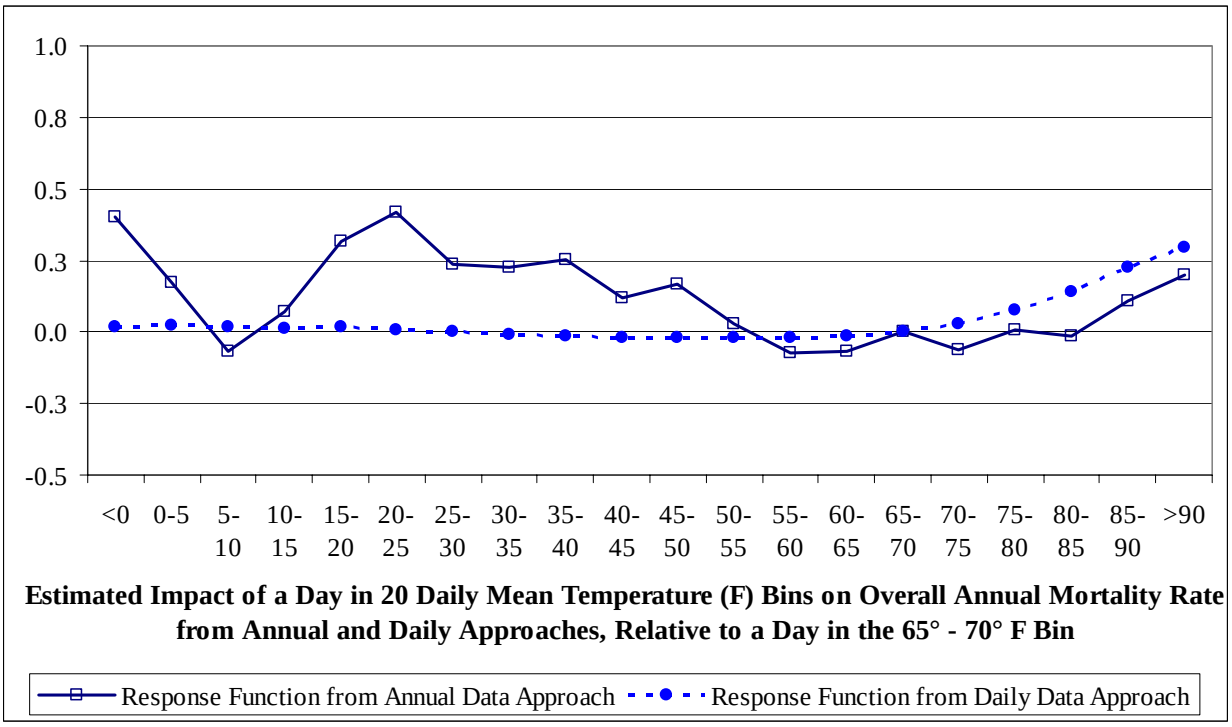
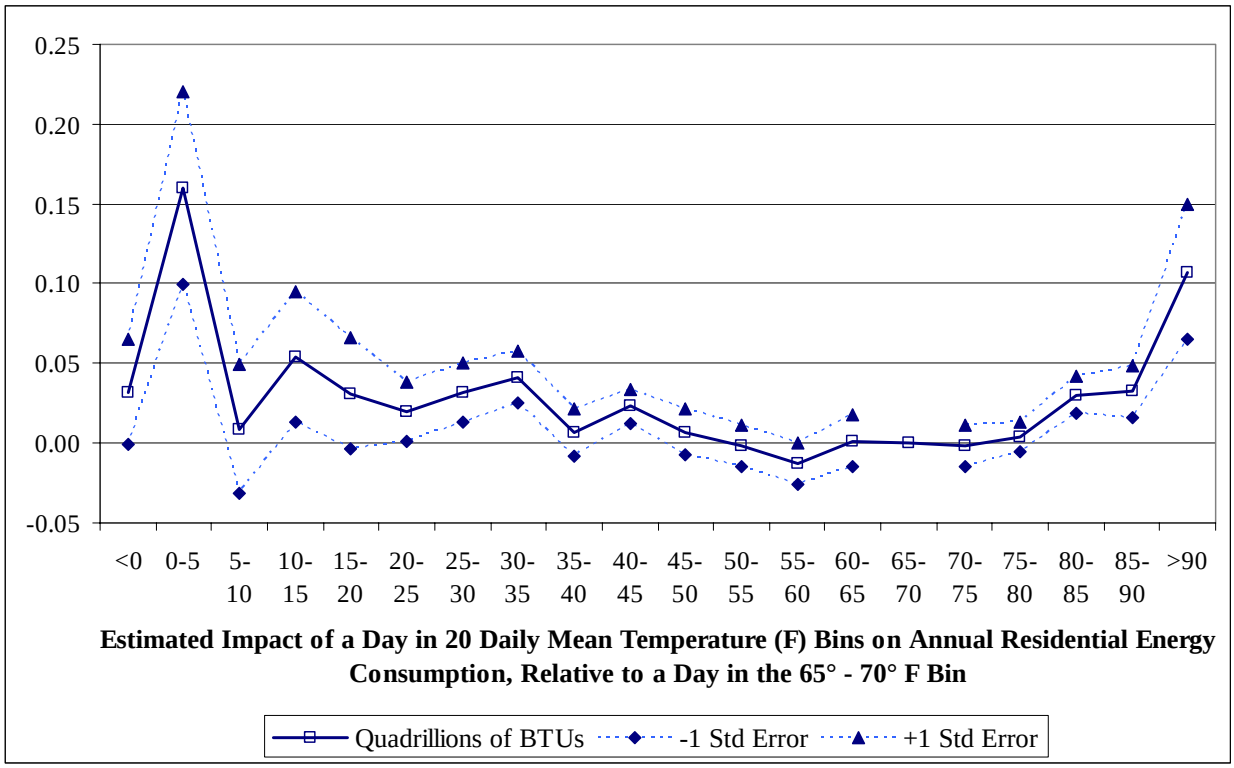
Figure 7: Population-Weighted Sum of Regression Estimates Across Age Groups, for Daily and Annual Approaches (relative to temperature cell 65-70)



Notes: Figures 7 compares the response functions obtained from fitting equation (5) with daily mortality data and annual mortality data. The objective is to highlight how using annual mortality data alleviates the problem of mortality displacement that plagues the relationship between on daily data. For simplicity, both models reported here pool males and females together. The response function based on annual mortality data follows directly the specification of equation (5) (except that it pools males and females). In the daily regressions, the unit of observation is a county by day and the dependent variable is the county-level mortality rate for an age group. This equation includes county fixed effects, state by year fixed effects, state by month fixed effects, and the 20 temperature variables. For both the daily and annual approaches, the figure reports the weighted sums of the $\hat{\theta}_{dj}^{TMEAN}$'s across the 8 age categories, where the weights are the population share in each age category (just as in Figures 6A and 6B, except here the population shares are based on both genders).

Figure 8: Estimated Impact on Total Energy Consumption in the Residential Sector



Notes: Figure 8 plots the estimated response function between aggregate residential energy consumption (in QBTU) and daily mean temperatures. This is obtained by fitting equation (6) on our sample of 1,715 state-year observations. The response function is normalized with the 65° - 70° F category so each θ_j corresponds to the estimated impact of an additional day in bin j on residential QBTU relative to the residential QBTU associated with a day where the temperature is between 65° - 70° F. The figure also plots the estimated θ_j's plus and minus one standard error of the estimates.

TABLE 1: AVERAGE ANNUAL MORTALITY RATES PER 100,000 POPULATION, 1968-2002

	All Causes of Death		Cardiovascular Disease		Neoplasms		Respiratory Disease		Motor-Vehicle Accidents	
Age Group:	**Females**	**Males**	**Females**	**Males**	**Females**	**Males**	**Females**	**Males**	**Females**	**Males**
Infants	1,031.1	1,292.1	21.1	25.4	4.6	4.7	45.2	58.6	---	---
1-14	29.9	41.8	1.5	1.7	3.9	4.9	1.6	1.8	3.1	4.7
15-24	53.2	151.6	3.1	4.5	4.9	7.2	1.4	1.8	11.8	36.1
25-44	68.0	148.5	10.8	24.3	18.0	15.8	2.2	3.1	4.8	16.5
45-54	386.1	699.1	100.1	269.0	158.1	165.0	14.3	22.1	7.0	20.3
55-64	917.3	1,696.0	315.8	757.6	361.4	501.4	46.2	82.3	7.1	18.4
65-74	2,108.0	3,754.8	942.6	1,789.2	644.8	1,073.0	136.3	272.8	9.3	19.6
75-99	7,571.8	9,982.7	4,512.1	5,357.6	1,088.3	1,942.1	578.0	975.6	13.3	34.4
All Ages	804.4	939.2	389.7	409.8	174.5	206.3	53.2	64.4	8.1	21.4

Notes: Averages are calculated for a sample of 57,531 county-year observations. All entries are weighted averages, where the weight is population in relevant demographic group in a county-year. The ICD-9 codes corresponding to the causes of deaths are defined as follows: Neoplasms = 140-239, Cardiovascular Disease = 390-459, Respiratory Disease = 460-519, Motor Vehicle Accidents = E810-E819.

TABLE 2: POPULATION-WEIGHTED AVERAGES OF DAILY MEAN ACROSS COUNTIES, 1968-2002

	Actual	Hadley 3, A1F1		CCSM 3, A2	
		Level	Difference	Level	Difference
Average Daily Mean					
All Counties	56.6	62.6	6.0	62.2	5.6
Northeast Region	50.9	56.5	5.6	55.7	4.8
Midwest Region	49.9	59.1	9.2	59.7	9.8
South Region	64.4	73.6	9.2	69.5	5.1
West Region	58.6	58.3	-0.3	61.6	3.0
Average Daily Minimum					
All Counties	46.0	52.5	6.5	---	---
Average Daily Maximum					
All Counties	67.2	72.7	5.5	---	---
Days with mean >90F (All Counties)					
Average Daily Mean	92.2	96.4	4.3	94.6	2.4
Average Daily Minimum	78.2	83.4	5.3	---	---
Average Daily Maximum	106.2	109.5	3.3	---	---

Notes: Averages are calculated for a sample of 57,531 county-year observations and are weighted by the total population in a county-year ("Actual") and by the average total population over 1968-2002 in a county ("CCSM 3, A2" and "Hadley 3, A1F1"). The average daily mean temperature is the simple average of the daily minimum and maximum temperatures.

TABLE 3: ESTIMATES OF THE IMPACT OF CLIMATE CHANGE ON ANNUAL MORTALITY, HADLEY 3 A1F1 SCENARIO

	FEMALES				MALES			
Age Group:	**Annual Fatalities** (1a)	**% Change in Mortality Rate** (1b)	**Annual Change in Life Years** (1c)	**F-test (p-values)** (1d)	**Annual Fatalities** (2a)	**% Change in Mortality Rate** (1b)	**Annual Change in Life Years** (2c)	**F-test (p-values)** (1d)
Infants	995.9	5.6	-77,302.5	0.180	1835.3	7.8	-128,671.4	0.468
	(518.7)	(2.9)			(681.7)	(2.9)		
1-14	578.4	7.9	-41,476.0	0.873	693.8	6.5	-44,643.9	0.658
	(320.6)	(4.4)			(414.4)	(3.9)		
15-24	-579.2	-5.9	34,723.6	0.038	263.4	0.9	-13,903.8	0.079
	(498.0)	(5.1)			(1408.3)	(5.0)		
25-44	860.1	2.2	-39,124.3	0.015	2993.5	3.7	-117,106.4	0.001
	(952.6)	(2.5)			(3096.1)	(3.8)		
45-54	947.9	1.9	-29,926.6	0.207	2935.6	3.4	-75,796.9	0.316
	(907.3)	(1.8)			(1674.7)	(1.9)		
55-64	1098.7	1.1	-25,369.0	0.133	4372.5	2.7	-79,360.6	0.003
	(1263.0)	(1.3)			(2166.6)	(1.3)		
65-74	2,166.8	1.2	-33,021.8	0.133	314.2	0.1	-3,735.2	0.001
	(2547.5)	(1.4)			(3398.0)	(1.3)		
75-99	11,528.6	2.0	-78,279.5	0.370	4,158.6	1.0	-22,581.4	0.009
	(5444.6)	(1.0)			(4128.8)	(1.0)		
Aggregate Impact	**17,597.2**	1.8	**-289,776.1**		**17,566.8**	1.6	**-485,799.6**	
	(12452.3)	(1.3)			(16968.5)	(1.6)		

Notes: The estimates are from fixed-effect regressions by demographic group. For each group there are 57,531 county-year observations. Each model includes county fixed-effects and state-by-year effects unrestricted for each demographic group. The dependent variable is the annual mortality rate in the relevant demographic group in a county-year. The regressions are weighted by the population count in the relevant demographic group in a county-year. Control variables include a set of 50 indicator variables capturing the full distribution of annual precipitations. Standard errors are clustered at the county-by-demographic group level.

TABLE 4: ALTERNATIVE ESTIMATES OF THE IMPACT OF CLIMATE CHANGE ON ANNUAL MORTALITY RATES

	HADLEY 3, A1F1		CCSM 3, A2	
	Females	**Males**	**Females**	**Males**
A. Baseline Estimates	**1.8**	**1.6**	**0.5**	**0.4**
	(1.3)	(1.6)	(0.8)	(0.7)
B. Alternative Specifications				
1. Year Effects Only	**2.0**	**1.4**	**1.0**	**0.7**
	(1.8)	(1.6)	(1.1)	(1.2)
2. Controls for Daily Minimum and Maximum Temperature Separately	**1.6**	**2.4**	**---**	**---**
	(1.3)	(1.3)		
3. Add Previous Year's Temperature Variables	**0.9**	**1.4**	**0.0**	**0.1**
	(2.1)	(2.2)	(1.2)	(1.3)
4. Add Variable for Number of "Heatwaves"	**2.0**	**1.8**	**0.6**	**0.5**
	(1.7)	(1.7)	(1.2)	(1.4)
C. Impacts of Estimating the Response Function on Subsets of the Data				
1. Post-1980 Data Only	**2.2**	**1.3**	**1.3**	**0.9**
	(1.2)	(1.5)	(1.1)	(1.3)
2. Counties with #Days Above 80° F Above National Median	**1.8**	**2.3**	**0.7**	**1.1**

Notes: The estimates are from fixed-effect regressions estimated separately by demographic group, and then summed across all age groups and for males and females. See the notes to Table 3 for more detail. Specification B.1 replaces the state by year fixed effects are replaced by year fixed effects. Specification B.2 models temperature with two separate sets of the same 20 temperature bins for the daily maximum and minimum temperatures, respectively, while specification B.3 uses separate sets of the 20 temperature bins for the current year's daily mean temperature and the previous year's daily mean temperature to allow for the possibility that equation (5) inadequately accounts for the dynamics of the mortality-temperature relationship. Specification B.4 include controls for "heatwaves", which are defined as episodes of 5 consecutive days where the daily mean temperature exceeds 90F (sample average = 0.9 such heatwaves per county-year). Specification C.1 estimates the models using data for 1980-2002 only. Finally, specification C.2 estimates the response function with data from the half of counties where the average number of days per year with a mean temperature above 80° F exceeds the national median (14 days).

TABLE 5: ESTIMATES OF THE IMPACT OF CLIMATE CHANGE ON STATE-LEVEL ANNUAL MORTALITY RATES (IN PERCENT)

	Hadley 3, A1F1			CCSM 3, A2	
	Impact	**(Std Error)**		**Impact**	**(Std Error)**
Arizona	4.1	(2.5)	California	2.3	1.4
California	4.0	(1.9)	Nevada	2.1	1.2
Florida	3.8	(2.6)	Arizona	1.8	0.8
Louisiana	3.6	(3.2)	Arkansas	1.6	1.9
Texas	3.4	(3.5)	Texas	1.4	1.5
Alabama	2.9	(2.2)	Utah	1.4	1.4
Mississippi	2.9	(2.1)	Idaho	1.4	1.0
Kansas	2.8	(1.7)	Mississippi	1.3	1.2
Missouri	2.7	(1.6)	Louisiana	1.1	0.9
New Mexico	2.3	(1.2)	New Mexico	1.1	1.1
Nevada	2.1	(1.3)	Missouri	1.0	1.7
Arkansas	1.9	(3.1)	Colorado	0.9	1.1
Tennessee	1.9	(2.3)	Tennessee	0.9	1.2
Nebraska	1.8	(1.9)	Oklahoma	0.9	1.9
Iowa	1.7	(2.0)	Alabama	0.8	0.9
Georgia	1.6	(1.7)	Kentucky	0.7	1.0
Oklahoma	1.6	(3.1)	Oregon	0.6	0.9
Indiana	1.4	(1.3)	Florida	0.5	0.5
South Carolina	1.4	(1.8)	Illinois	0.5	1.8
Ohio	1.4	(1.3)	Indiana	0.5	1.5
Pennsylvania	1.3	(1.4)	Georgia	0.4	0.8
Kentucky	1.3	(2.3)	Iowa	0.4	1.9
Illinois	1.2	(1.3)	Washington	0.4	0.8
South Dakota	1.1	(2.3)	Kansas	0.3	1.5
Minnesota	1.0	(2.9)	New York	0.2	0.5
New Jersey	0.8	(0.9)	Ohio	0.2	1.0
North Carolina	0.7	(2.1)	Wyoming	0.2	1.1
Connecticut	0.6	(0.8)	Montana	0.1	0.9
New York	0.6	(1.0)	South Carolina	0.0	0.9
Colorado	0.5	(1.3)	Minnesota	0.0	1.7
Michigan	0.5	(1.6)	Wisconsin	-0.1	1.4
Utah	0.5	(1.1)	Nebraska	-0.1	1.1
Rhode Island	0.4	(0.9)	West Virginia	-0.2	0.9
North Dakota	0.4	(3.4)	Virginia	-0.2	0.8
Wisconsin	0.3	(1.9)	South Dakota	-0.2	1.6
Oregon	0.2	(1.4)	Pennsylvania	-0.3	0.8
Massachusetts	0.2	(0.9)	Michigan	-0.3	0.7
Virginia	-0.1	(2.2)	North Carolina	-0.4	1.0
Idaho	-0.1	(1.4)	North Dakota	-0.5	2.5
New Hampshire	-0.4	(1.2)	Rhode Island	-0.6	0.8
Dist Columbia	-0.5	(1.8)	Maine	-0.7	0.8
Vermont	-0.5	(1.4)	Massachusetts	-0.8	0.8
Maine	-0.6	(1.4)	Vermont	-0.8	1.2
Delaware	-0.6	(2.4)	Dist Columbia	-0.9	0.8
Maryland	-0.6	(2.5)	Delaware	-1.1	1.1
Washington	-0.8	(1.7)	Maryland	-1.2	1.2
Wyoming	-0.9	(1.8)	New Hampshire	-1.3	1.2
Montana	-0.9	(1.8)	Connecticut	-1.5	1.2
West Virginia	-1.0	(2.4)	New Jersey	-1.6	1.3

Notes: The estimates are from the same regressions as for Table 3. The climate change impacts (as a percent of annual deaths) are calculated separately by state.

TABLE 6: ESTIMATES OF THE IMPACT OF CLIMATE CHANGE ON ANNUAL RESIDENTIAL ENERGY CONSUMPTION

	Hadley 3, A1F1		CCSM 3, A2	
	20 Cells	**CDD and HDD (Base 65F)**	**20 Cells**	**CDD and HDD (Base 65F)**
	(1)	**(2)**	**(3)**	**(4)**
A. Baseline Estimates	**4.9**	**6.0**	**2.3**	**2.5**
	(1.9)	(1.5)	(0.9)	(0.8)
B. Alternative Specifications				
1. Year Effects Only	**2.7**	**7.8**	**1.5**	**1.4**
	(1.8)	(1.9)	(0.8)	(0.5)
2. Controls for Daily Minimum and Maximum Temperature Separately	**4.9**	**9.7**	**---**	**---**
	(1.6)	(2.6)		
3. Add Previous Year's Temperature Variables	**4.4**	**6.8**	**2.2**	**2.8**
	(2.7)	(2.0)	(1.4)	(1.1)
4. Add Variable for Number of "Heatwaves"	**6.1**	**6.0**	**2.3**	**2.5**
	(1.8)	(1.5)	(0.9)	(0.8)
C. Impacts of Estimating the Response Function on Subsets of the Data				
1. Post-1980 Data Only	**3.0**	**3.6**	**1.3**	**1.4**
	(1.1)	(1.0)	(0.6)	(0.5)
2. States with #Days Above 80° F Above National Median	**-2.5**	**4.7**	**-1.4**	**2.6**
	(1.9)	(1.7)	(1.1)	(0.8)

Notes: The estimates are from fixed-effect regressions based on a sample of 1,715 state-year observations. Each model includes state fixed-effects and census division-by-year effects. The dependent variable is the log of the total residential energy consumption in a state-year. Control variables include quadratics in population, state GDP, and their interactions, as well as a set of 50 indicator variables capturing the full distribution of annual precipitations. “Heatwaves” are defined as episodes of 5 consecutive days where the daily mean temperature exceeds 90F. The state-level measure of heatwaves used in the regression is the weighted average of the number of heatwaves across all counties in a state. Standard errors are clustered at the state level.