Adapting to Climate Change: The Remarkable Decline in the U.S. Temperature-Mortality Relationship over the 20^{th} Century*

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Abstract

A critical part of adapting to the higher temperatures that climate change brings will be the deployment of existing technologies to new sectors and regions. This paper examines the evolution of the temperature-mortality relationship over the course of the entire 20^{th} century in the United States both for its own interest but also to identify potentially useful adaptations that may be useful in the coming decades. There are three primary findings. First, the mortality impact of days with a mean temperature exceeding 80° F has declined by about 70%. Almost the entire decline occurred after 1960. There are about 14,000 fewer fatalities annually than if the pre-1960 impacts of high temperature on mortality still prevailed. Second, the diffusion of residential air conditioning can explain essentially the entire decline in hot day related fatalities. Third, using Dubin-McFadden's discrete-continuous model, we estimate that the present value of US consumer surplus from the introduction of residential air conditioning (AC) in 1960 ranges from $83 to $186 billion ($2012) with a 5% discount rate. The monetized value of the mortality reductions on high temperature days due to AC accounts for a substantial fraction of these welfare gains.

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I. Introduction

The accumulation of greenhouse gases (GHGs) in the atmosphere threatens to alter the climate dramatically and in a relatively short period of geological time. While much attention has been devoted to reducing GHG emissions, comparatively little has been devoted to understanding how societies will adapt to climate change. Adaptation, according to the Intergovernmental Panel on Climate Change (IPCC), is defined as "adjustment in natural or human systems in response to actual or expected climatic stimuli or their effects, which moderates harm or exploits beneficial opportunities" (IPCC 2007). These adjustments can take the form of alterations in the uses of existing technologies and/or the invention of new technologies. The poor state of knowledge about adaptation opportunities and adaptation's costs proves a challenge both for developing reliable estimates of the costs of climate change and for identifying solutions to the risks that climate change poses.

The health and broader welfare consequences of increases in temperatures are an area of special concern. For example, the identification of adaptation opportunities that can reduce the human health costs of climate change is recognized as global research priority of the 21st century (WHO 2008; NIEHS 2010). This need is especially great in developing countries where high temperatures can cause dramatic changes in life expectancy (Burgess et al. 2014). High temperatures, beyond their health consequences, can have a range of other negative consequences, including causing workers to be less productive, making it difficult for children to study, and generally leading to less pleasant lives (Hsiang 2010, Sudarshan et al. 2014).

This paper provides the first large-scale empirical evidence on long-run adaptation opportunities through changes in the use of currently existing technologies. The empirical analysis is divided into three parts. The first part documents a remarkable decline in the mortality effect of temperature extremes: the impact of days with a mean temperature exceeding 80° F has declined by about 70% over the course of the 20th century in the United States, with almost the entire decline occurring after 1960. The result is that there are about 14,000 fewer fatalities annually than if the pre-1960 impacts of mortality still prevailed. At the same time, the mortality effect of cold temperatures declined by a substantially smaller amount. In effect, U.S. residents adapted in ways that leave them largely protected from extreme heat.

The second part of the analysis aims to uncover the adaptations that muted the relationship between mortality and high temperatures. We focus attention on the spread of three health-related innovations in the 20th century United States: residential electricity, access to health care, and residential air conditioning (AC). There are good reasons to believe that these innovations mitigated the health consequences of hot temperatures (in addition to providing other services). Electrification enabled a wide variety of innovations including fans, refrigeration, and later air conditioning. Increased access to health care allowed both preventative treatment and emergency intervention (e.g., intravenous administration of fluids in response to dehydration, see Almond, Chay and Greenstone (2006)). Air conditioning made it possible to reduce the stress on their thermoregulatory systems during periods of extreme heat.

The empirical results point to air conditioning as a central determinant of the reduction of the mortality risk associated with high temperatures during the 20th century. Specifically, the diffusion of residential AC after 1960 is related to a statistically significant and economically meaningful reduction in the temperature-mortality relationship at high temperatures. Indeed, the adoption of residential air conditioning explains essentially the entire decline in the relationship between mortality and days with an average temperature exceeding 80 °F. In contrast, we find that electrification (represented by residential electrification) and access to health care (represented by doctors per capita) are not statistically related to changes in the temperature mortality relationship.

The mortality analysis is conducted with the most comprehensive set of data files ever compiled on mortality and its determinants over the course of the 20th century in the United States or any other country. The mortality data come from newly digitized state-by-month mortality counts from the United States Vital Statistics records, which is merged with newly collected data at the state level on the fraction of households with electricity and air conditioning and on the number of doctors per capita. These data are matched to daily temperature data, aggregated at the state-month level, for the 1900-2004 period.

These data are used to fit specifications that aim to produce credible estimates of the relationship between mortality rates and high temperatures, as well as the adaptations that modify that relationship. Specifically, the baseline specification includes state-by-month (e.g., Illinois-by-July) fixed effects and year-by-month (e.g., 1927-by-March) fixed effects, so the estimates are identified from the presumably random deviations from long-run state-by-month temperature distributions that remain after non-parametric adjustment for national deviations in that year-by-month's temperature distribution. The baseline specification also includes a quadratic time trend that varies at the state-by-month level and in the preferred specification state-level per capita income that is allowed to have a differential effect across months. Further, the models control for current and past exposure to temperature, so the estimates are robust to short-term mortality displacement or “harvesting”.

Although quasi-experimental variation in AC adoption is unavailable, three sets of additional results lend credibility to the findings about the importance of residential AC. First, residential AC penetration rates do not affect the mortality consequences of days with temperatures below 80 °F, suggesting that the adoption of AC is not coincident to factors that determine the overall mortality rate. Second, the protective effect of residential AC against high temperature exposure is substantially larger for populations that are more vulnerable (i.e., individuals age 65 or older and blacks, relative to whites). Third, residential AC significantly lessened mortality rates due to causes of death that are physiologically and epidemiologically related to high temperature exposure (e.g., cardiovascular and respiratory diseases). In contrast, residential AC is not associated with causes of death where there is little evidence of a physiological or epidemiological relationship with high temperature exposure (e.g., motor vehicle accidents or infectious diseases).

The third part of the analysis develops a measure of the full consumer surplus associated with residential AC, based on the application of Dubin-McFadden's (1984) discrete-continuous model. This analysis is conducted with household-level Census data on AC penetration rates and electricity consumption, as well as data on electricity prices. We find that AC adoption increases average household electricity consumption by about 1,100 kwh or 11.6%. We estimate that the gain in consumer surplus associated with the adoption of residential AC ranged from $5 to $10 billion (2012$) annually at the 1980 AC penetration rate, depending on the assumptions about the shape of the long run electricity supply curve. This translates into an increase in consumer surplus per U.S. household in 1980 of $120 to $240. The present value of US consumer surplus from the introduction of residential AC in 1960, which is the first year in which we measure the AC penetration rate, ranges from $83 to $186 billion ($2012) with a 5% discount rate.

The paper contributes to several literatures. First, a nascent literature that aims to uncover adaptation opportunities that are available in response to climate change with existing technologies (e.g., Auffhammer and Schlenker (2014), Klein et al. (2014), Hsiang and Narita (2012)). Second, there is a voluminous literature that explains the tremendous increases in life expectancy over the course of the 20th century that has to date not recognized the systematic role of air conditioning (e.g., Cutler et al. 2006). Third, an important literature has examined the welfare consequences of technical progress in household production, especially in appliances (e.g., Bailey (2006), Coen-Pirani et al. (2010), Greenwood et al. (2005)).

The paper proceeds as follows. Section II presents the conceptual framework where we review the physiological relationship that links temperature and health, and the mechanisms that link the modifiers to the temperature-mortality relationship. Section III describes the data sources and reports summary statistics. Section IV presents the econometric models used to examine the evolution of the temperature-mortality relationship and the causes of its change over the 20th century, as well as the results from fitting these models. Section V develops a measure of the consumer surplus associated with the adoption of residential AC. Section VI interprets the results and Section VII concludes.

II. Conceptual Framework

This section reviews evidence on the temperature-mortality relationship and discusses the three innovations that are candidate explanations for the decline in hot day mortality rates. It also outlines how we estimate the welfare effects of residential AC, which the empirical section finds as easily the most important of the three innovations.

A. The Temperature-mortality Relationship

The human body can cope with exposure to temperature extremes via thermoregulatory functions. Specifically, temperature extremes trigger an increase in the heart rate to increase blood flow from the body to the skin, which can lead to sweating in hot temperatures or shivering in cold temperatures. These responses allow individuals to pursue physical and mental activities within certain temperature ranges. However, exposure to temperatures outside these ranges or exposure to temperature extremes for prolonged periods of time endangers human health and can result in mortality.

An extensive literature has documented a non-linear relationship between temperature and mortality. Hot temperatures are associated with excess mortality due to cardiovascular, respiratory, and cerebrovascular diseases (see, e.g., Basu and Samet 2002 for a review). For one, hot temperatures are associated with increases in blood viscosity and blood cholesterol levels. Exposure to cold days has also been found as a risk factor for mortality (e.g. Deschenes and Moretti 2009). Exposure to 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 increased levels of red blood cell counts, plasma cholesterol, and plasma fibrinogen (Huynen et al. 2001). For these reasons, the empirical model allows for a non-linear relationship between daily temperatures and mortality.

B. Three Innovations

We focus on three important technological and public-health innovations of the 20th century United States that are plausible explanations for the changing temperature-mortality relationship. These innovations are access to health care, electricity, and residential air conditioning. Utilization and availability of these innovations varied across states and over time, which help identification of their effects on the temperature-mortality relationship. Some of these innovations have more direct effects on heat-related mortality by mitigating health impacts as they happen, e.g. air conditioning. However, any of the innovations could reduce heat-related mortality indirectly by raising health capital throughout the year and, thus, mitigating mortality risk from a heat-related health shock (or any health shock for that matter).

Access to Health Care. Health care could mitigate heat-related mortality risk by treating heat-related health complications such as heart attacks and heat stroke as they occur (Kovats et al 2004). It could also raise overall health capital, which would help populations tolerate the additional stress from exposure to temperature extremes. As we discuss below, both access and the returns to health care varied substantially over time, which has implications for identification.

Medical personnel and hospitals are two potential measures of "access to health care" at the state-level. For medical personnel, one could use doctors and/or nurses per capita. For hospitals, one could use number of hospitals or numbers of hospital beds. All of these measures are imperfect proxies without detailed data on location, distance, prices, incomes, and, during later periods, insurance. We focus on doctors per capita, largely because they provided, and continue to provide, the majority of patient care outside and inside hospitals.[1] To the extent that doctors per capita is a noisy measure of access, we expect our estimates to be biased downward for measurement error reasons.

Any measure of health care access is complicated by changes in quality of care over time. In the early part of the twentieth century doctors had limited ability to improve health, which, according to the Flexner Report (1910), was at least partially due to the poor quality of most medical schools and doctors (Hiatt and Stockton 2004). Medical historian Edward Shorter concluded, "It would be unwise to exaggerate the therapeutic accomplishments of the modern doctor before 1935."[2] So, one might expect that mortality would be unaffected by – or possibly negatively affected by – doctors and hospitals.

By the mid-1940s, public health and medical training had improved, sulfa drugs were available, antibiotics were becoming available, and hospitals were better able to offer meaningful care (Rosenberg

[1] Roemer (1985) provides some insight into this. Families with median income had 2.5 physician contacts and 0.06 hospital visits per person per year in 1928-1931. In 1981, families with median income had 4.6 physician contacts and 0.12 hospital visits per year.

[2] Shorter (1996) quoted in Murray (2007), p. 108.

1987, Duffy 1993). Health stock was largely attributable to primary care doctors, who had the most contact with the patients and could treat some heat-related complications, like heat exhaustion and heat stroke. Individuals with heart attacks were better off trying to reach hospitals, although the protocols for treatment were not particularly well developed (Fye 1996). Overall, there was a much stronger case to believe that access to health care reduced the mortality effects of hot days by the 1940s.

By the 1960s and 1970s, access to medical care was improving on multiple fronts. More doctors were available per capita thanks to expansion of medical schools, and these doctors were better trained. Due to programs like Hill-Burton, far more counties had hospitals or were adjacent to counties with hospitals than ever before.[3] In hospital treatment of heat-related illness had progressed as well due to advances in intravenous and oral rehydration and improvements in treatment protocols for heart attacks (Rosamond et al 1998). These health advances, in particular, may have dampened the relationship between heat shocks and mortality. With these trends in mind, our empirical model allows the health care access modifier to have differential impacts across the pre-1960 period and post-1960 period.

Access to Electricity. In 1900, only 3 percent of households had electricity, and virtually all of these homes were in urban areas. Urban areas were electrified first, because of the dense location of housing and limited transmission distances.[4] Rural regions were not economically attractive to electric utilities. By 1930, 68 percent of dwellings had electricity. Eight-five percent of urban and rural non-farm dwellings had electricity, while only 10 percent of farm dwellings had electricity. By 1943, 81 percent of dwellings had electricity, though still only 40 percent of farm dwellings. In 1956, the last year national summaries are available, 99 percent of all dwellings and 96 percent of farm dwellings had electricity.[5]

Residential access to electricity can modify the impact of temperature extremes on health through at least three channels. First, electricity access made the pumping of water feasible on a wide scale, bringing running water into many households for the first time. Indoor water reduced the chances of dehydration, reduced exposure to disease like hookworm and typhoid that are associated with outdoor toilets (Brown 1979), and improved hygiene that helped prevent the spread of bacteriological and viral conditions whose spread varies with temperature. Second, electricity allowed the mechanical

[3] Hill Burton was designed to address shortages of hospitals and hospital beds in some regions of the United States. In 1948, 22 percent of counties did not have a hospital. From 1947 to 1971, $3.7 billion in construction subsidies were provided to build or modernize hospitals. For more on the program, see Chung et al. 2012.

[4] On the history of electrification, see Nye (1990).

[5] Carter et al (2006). Table Db234–241 Electrical energy – retail prices, residential use, and service coverage: 1902–2000. http://hsus.cambridge.org/HSUSWeb/toc/tableToc.do?id=Db234-241

refrigeration of food that made it possible to store more food for longer periods of time, postponing and/or preventing spoilage and associated food poisoning during heat. Third, electricity permitted artificial indoor temperature control by fans and electric heaters that could contribute to lowering excess morality associated with temperature extremes.

As with access to health care, the returns to electrification likely varied over time. Our estimates of the effect of electrification are driven primarily by variation in rural areas, between 1929 and 1960. Thus, these results should be interpreted as acting through the technology of the period available in rural areas, and largely independent from air conditioning (as explained in the next subsection).

Residential Air Conditioning. Access to AC at home or in cooling centers is often at the top of the list of medical guidelines to treat and prevent heat-related illness (CDC 2012). Thermoregulation is the physiological process by which core body heat produced through metabolism and absorbed from ambient temperatures is dissipated to maintain a body temperature of 37 °C or 98.6 °F. A rise in the temperature of the blood by less than 1 °C activates heat receptors that begin the process of thermal regulation by increasing blood flow in the skin to initiate thermal sweating (Bouchama and Knochel 2002). Heat-related illness results from the body's inability to dissipate heat produced by metabolic activity. Due to the strong connection between ambient temperature and heat-related illness, air conditioning is probably the most prominent technology used to reduce the risks of heat stress. [6]

In terms of policy prescription, electrification is a necessary condition for adopting air conditioning. Consequently, the estimated effect of air conditioning will necessarily only be externally valid to settings where electricity is readily available.

C. Welfare Consequences

The empirical section finds that residential AC is the most important of these three innovations for reducing hot day mortality, so estimates of AC's welfare consequences are naturally of interest to researchers and policymakers. Below, we estimate the welfare consequences of the reductions in hot day mortality by multiplying the number of avoided fatalities by the value of a statistical life. However, the full welfare effects of AC extend well beyond mortality and certainly include reduced rates of morbidity, increased indoor comfort, and greater productivity. Indeed, it has been claimed that the availability of residential AC is a major reason for the population shift to the South over the last several decades (Gordon (2000), Holmes (1998)). To obtain a more complete measure of the welfare effects of

[6] Rogot et al. (1992) report cross-tabulations of in home AC status and mortality and finds that mortality is reduced in summer months among the population with residential AC.

the introduction of AC, we estimate the area between the electricity demand curves of households with and without AC, using the discrete-continuous two-stage model pioneered by Dubin and McFadden (1984).

III. Data and Summary Statistics

The empirical exploration of the temperature-mortality relationship is conducted with the most comprehensive set of data files ever compiled on mortality and its determinants over the course of the 20th century in the United States or any other country. These data are complemented with micro data on electricity prices and quantities, along with AC penetration, that allows for estimation of the demand for electricity among households with and without AC. This section describes the data sources and presents some summary statistics.

A. Data Sources

Vital Statistics Data. The data used to construct mortality rates at the state-year-month level for the 1900-2004 period come from multiple sources. Mortality data are not systematically available in machine-readable format before 1959. The unit of analysis is state-year-month because these are the most temporally disaggregated mortality data available for the pre-1959 period.[7] For the years prior to 1959, state-year-month death counts were digitized from of the Mortality Statistics of the United States annual volumes. Death counts by demographic group (e.g. over 65 years old, white, etc.) or information by cause of death (e.g. cardiovascular) are not available at the state-year-month level in these data.

From 1959 to 2004, our mortality data come from the machine-readable Multiple Cause of Death (MCOD) files. These data have information on state and month of death for the universe of deaths in the United States. However, geographic information on state of residence in not available in the public domain MCOD files starting after 2004, which explains why we limit our sample to the years up to 2004. Note that the MCOD data also include information on the demographic characteristics of the decedent as well as the cause of death. Therefore, for the 1959-2004 period, we can estimate impacts on demographic groups that are potentially more vulnerable to heat-related health shocks. For this latter period, we separately explore the relationship between temperature and causes of death that

[7] States began reporting mortality statistics at different points in the early 1900s. For example, only 11 states reported mortality data in 1900, but 36 states were reporting by 1920. Texas was the last state to enter the vital statistics system in 1933. See Appendix Table 1 for the year in which each state enters the vital statistics registration system. No vital statistics data were reported in 1930.

are plausibly related to high temperatures (e.g., cardiovascular and respiratory deaths) as well as causes of death that are unrelated to high temperature (e.g., infectious disease).

We combine the mortality counts with estimated population to derive a monthly mortality rate (per 100,000 population). Population counts are obtained from two sources. For the pre-1968 period, we linearly interpolate population estimates using the decennial Census (Ruggles et al. 2010). For the years 1969 through 2004, we use state-year population estimates from the National Cancer Institute (2008).

The final sample consists of all available state-year-month observations for the continental United States over the 1900-2004 period. Per capita income is only available for 1929 onwards (Bureau of Economic Analysis 2012). Further, as noted earlier, vital statistics were not reported in 1930, so our preferred specifications that control for per capita income focus on the 1931-2004 period.

Weather Data. The weather station data are drawn from the National Climatic Data Center (NCDC) Global Historical Climatology Network-Daily (GHCN-Daily), which is an integrated database of daily climate summaries from land surface stations that are subjected to a common set of quality assurance checks. According to NCDC, GHCN-Daily contains the most complete collection of U.S. daily climate summaries available. The key variables for the analysis are the daily maximum and minimum temperature as well as the total daily precipitation.[8,9]

To construct the monthly measures of weather from the daily records, we select weather stations that have no missing records in any given year. On average between 1900 and 2004 there are 1,800 weather stations in any given year that satisfy this requirement, with around 400 stations in the early 1900s and around 2,000 stations by 2000. The station-level data is then aggregated to the county level by taking an inverse-distance weighted average of all the measurements from the selected stations that are located within a fixed 300km radius of each county's centroid. The weight given to the measurements from a weather station is inversely proportional to the squared distance to the county centroid, so that closer stations are given more weight. Finally, since the mortality data are at the state-year-month level, the county-level variables are aggregated to the state-year-month level by taking a

[8] Wind speed can also affect mortality, especially 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 ambient temperature levels in explaining mortality rates (Kunst et al. 1994).

[9] Daily humidity data are not available in the GHCN-Daily data. Using U.S. data from the 1973-2002 period, Barreca (2012) shows that controlling for humidity has little impact on aggregate estimates of the effect of temperature on mortality since temperature and humidity are highly collinear. As such, the absence of humidity data is unlikely to be an important concern here. Nevertheless, we consider a model where precipitation and temperature are interacted.

population-weighted average over all counties in a state, where the weight is the county-year population. This ensures that the state-level temperature exposure measure correspond to population exposure, which reduces measurement error and attenuation bias.

Doctors Per Capita. We have collected state by decade counts of physicians from the decennial censuses of 1900 to 2000 (Ruggles et al. 2010). The 1900, 1980, 1990, and 2000 censuses are 5% samples, and the 1910, 1920, 1930, 1940, 1950, 1960, and 1970 are 1% samples. We construct physicians per 1,000 by dividing the physician counts by the total population.[10] Finally, we linearly interpolate the rates across the census years.

Electrification Data. We collected information on the share of US households with electricity for the years between 1929 and 1959. We focus on this period since per capita income data are available for these years, and electrification coverage was nearly 100% by 1959. The electrification data come from digitized reports of the Edison Electric Institute and its predecessor, the National Electric Light Association.[11] These reports list the number of electricity customers by state and year. To our knowledge, these are the most comprehensive data available on electricity for this time period. For example, the US Census Bureau's (1975) standard reference, *Historical Statistics of the United States*, uses these data. The denominator of the electrification rate (i.e., the number of occupied dwellings) comes from the decennial US Census of Population.[12]

Residential AC Data. We construct a data series on AC ownership rates for the 1960-2004 period at the state-year level from the 1960, 1970, and 1980 U.S. Census of Population. For the 1960-1980 period, we linearly interpolate state-year ownership rates between each decennial census. We then linearly extrapolate state-year ownership rates from 1980 to 2004 using the annual rate of change between the 1970 and 1980 censuses, and bound the AC ownership rate at 100%. The state-year series on AC ownership rate (like the other modifiers we consider) is then merged to the state-year-month

[10] The occupational codes are based on 1950 definitions for consistency across censuses.

[11] The data are from: The Electric Light and Power Industry (1930); The Electric Light and Power Industry in the United States (1940, 1950); and the Electric Utility Industry Statistics in the United States (1959). Bailey and Collins (2011) use these same data to investigate the role that electrification played in the post-World War II baby boom. The Census of Electrical Industries provides another possible electricity data source. We chose not to use these data because much of the state data do not distinguish domestic or residential from commercial and industrial customers; and because some state-year cells are suppressed or combined for confidentiality reasons.

[12] The 1940, 1950, and 1960 come from Haines (2005). For 1930 only, we digitize housing data from a printed volume of the 1930 census. The 1930 census did not record the number of occupied dwellings. However, the 1930 census does record the number of "homes," as distinct from the number of "dwellings." In the *Historical Statistics of the United States* (US Census 1975), the 1930 census count of "homes" is equated with the number of "occupied housing units."

data on mortality rates. Thus AC ownership rates are restricted to be constant across months within a year.

The decennial censuses, despite the limited temporal coverage, are the best data for our purposes given we require state-level identifiers. Detailed housing and energy expenditure surveys like the American Housing Survey (AHS) and Residential Energy Consumption Survey (RECS) contain information on AC ownership beginning in the mid-1970s. However, in the AHS the smallest geographical identifier is the MSA of residence, while in RECS it generally is the Census division.[13] Given that our analysis is conducted at the state level, data from AHS and RECS is not detailed enough geographically to construct a data series at the state-year level.

We address the possible concerns related to imputation though linear interpolation in an array of ways. First, we note that any measurement error in the AC ownership rate series will be unrelated by construction to other key variables in the regressions models, namely mortality rates and temperature. Thus, this measurement error would tend to attenuate the estimated protective effect of AC. Second, we show in Appendix Figure 1 that the interpolated data are highly correlated with independent estimates from other nationally representative surveys that do not include state-level identifiers. Finally, we conduct a robustness check based on alternative specifications and restricting our estimation sample to the years immediately preceding/following the 1960, 1970, and 1980 census (i.e., the years with fresh AC ownership information in the Census) so as to mitigate measurement error with the interpolation of AC ownership rates. As we show below, the estimated effects are very similar to those found in the full sample are and statistically significant.

Electricity Quantities and Price Data. We use household-level data from the 1980 U.S. Census of Population to infer electricity consumption quantities.[14] Specifically, the sample is limited to occupied dwellings with non-missing air conditioning and non-missing electricity expenditure data. We define electricity consumption as the reported electricity expenditure divided by the residential-sector electricity price. The data on prices comes from the State Energy Database System (SEDS), which we obtained from the Energy Information Agency (EIA). The final estimation sample includes 3.7 million

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[13] In some years, RECS reports AC ownership statistics for the 4 largest population states is reported (CA, TX, NY, FL).

[14] The U.S. Census of Population contains information about AC ownership in 1960, 1970, and 1980. However, the necessary information on annual electricity expenditure (which we use to derive annual electricity consumption) is only available in 1970 and 1980. We focus on the 1980 sample only since the 1970 one contains relatively fewer households and because 1980 represents the middle of the post-1960 sample period relevant in the rest of this paper (1960-2004).

unique households. Quantities are measured in thousands of kilowatt-hour and prices are in ($2012) dollars per kilowatt-hour. More details about the sample construction are presented in the appendix.

B. Summary Statistics

Weather and Mortality Rate Statistics. The bars in Figure 1 depict the average annual distribution of daily mean temperatures across ten temperature-day categories over the 1900-2004 period. The daily mean is calculated as the average of the daily minimum and maximum. The temperature categories represent daily mean temperature less than 10 °F, greater than 90 °F, and the eight 10 °F wide bins in between. The height of each bar corresponds to the mean number of days of exposure per year for the average person; these national means are calculated as population-weighted means. In terms of high temperature exposure, the average person is exposed to about 20 days per year with mean temperatures between 80 °F and 89 °F and 1 day per year where the average temperature exceeds 90 °F.[15]

Our core empirical model estimates a non-linear temperature-mortality relationship using these ten bins. As we discuss below, the model restricts the marginal effect of temperature on mortality to be constant within 10 °F ranges. Further, the station level temperature data is binned and then the binned data is averaged as described in Section III A.; this approach preserves the daily variation in temperatures, which is important given the considerable nonlinearities in the temperature-mortality relationship (Barreca 2012, Deschenes and Greenstone 2011).

Table 1 summarizes the mortality rates and temperature variables for the whole U.S. and by U.S. climate regions as defined by the National Oceanic and Atmospheric Administration (NOAA). Within this classification, each state is assigned to one of nine regions with similar climates (Karl and Koss 1984).[16] The focus on climate regions allows us to test the hypothesis that the impact of temperature extremes on mortality is inversely related to baseline climates, as basic adaptation theory would suggest.

To highlight differences over time, Table 1 reports averages separately for the 1900-1959 and 1960-2004 periods. Over the 1900-1959 period the average annual mortality rate was 1,111 per 100,000 population, and this rate declined to an average of 885.8 over 1960-2004. Temperatures were increasing over our sample period. For example, the average number of days with daily average temperature ranging from 80-89°F is 23.3 over 1900-1959 and 26.0 over 1960-2004. There is also sizable variation

[15] On days where the daily *mean* temperature exceeds 90°F, the daily *maximum* temperature was 106 °F, on average. The minimum daily temperature on these days was 80 °F, on average.
[16] Other definitions of climate zones based on county or other sub-state boundaries exist.

across the different climate regions. Average exposure to 80-89 °F days in the South is about 70 days per year but only 2 in the Northwest.

There was also an increase in >90 °F days over the two sample periods. There were 0.5 days and 1.1 day per year in the 1900-1959 and the 1960-2004 periods, respectively. Not surprisingly, the national mean number of >90°F days masks important variation across climate zones. For example, there is almost no exposure to >90°F temperature-days in the climate zones at higher latitudes (i.e. from the Northeast to the Northwest). The West, Southwest, and South have the highest number of >90 °F days. Notably, the remarkable increase in exposure to >90°F temperature-days in the Southwest (from 3 to 14) is driven to a large extent by changes in population within this area after 1960. When pre-1960 population weights are used, the post 1960 average annual days per year in excess of 90°F is about 7. Thus, population mobility played an important role in explaining increased exposure to high temperatures after 1960. The primary specifications in the below analysis are weighted to reflect contemporaneous population, the qualitative findings for the 1960-2004 period are unchanged when each state's observation is weighted by its average population from the 1900-1959 period.

Modifiers of the Temperature-Mortality Relationship. Table 2 summarizes the trends over time in the three modifiers of the temperature-mortality relationship. Importantly for identification purposes, there is both cross- and within-state variation in the rate of diffusion of the modifiers or technologies. The subsequent analysis exploits this variation, while also adjusting for likely confounders.

Doctors Per Capita. Through the 1930s, the number of physicians per capita actually declined as the medical profession focused on training fewer individuals to a higher standard. This change was recommended in the influential 1910 Flexner Report. As Table 2 illustrates, the number of physicians per capita was relatively constant through 1960, at which point it began to rise (Blumenthal 2004). The 2004 average is 2.9 doctors per 1,000 population.

Electrification. Table 2 reports that 69% of US households had access to electricity by 1930. Notably, only 36-37% of households in the South and Southeast had electricity by 1930 compared to 90% of households in the Northeast. By the early 1960s, essentially all households in the US had access to electricity. Thus, variation in adoption rates in the pre-1960 period will drive the estimates of the impact of electrification on the temperature-mortality relationship.

Residential Air Conditioning. Table 2 illustrates the fraction of households with residential AC in the United States. Prior to the mid-1950s, the share of households with AC was negligible, even though residential AC had been developed and marketed since the late 1920s (Biddle 2008). At the same time, many office buildings, movie theaters and shops offered AC to their patrons, so a large share of the population was likely aware of the benefits of this technology. Following a 1957 regulatory change that allowed central AC systems to be included in FHA-approved mortgages, central air conditioning became more common (Ackermann 2002). The percent of households with AC was 12% in 1960, 55% in 1980, and 87% in 2004.

Table 2 also highlights some of the key geographical differences in residential AC adoption. Although South and Southeast states were slower to receive residential electricity, they were quicker to adopt AC with our diffusion measuring reaching complete adoption by 2004. Residential AC is likely to offer more indoor comfort and health benefits to a resident of a warm climate than to a resident of a more moderate climate.

Electricity Quantities and Prices.

The last 3 columns of Table 2 report summary statistics for household-level electricity consumption (measured in thousands of kwh) and state-level prices. The underlying micro data from the 1980 Census of Population allows us to separate between the households that owed and did not owned AC units in 1980. There are clear differences in electricity consumption across the nine climate zones, reflecting in part differences in climate and electricity prices. Not surprisingly, households with AC units consume about 2,500 kwh per year more than households without. The AC contrast is especially notable in some of the warmer group of states (South, Southeast) where the difference across AC status exceeds 4,000 annual kwh.

IV. The Evolution of the Temperature-mortality Relationship over the 20th Century

This section describes the models that we estimate to infer the relationship between mortality and daily temperatures, as well as factors that modify that relationship. It then describes the results from fitting these models.

A. Econometric Approach

We begin by describing the regression models used to estimate the temperature-mortality relationship. These models are identified by plausibly random inter-annual variation in state by month weather distributions. Specifically, we estimate variants of the following equation:

$$(1)\ \log(Y_{sym}) = \sum_j \theta_j TMEAN_{symj} + \pi_L LOWP_{sym} + \pi_H HIGHP_{sym} + X_{sym}\beta + \alpha_{sm} + \rho_{ym} + \varepsilon_{sym}$$

where $\log(Y_{sym})$ is the log of the monthly mortality rate in state s, year y, and month m. The vector of control variables, X_{sym}, includes the share of the population living in urban areas and the share of the state population in one of four age categories: less than one (infants), 1-44, 45-64 and 65+ years old.[17] All of these covariates are interacted with month indicators. Whenever possible, the vector also includes interactions of log per capita income with calendar month to account for the possibility that changes in annual income provide relatively greater health benefits across months of the year. In practice, per capita income is available at the state level from 1929 onwards, and since there are no vital statistics data in 1930, the preferred specification sample that controls for per capita income interacted with month indicators begins in 1931. Finally, the vector also includes a quadratic time trend that is allowed to vary at the state-month level to control for smooth changes in local mortality rates over time.

The specification also includes a full set of state-by-month fixed effects (α_{sm}) and year-month fixed effects (ρ_{ym}). The state-by-month fixed effects are included to absorb differences in seasonal mortality (which is the largest in the winter months and smallest in the summer months). These fixed effects adjust for permanent unobserved state-by-month determinants of the mortality rate, such as fixed differences in hospital quality or seasonal employment. The year-by-month fixed effects control for idiosyncratic changes in mortality outcomes that are common across state (e.g., the introduction of Medicare and Medicaid).

The variables $LOWP_{sym}$ and $HIGHP_{sym}$ are indicators for unusually high or low amounts of precipitation in the current state-year-month. More specifically, these are defined as indicators for realized monthly precipitation that is less than the 25th ($LOWP_{sym}$) or more than the 75th ($HIGHP_{sym}$) percentiles of the 1900-2004 average monthly precipitation in a given state-month. In the interest of space, we do not report the estimated coefficients associated with these variables. In the remainder of this paper, we refer for the specification of the control variables that includes the state-by-month fixed effects, year-by-month fixed effects, quadratic time trend interacted with state-month indicators, the two precipitation indicators, the share of population living in urban areas and the share of the state population in one the four age categories (all interacted with month indicators) as the 'baseline set of covariates'.

The variables of central interest are the measures of temperature $TMEAN_{symj}$. These TMEAN variables are constructed to capture exposure to the full distribution of temperature and are defined as

[17] There is no data available at state-year-month level that identifies vital statistics separately for rural and urban populations. As such, we control for urban population shares interacted with month in all specifications to account for the possibility that trends in urbanization are correlated with changes in high temperature exposure.

the number of days in a state-year-month where the daily mean temperature is in the jth of the 10 bins used in Figure 1. In practice, the 60–69 °F bin is the excluded group so the coefficients on the other bins are interpreted as the effect of exchanging a day in the 60 °F – 69 °F bin for a day in other bins.[18] The primary functional form restriction implied by this model of temperature exposure is that the impact of the daily mean temperature on the monthly mortality rate is constant within 10 °F intervals. The choice of 10 temperature bins represents an effort to allow the data, rather than parametric assumptions, to determine the temperature-mortality relationship, while also obtaining estimates that are precise enough that they have empirical content.

We also use a more parsimonious model that focuses entirely on the upper and lower tails of the daily temperature distribution. Specifically, we focus on 3 "critical" temperature-bin variables: the number of days below 40° F, the number of days between 80 and 89° F and the number of days above 90 °F. Thus the number of days in the 40° F – 79° F bin is the excluded category in this case. This choice of degree-days bins is informed by the estimated response function linking mortality and the 10 temperature-day bins. As we show below, estimates of the θ parameters associated with high daily temperatures (i.e., 80-89 °F and >90 °F) are very similar across the different models so we will heavily rely on the parsimonious approach to present the estimation results.

Regardless of the functional form of the weather variables, the θ_j parameters are identified from inter-annual variation in temperature realizations. Specifically, the specification exploits inter-annual variation in month of the year (e.g., June) temperatures after adjustment for the covariates and non-parametrically controlling for national shocks to the mortality rate at the month by year (e.g., June 1956) level. It is difficult to think of potential confounders that would remain after fitting such a rich specification, suggesting that the identifying assumption is likely to be credible.

The aim of equation (1) is to capture changes in the mortality rate that are associated with meaningful changes in life expectancy. However, it is has been shown that spikes in daily or weekly mortality rates are often immediately followed by periods of below trend mortality (Braga et al. 2001). Thus, examinations of the day-to-day correlation between mortality and temperature may overstate the substantive effect of temperature on life expectancy. In the other direction, the possibility of delayed effects (e.g., cold temperature leading to pneumonia that leads to death several weeks later) means that day-to-day temperature mortality associations may understate the loss of life expectancy.

[18]A normalization is necessary since the number of days in a given month is constant and the temperature-day bins always sum to that constant.

Our model has two safeguards against the possibility of both of these forms of inter-temporal mortality displacement. First, it is estimated at the monthly level, rather than daily-level, so these dynamics will naturally be less of a concern. Second, the preferred model includes temperature variables for the current and prior month and the below tables report the cumulative dynamic estimate of temperature effects by summing the estimated coefficients for each of the two months. This is a conservative modeling approach since 2 months is a longer exposure window than has been used in much of the previous literature.[19] Longer exposure windows are examined as a robustness check in Table 5 and Appendix Figure 2.

We now describe the augmented models used to quantify the effects of each modifier on the temperature-mortality relationship. In this case, equation (1) is augmented by adding interactions of the temperature variables with state-by-year measures of our three modifier variables. Specifically, we estimate:

$$(2)\ \log(Y_{sym}) = \sum_j \theta_j TMEAN_{symj} + \sum_j \delta_j TMEAN_{symj} \times MOD_{sy} + MOD_{sy}\phi + \pi_L LOWP_{sym} + \pi_H HIGHP_{sym} + X_{sym}\beta + \alpha_{sm} + \rho_{ym} + \varepsilon_{sym}$$

Equation (2) is identical to equation (1), except for the addition of main effects for the modifiers (denoted by MOD_{sy}) and their interactions with the temperature variables. The modifier variables control for determinants of annual mortality rates at the state-by-year level that covary with the adoption of the relevant modifier. The 60–69 °F temperature bin is again the excluded group among the j temperature ranges. Thus, the interaction of a modifier with a temperature bin variable measures whether the effect of an additional day in a given temperature range on the mortality rate is affected, relative to the effect of the modifier on the mortality impacts of a day in the 60–69 °F range. For example, in the case of AC, this specification assess whether the availability of AC alters the mortality effect of a day where the temperature exceeds 90 °F, relative to the effect of AC on the mortality effect of a day in the 60–69 °F range.

Our hypothesis is that the coefficients on the interaction terms (δ_j) will be negative at the extreme temperature categories. A negative coefficient would be interpreted as evidence that the diffusion of a particular modifier reduced a population's vulnerability to temperature extremes, relative to the modifier's effect on the mortality impact of days in the 60–69 °F range. In particular, the modifier variables are expected to play a key role in dampening the mortality effects of high temperatures (e.g.

[19] Most papers in the epidemiology literature consider displacement windows of less than 3 weeks. Deschenes and Moretti (2009) use a window of 1 month in their baseline specification, Barreca (2012) uses a two-month exposure window, and Deschenes and Greenstone (2011) implicitly use a window of up to 1 year.

days >90 °F). Further in the case of air conditioning, the interaction between AC and low temperatures (e.g., below 60 °F) serves as a placebo check since AC will not directly protect people from low temperatures. This underscores that any threats to internal validity need to differentially affect mortality on days with temperatures at either end of the temperature distribution.

More broadly, the variation in the modifiers is not experimental, nor is it based on inter-annual variation in weather realizations, so it is natural to question whether the estimated δ_j coefficients are likely to be unbiased. For concreteness, consider the interaction of AC prevalence with the variable for the number of days where the temperature exceeds 90 °F. Since the regressions include state-by-month fixed effects and state-by-month trends, any source of bias cannot operate through fixed state-by-month differences (e.g., Arizona has a high AC penetration rate and high number of >90 °F days, along with a sick population) or gradual changes in seasonal mortality (e.g., the Arizona population is gradually becoming more vulnerable to summer temperatures and increasing the adoption of AC). Rather, the threat to identification comes from unobserved determinants of mortality that covary with both a year's realization of > 90 °F days and the AC adoption rate. So, for example, if households tended to purchase AC in a given year and there was also an increase in purchases of fans for personal cooling in that year, then the beneficial effects of AC would be overstated due to confounding AC with the effects of fans. Alternatively if people installed AC in abnormally hot months that coincided with increases in latent mortality risk, the beneficial effects of AC would be understated.

Our judgment is that such potential sources of bias are unlikely to be important factors in the estimation of equation (2), although we cannot rule them out. As one further check on this concern, the key robustness check table for the effect of AC (Table 8) report on specifications that control for the interaction between the temperature variables and a linear time trend. This allows for the possibility that mortality risk from exposure to temperature extremes parametrically changed over time for reasons unrelated to the modifiers.

Finally, two additional econometric issues bear noting for the estimation of equations (1) and (2). First, the standard errors are clustered at the state level, which allows the errors within states to be arbitrarily correlated over time.[20] Second, we estimate the models using GLS, where the weights correspond to the square root of the contemporaneous state population. The estimates of mortality rates from large population states are more precise, so GLS corrects for heteroskedasticity associated

[20] This approach is more conservative (though possibly less efficient) than modelling the pattern of serial correlation directly. Bertrand, Duflo, and Mullainathan (2004) and Cameron and Miller (2013) find that this approach to estimating the confidence region obtains hypothesis tests with correct size even with panel data of around 50 states that include a variety of fixed effects.

with these differences in population size. Further, the GLS results reveal the impact on the average person, rather than on the average state.

B. Estimates of the Temperature-Mortality Relationship

Daily Mean Temperatures. Figure 2 (a) presents estimates of the temperature-mortality relationship from the fitting of the 10 bin version of equation (1) to data from 1900-2004. Recall that the temperature exposure window for all figures is 2 months and that the figure reports the associated cumulative dynamic estimates. The specification includes the baseline set of covariates, but exclude month×log per capita income interactions (since these data are only available beginning in 1929). The figure plots the regression coefficients associated with the daily temperature bins (i.e. the θ_j's) where the 60-69 °F bin is the reference (omitted) category. That is, each coefficient measures the estimated impact of one additional day in temperature bin j on the log monthly mortality rate, relative to the impact of one day in the 60-69° F range.

The figure reveals that mortality risk is highest at the temperature extremes, and particularly so for temperatures above 90 °F. The point estimates underlying the response function indicate that swapping a day in the 60-69 °F range for one above 90 °F increases the mortality rate by approximately 1% (i.e. 0.98 log mortality points), while an additional 80-89 °F day increases the mortality rate by about 0.2%. Cold temperatures also lead to excess mortality: the coefficients associated with the lowest three temperature bins (i.e. < 10, 10-19, and 20-29 °F) range from 0.7% to 0.8%. All estimates associated with temperature exposures above 80 °F and below 60 °F are statistically significant at the 5% level. This U-shaped relationship is consistent with previous temperature-mortality research (see Deschenes 2014 and NIEHS 2010 for reviews of the literature), although these are the first comprehensive estimates of the temperature-mortality relationship over the entire 20th century.

Figure 2 (b) plots estimates from the same specification as 2 (a), except that controls for interactions between log per capita income and month are added to the model. As explained above, since the data on per capita income are only available from 1929 onwards, there is no vital statistics reported in 1930, and since we use a 2 months exposure window, the sample period is 1931-2004. Comparison between Figures 2 (a) and (b) indicate that the estimates are robust to controlling for log per capita income, as well as beginning the sample in 1931.

Figures 2 (c) and (d) illustrate how the temperature-mortality relationship has changed over time. Specifically, Figures 2 (c) and (d) plot the estimated coefficients on the temperature bin variables for the 1931-1959 and 1960-2004 periods, respectively. The estimates are adjusted for the same controls as in Figure 2 (b). The "breakpoint" of 1960 was chosen since virtually all U.S. households had electricity by then but only a small fraction had residential AC as of 1960**.**

Two key results emerge from Figures 2 (c) and (d). First, there is a sharp decline in the mortality impact of high temperature days after 1960. Specifically, the relative impact of >90 °F days on mortality declined by a factor of 6 (or by 84%) after 1960. There is a similarly large decline in the mortality impact of days in the 80-89° F range. Second, there is a considerably smaller decline in the impact of low temperatures on mortality. For example, the mortality impact of a <10 °F day declined by only 49%. In sum, vulnerability to temperature extremes declined over the 20th century at both ends of the distribution, but the mortality impact of very high temperatures declined more dramatically. Technologies that interact with high temperatures, therefore, are more likely explanations for these changes, compared to broad health policies and changes in health capital that generically reduce mortality rates.

Figure 3 explores the historical change in the temperature-mortality relationship with more temporal detail. Specifically, it reports estimates of the temperature-mortality relationship based on 3 critical temperature bins (<40°F, 80-89°F, and >90°F) and the specification of equation (1) for 8 distinct periods: 1900-1929, 1931-1939, 1940-1949, 1950-1959, 1960-1969, 1970-1979, 1980-1989 and 1990-2004.[21] As in Figure 2, the plotted coefficients represent the sum of the coefficients on the current and lagged month's temperature bin variables. Two set of estimates are reported. The estimates depicted by the dashed red line (circle markers) are based on models that exclude month*log per capita income interactions but include all other controls, fixed effects and interactions listed in the description of equation (1). The preferred estimates are denoted by the blue line (square markers) and are based on models that add month*log per capita income interactions to the specification. Figures 3(a), 3(b), and 3(c) report the evolution of the coefficient on >90 °F, 80-89 °F, and <40 °F days, respectively.

The results confirm the basic finding in Figures 2(c) and 2(d) that the mortality effect of >90 °F days fell dramatically over the course of the 20th century, especially compared to colder ends of the temperature distribution. Moreover, Figures 3 (a) provide compelling evidence that the biggest period to period decrease in the mortality effect of >90 °F days measured in ln points (-0.0091) occurred between the 1950s and 1960s.[22] This decadal change represents roughly 50% of the post-pre 1960

[21] Estimates for 1900-1929 are pooled to increase the statistical precision since exposure to >90°F days is relatively low before the mid-1920s due to the geographical distribution of the U.S. population.

[22] The apparent increase in the mortality impacts of >90 °F days between 1900-29 and 1930-39 is largely an artefact of the imprecision of the earlier period's estimate; this is evident in the 95% confident interval that ranges

change in the estimated effect of >90° F on log mortality rates. The adoption rate of residential AC greatly increased during the 1960s, so this figure provides some suggestive evidence that this technology may have played an important role. The decline in the mortality effect of days in the 80-89° F range is also notable although it appears that much of it occurred before the widespread adoption of AC. The next subsection more formally tests the hypothesis that air conditioning explains the declines in the mortality effects of hot days.

Table 3 provides an opportunity to quantify the qualitative impressions from Figures 2 and 3 more precisely. In the interest of making the table accessible, the model is simplified to include only three temperature-bin variables: the number of days below 40° F, the number of days between 80-89°F and the number of days above 90°F (thus the number of days with mean temperature between 40°-79° F is excluded). This simpler functional form is motivated by the estimates in Figure 2 that suggested that the θ_j's were approximately equal in the below 40° F and 40° - 79° F categories. As in Figures 2 and 3 and the remainder of the paper (unless otherwise noted), we use cumulative dynamic models that include the current and previous month's temperature bins and allow their effects to differ; the reported entries for each temperature bin are the sum of coefficients from the two months. All estimates are adjusted for the full set of covariates outlined in the description of equation (1) and that is henceforth referred to as the baseline specification. Finally, the three columns of Table 3 correspond to different estimation periods used in Figure 2: 1931-2004, 1931-1959, and 1960-2004.

The Table 3, Panel A results confirm the findings above that temperature extremes increase mortality risk and that there was a sizable decline in the temperature-mortality relationship across decades. Over the 1931-2004 period, for example, one additional day with a mean temperature above 90 °F leads to a 0.9 percent increase in the monthly mortality rate (relative to one day between 40-79 °F). A comparison of columns (2) and (3) reveals that this effect declined by more than 80% between the 1931-1959 and 1960-2004 periods (from 2.16% to 0.34%). The mortality impacts of days between 80-89°F and days below 40°F also fell across the two sample periods (1931-1959 and 1960-2004), with a comparable percent decline in the effect of days in the 80-89°F range and a smaller decline in the effect of cold days.

Panel B reports on a specification that decomposes daily average temperature into its daily minimum and maximum temperatures components, but is otherwise identical to the model used in Panel A. This specification allows for an examination of potential non-linear effects at temperature

from -0.0264 to 0.0417. Indeed, the null that the 1900-29 and 1930-39 coefficients are equal cannot be rejected at conventional levels (p-value = 0.44).

extremes that could be missed in the mean temperature analyses.[23] Specifically, there are three separate daily temperature bins for a day's maximum and minimum, respectively, thus the effect of any bin is conditional on the effects of the other bins.

The evidence confirms our core finding above that there was a significant dampening of the temperature-mortality relationship at high temperatures, but also suggests that the change was not uniform across the diurnal temperature range. Specifically, there is a relatively larger decline in the effects of high daily *minimum* temperatures (i.e., >80° F and 70-79° F) in the later period, as opposed to a decline in the effect of high daily *maximum* temperature (i.e., >100°F). For example, the >80° F minimum coefficient declines by roughly 95% from 0.0208 to 0.0010, while the percent decline in the coefficient on days with a maximum above 100 °F is smaller.

With regards to the mechanisms underlying the results in Panel B, it is important to note that minimum temperatures are typically achieved at nighttime as opposed to daytime for maximum temperatures. A potential explanation of the Panel B results is that the reduction in the mortality impact of high temperatures is due to changes in the home environment, instead of the workplace environment. This would tend to point to increased usage of *residential* AC leading to reductions in thermal stress in the evenings and night. As one caveat to this interpretation, even when holding daily maximum temperature constant, changes in the daily minimum temperature are likely to be correlated with other climatic factors, e.g. humidity and rainfall that might affect mortality independent of the daily minimum.[24]

Heterogeneity by Climatic Region. Table 4 estimates the temperature-mortality relationship separately by the NOAA U.S. climatic regions defined in Tables 1 and 2. It allows us to document any heterogeneity in the response functions across climate areas and test whether areas that are more accustomed to temperature extremes have adapted better such that they have a more muted temperature-mortality relationship. For example, regions that experience high temperature-days more frequently (e.g., West, South, and Southwest) may have higher adoption rates of technologies that mitigate the detrimental impacts of heat or be more familiar with self-protection techniques (e.g., proper hydration).

The estimates reported in Table 4 are from a single regression where the temperature bin variables are interacted with indicators for the nine climate regions by two time periods. In five (six) out

[23] The results are similar when we control for daily minimum and maximum temperature-bins in the same regression models or if these variables enter in separate regression models.
[24] The spread of temperatures, which might be important for health outcomes, is also mechanically determined by diurnal temperatures.

of nine regions, the impact of >90°F and 80-89 °F days on mortality is positive and statistically significant, both in the pre-1960 and post 1960 periods. The mortality impact of hot days tends to be largest in the regions (e.g., Northeast, Central, East North Central, and West North Central) where such days are the least frequent. Using an F-test, we can easily reject the null hypothesis (p-values < 0.01) that the estimated effect of >90°F days is equal across climate zones in the pre-1960 and post-1960 samples, respectively.[25] This finding of larger effects in cooler places is consistent with the idea that hotter places adapt to the higher temperatures and the heterogeneity suggests that these adaptations are costly (otherwise all places would undertake them).

With respect to changes over time, the post 1960 estimates of hot days on mortality are generally smaller than their pre-1960 counterparts. For example, the null hypothesis of equality across periods *within* the following five climate zones is rejected for the >90° F coefficients: Central, East North Central, West, and Southwest, and South. There is less evidence of within climate zones declines for the 80-89°F coefficients. See Barreca et al. (2015) for a more thorough examination of the regional differences in the impacts of hot days on mortality rates and the implications for adaptation to climate change.

Robustness tests. Table 5 reports on our efforts to probe the robustness of the estimated effect of hot days on mortality and how it changed before and after 1960. The rows detail how the control variables, subsamples, and fixed effects are varied. Columns (1) and (2) report the coefficients for days >90F and columns (3) and (4) report the coefficients for days 80-89F.

The baseline estimates from Table 3, Panel A are reported in row 1 and are intended to be compared with the subsequent rows. It is apparent from row 2 that the results are qualitatively unchanged by allowing for two additional lags of temperature. Further, it is evident from rows 3-4 that the qualitative results are unchanged by stratifying the sample by states that that are above and below median per capita income.[26] The results are also robust to adding controls for state-year estimates of the fraction living on farms, the fraction black, and the fraction of state residents born in a different state (row 5).[27] Row 6 adds interactions between the temperature variables and the precipitation variables (*LOWP* and *HIGHP*) and reports the marginal temperature effects evaluated at the sample means. This addresses the possibility of temperature effects that depend on the degree of humidity, as

[25] The analogous null hypothesis for 80-89° F days is not rejected for the period 1931-1959 (p-value = 0.15), but easily rejected for the 1960-2004 sample (p-value < 0.01).

[26] The medians are calculated over all sample years (and weighted by population), so the assignment of a state to a below or above median group remains constant across all years.

[27] All of these variables are obtained from Decennial population censuses and interpolated across census years. See Almond, Chay and Greenstone (2006) on differential access to health care by race

warmer and wetter days are generally humid. Across all additional specifications, there is no meaningful change in the effects of 80-89°F and >90 °F days.

In addition, we also estimated a variant of the baseline specification (row 1) augmented to include leads in the temperature variables as a "placebo" test: any significant difference in the estimates from the model including leads and the baseline specification would be an indication that the main results may be driven by trends or factors that we fail to control for. There is virtually no difference in the point estimates of the mortality impact of 80-89°F and >90°F temperature-days in the model where leads are added to the baseline specification. Further, the estimated lead coefficients are very small and statistically insignificant.[28] [29]

Overall, Table 5 fails to contradict the earlier findings of an important relationship between mortality rates and hot days prior to 1960 and a marked decline in the magnitude of this effect after 1960. The next subsection explores the roles of increased access to health care, residential electricity, and residential air conditioning in muting the temperature-mortality relationship during the 20th century.

C. The Impact of the Modifiers of the Temperature-Mortality Relationship

Table 6 presents the results from the fitting of several versions of equation (2). It reports on tests of whether the share of the residential population with electricity, log doctors per capita, and the share of the population with residential AC modify the relationship between mortality and daily temperatures. The specifications includes temperature variables for the number of days below 40° F, the number of days between 80-89°F, and the number of days above 90°F (so the number of days with mean temperature between 40°-79° F is excluded). Due to the pattern of the preceding results, the table only reports the relevant modifier interactions (i.e., δ_j) on the >90 °F and 80-89° F days variable, because the preceding results revealed that the mortality effects of hot days changed the most

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[28] We also performed other robustness analyses that are not reported here due to space limitations. Specifically, we have re-estimated the baseline specification for 1960-2004 using 1940 population weights (as opposed to annual population weights for all sample years). 1940 was chosen as it pre-dated the central city to suburban areas mobility that began in the 1950s (see e.g., Baum-Snow 2007). Such mobility could confound our estimates if urban heat island effects are important, and if suburban mobility reduces high temperature exposure (see Arnfield 2003 for a review of urban heat island studies). The estimates are qualitatively unchanged when the fixed 1940 population is used as the weight. We also experimented with interacting population density with the temperature variables in the baseline model: the null that these interactions are equal to zero cannot be rejected.

[29] Specifically, for the pre-1960 sample, the lead coefficients (standard errors) on the >90°F, 80-89°F and <40°F temperature variables are respectively, 0.0015 (0.0015), 0.0002 (0.0002), 0.0000 (0.0003). The corresponding estimates for the post-1960 sample are: -0.0009 (0.0005), -0.0002 (0.0002), -0.0003 (0.0002)

throughout the 20th century. The coefficients for the interactions of the potential modifiers and the <40° F days are reported in Appendix Table 2. Finally, the specifications include the full set of baseline controls and the estimates are based on the current and previous month's temperature realizations.

Columns (1a) through (3a) focus on the 1931-59 period, and columns (1b) through (3b) analyze 1960-2004 data. In 1960 virtually all households in the United States had access to electricity and few households had air conditioning. As such, the estimated modifying effect of electrification is only reported in Panel A, and the estimated modifying effect of residential AC is only reported in Panel B. The effect of doctors per capita can be estimated in both samples. This approach allows the effects of doctors per capita to vary across these two sample periods, which is important given the substantial improvements in the efficacy of treatments for heat stress in the 1950s and 1960s (see Section II). We consider specifications where the effect of each modifier enters individually, as well ones where multiple modifiers enter the same specification.

Over the 1931-1959 period, the share of the population with residential electricity and doctors per capita appear to have little beneficial effect on reducing hot day mortality. Indeed, the coefficients on the interaction of these two modifiers with the number of >90 °F days variable are perversely sign. That is, they suggest that these modifiers *increase* the hot day mortality rate, although they would all be judged to be statistically insignificant by conventional criteria. In the case of the interactions with the variable for the number of days in the in the 80-89 °F range, there is little evidence that the number of doctors or the share of houses with electricity modify the mortality effects of these days. In contrast, Appendix Tables 2 indicates that electrification is associated with statistically significant declines in vulnerability to <40 °F days in this period.

Panel B indicates that the diffusion of residential air conditioning is associated with a sizeable and statistically significant decrease in mortality due to hot days in the 1960-2004 period. The estimates in columns (2b) and (3b) suggest that each 10 percentage point increase in residential AC ownership is associated with a decrease in the mortality effect of >90 °F days by 0.002 log points; this is roughly 10 percent of the effect of a >90 °F day in the pre-1960 period. Thus, the regressions imply that an increase in AC coverage from 0% to 59% (which is the average share of the population with residential AC in the 1960-2004 period) reduces the effect of >90°F days on log monthly mortality rates by 0.0132 (=0.59*-0.0223). In the case of the effect of 80-89°F days, an increase in AC coverage of 59% reduces the effect of an additional day in this range on the monthly mortality rate by .0039 (=0.59*-0.0066).

Panel B also lends insight into the effect of doctors per capita on the monthly mortality rate. It is evident that increasing doctors per capita did not contribute to reducing the mortality effect of a >90 °F day. There is some evidence that the number of doctors reduces the mortality effects of days in the 80-89 °F range in column (1b) but this finding disappears in the richer column (3b) specification that adjusts for air conditioning and its interactions with the temperature variables. Overall, the increase in doctors per capita does not appear to have played a substantive role in the twentieth century's decline in heat-related mortality.[30] [31]

Figure 4 lends further insight into the air conditioning finding. It plots the coefficients (i.e., the δ_j's) on the interaction of the air conditioning variable with the 9 daily temperature bin variables from the estimation of a version of equation (2) where AC is the only modifier and includes the baseline coefficients. For the >90 °F and 80-89 °F temperature bins, the interaction estimates are nearly identical to those in Table 6, indicating that AC reduces the mortality effect of high-temperature days. Consistent with AC use during hot weather being the driving mechanism, the estimated AC-temperature interactions are small, precisely estimated and statistically insignificant, for all temperature bins below 80°F. Any relationship between unobservables, AC, and mortality would need to change in a discontinuous manner around 80°F to bias estimation.

Estimates by Age, Race and Cause of Death. Table 7 presents the air-conditioning modifier analysis by age group, race, and cause of death using the more detailed Multiple Causes of Death data. Based on the results from Table 6, Table 7 only reports the interaction effect between residential air-conditioning and high temperature days (i.e., 80-89°F and >90 °F) from the baseline specification where AC is the only included modifier. Residential AC continues to be measured at the state-by-year level.

It is apparent in Panels A and B that there is a stronger protective effect of AC for more vulnerable populations. The effect of residential air conditioning in mitigating the mortality impact of high temperatures is largest for infants and for the 65+ population. While AC is protective against days where the temperature exceeds 90° F for both whites and blacks, the point estimates suggest that it is more than twice as protective for blacks (although the 95% confidence intervals overlap). In contrast if the point estimates are taken literally, AC does more to mitigate the mortality effects of 80-89° F days for whites.

The estimates in Panel C suggest that the protective effects of AC operate through reduced heat stress, as opposed to alternative channels. Specifically, we find that AC reduces the impacts of high

[30] In contrast, the estimates in Appendix Tables 2 suggest that an increase in the number of the doctors in the population played a role in reducing the mortality effects of days <40 °F over the 1960-2004 period.

[31] In additional analyses, we also considered alternative proxies for access to health care such as nurses per capita and number of hospital beds in a state-year. These additional measures lead to qualitatively similar results as doctors per capita.

temperature days on cardiovascular-related and respiratory-related mortality (columns (1) and (2)). In contrast, there is no significant interaction effect on fatalities due to motor vehicle accidents or infectious disease, suggesting that the AC results do not simply reflect an unobserved reduction in mortality risk due to hot days that is correlated with AC adoption (columns (3) and (4)). A potentially puzzling result is the finding that AC is also associated with reductions in the impacts of >90 °F days on The evidence on neoplasm mortality is mixed, with a statistically significant effect of >90 °F and a smaller and statistically insignificant corresponding estimate for 80-89°F. Overall, these findings are broadly consistent with the decline in hot weather deaths operating through the thermoregulatory channel that has been established in the epidemiology literature (e.g., Basu and Samet 2002).

Robustness Tests. Table 8 presents a detailed robustness analysis of our key findings with regards to air conditioning. Column (1) reports estimates from the baseline specification (i.e., Table 6, Panel B, column 2b). Column (2) reports on a specification that models the state-by-month time trend with a cubic, instead of with a quadratic, which more flexibly controls for unobserved trends that may be correlated with the patterns of AC adoption. These estimates are qualitatively identical to the baseline ones.

Recall, we construct the state-year measure of the share of households with AC using data from the 1960, 1970, and 1980 Censuses of Population by interpolating across census years and then extrapolating beyond 1980. The reliance on interpolation raises legitimate questions about the role of measurement error and other concerns in the baseline results. To explore these questions, column (3) is based on a regression with the observations for 1959-61, 1969-1971, and 1979-1981 only, resulting in a sample of 4,655 observations. Centering these windows around the 3 census years where AC information is available mitigates the bias from imputation-related measurement error.[32,33] Remarkably, the point estimates in column (3) are very similar to those reported in column (1), although they naturally have larger standard errors due to the smaller sample.[34]

The table reports on two additional exercises. Column (4) adds year-by-temperature trends (i.e., interactions between calendar year and the 3 temperature bin variables) in the baseline specification to control for unobserved factors that may lead to a smooth and secular reduction in vulnerability to temperature extremes. This specification leads the coefficient on the interactions of the AC variable with

[32] We thank an anonymous referee for suggesting this approach.

[33] We also estimated a corresponding model for county-year-month data for 1960, 1970, 1980 and found qualitatively similar estimates.

[34] Further, if we restrict the sample to only 1960, 1970, 1980, (N=1,715), the point estimate on the interaction between AC and >90°F is similar (-0.0305), but with a twice larger standard error (0.0701).

the >90° F variable to double and with the 80-89° F variable to increase by more than 40 percent, suggesting that the baseline specification might understate the true effect. Finally, the estimates in column (5) extend the baseline specification to include a 4-month exposure window, leading to a slightly larger estimate of the protective effect of AC on high-temperature days.[35] In sum, the robustness checks in Table 8 support our key finding that the diffusion of residential AC led to a large reduction in heat-related mortality.

V. Developing a Measure of the Consumer Surplus from Residential Air Conditioning

The preceding section finds that the proliferation of residential AC played a critical role in reducing the incidence of heat-related fatalities, yet AC offers other benefits too. These other benefits include increased comfort, reduced morbidity, and increased productivity (Cooper 2002, Biddle 2008), but they can be difficult to measure.[36] AC has also been linked with fundamentally changing the population distribution of the United States by making living and working in the South and Southwest more comfortable, although this too is difficult to measure.

Rather than trying to piece together a measure of the welfare benefits by summing the benefits across a wide variety of sectors, we turn to estimating the full consumer surplus associated with AC. This is measured as the area between the electricity demand curves of households with and without residential AC after correction for selection into AC ownership. Specifically, we apply Dubin and McFadden's (1984) discrete-continuous model for estimating demand to electricity and AC. The basic idea is that households make a joint decision regarding whether to purchase an AC unit and then how much electricity to consume, conditional on the AC ownership decision.

Following this approach, we specify the conditional electricity demand function as:

$$(3)\ q_{\mathrm{is}} = \beta_0 + \beta_1 AC_{is} + \beta_2 p_{is} + X_{is}\gamma + \varepsilon_{is}$$

[35] We also estimated additional models to investigate how the protective effect of AC on high-temperature days may have changed over time. Specifically, we estimate the regression underlying the results in column (1) of Table 8 by decade (1960-69, 1970-79, 1980-89, 1990-04) and found that the protective effect is significant in all decades, but declines over time. The point estimates (standard errors) for the temperature >90°F × AC interaction are 1960-69: -0.0484 (0.0098), 1970-79: -0.0337 (0.0105), 1980-89: -0.0294 (0.0049), 1990-04: -0.0213 (0.0033). Similarly, the temperature 80-89°F × AC interaction are: 1960-69: -0.0038 (0.0022), 1970-79: -0.0100 (0.0021), 1980-89: -0.0082 (0.0010), 1990-04: -0.0070 (0.0012).

[36] Some studies have attempted to measure these benefits. See, for example, Burch and DePasquale (1959) on the benefits to air conditioning hospital wards.

where q_{is} denotes the annual consumption of electricity by household i, residing in state s (measured in million Btu), AC_{is} is an indicator variable denoting the ownership of a AC unit, p_{is} denotes electricity price in state s, and X_{is} denotes a vector of household-level and state-level predictors of electricity demand, including indicators of climate (the long-term average of the temperature bins variables used earlier in the paper), household income, size, number of rooms, number of units in the building, and age of the structure.[37] All household-level and state-level predictors of electricity demand are modelled using dummy variables. The error term, ε_{is}, represents unobserved differences across households in the demand for electricity.

The coefficients of interest in the demand equation (3) are β_1 and β_2, which measure the effects of AC ownership and electricity prices on electricity demand, respectively, after conditioning on the demand shifters in X_{is}. These parameters can be used to infer how electricity demand curves differ for households who do and do not own conditioning units. However, electricity demand and AC ownership decisions are unlikely to be independent. For example, households who prefer cooler temperatures may decide to purchase an air conditioning unit and consume more electricity conditional on their air conditioning choice. Hence, the distribution of ε_{is} among households who decide to purchase air conditioning units may differ from the unconditional distribution of ε_{is}, and failure to account for this correlation would lead to biased estimates of the parameters in equation (3). In practice, this interdependence is embodied in the model by allowing the error terms in the indirect utility function underlying the decision to own or not own an AC unit to be correlated with the error terms in the electricity demand equation.

We follow Dubin and McFadden's control function solution to this garden-style problem of identification. Specifically, we assume that the errors in the AC ownership decision equation are iid extreme value type I and that the errors in the electricity demand equation are functions of the errors in the AC ownership decision equation. In this case, selection correction terms for households that do and do not own AC are $P_{0is}\ln(P_{0is})/(1-P_{0is}) + \ln(P_{1is})$ and $P_{1is}\ln(P_{1is})/(1-P_{1is}) + \ln(P_{0is})$, respectively, where $P_{1is} = \Pr(AC_{is}=1|p_{is},X_{is},Z_{is})$ and $P_{0is} = \Pr(AC_{is}=0|p_{is},X_{is},Z_{is})$. In practice, we obtain estimates of these response probabilities by fitting the following logit equation for owning an AC unit:

$$(4)\ \Pr(AC_{is}=1|p_{is},X_{is},Z_{is}) = \frac{\exp(\alpha_0+\alpha_1 p_{is}+X_{is}\gamma+Z_{is}\delta)}{1+\exp(\alpha_0+\alpha_1 p_{is}+X_{is}\gamma+Z_{is}\delta)}$$

[37] Sub-state electricity price information is not available for our sample.

where X_{is} is defined as above and Z_{is} includes interactions between electricity prices and the climate indicators, dummy variables in the number of rooms, and dummy variables in household size. Thus, identification comes from a combination of the logit functional form and the exclusion of the interactions from the demand equation.

Table 9 reports the estimates of the key parameters from the electricity demand equation. The dependent variable is annual electricity consumed per household (in thousand kWh) and the electricity price is measured in ($2012) dollars per kWh. Column (1) reports estimates from a model that only includes electricity price and the AC indicator as predictors of electricity demand, while column (2) adds an interaction between electricity price and the AC indicator in order to detect if AC ownership changes the slope of the electricity demand curve. Column (3) adds the full set of controls to the specification in (1).

The column (1)-(3) estimates reflect the assumption that cross-state differences in electricity prices do not reflect unobserved variation in residential electricity demand. Typical problems of price endogeneity are less relevant here than in many settings partly because the census microdata let us include rich household- and dwelling-level controls for determinants of heating demand. Additionally, much of the cross-sectional variation in electricity prices is due to differences in fuel shares across states. For example, the availability of cheap hydropower in the West or coal in Appalachia contributes to those states' low electricity prices. Because large differences in fuel shares are across regions of the country, because regional electricity integration helps link electricity prices across states within regions of the country, and because state-level electricity prices may suffer from measurement error, we also report estimates which instrument for electricity prices using Census division indicators (column 4).[38] Finally, we add selection correction terms to the instrumental variables regressions (column 5).[39] Since our measure of electricity prices only varies at the state level, the reported standard errors are clustered at the state level.

There are three key results in the upper panel of Table 9. First, the residential electricity demand curve is downward sloping, with statistically significant point estimates ranging from -53. 6 to -92.3 (these imply price elasticities of demand ranging from -0.8 to -1.3). Second, AC ownership shifts the electricity demand curve to the right as shown by the positive and statistically significant estimates on

[38] The F-statistics on the excluded instruments in columns (4) and (5) are: 10.18 and 10.16, respectively, both with p-values less than 0.001.

[39] Davis and Killian (2011, p. 223) provide analogous arguments for the validity of applying the Dubin-McFadden methodology to cross-sectional energy prices, and they also report results using census region dummies as instruments for natural gas prices.

the AC ownership indicator. Households with residential AC consume more electricity, ranging from 1.1 to 3.4 thousand additional kwh per year, depending on the specification.[40] The more robust specifications suggest an increase of about 1.1 thousand kwh per year, which is about 11.6% of annual electricity consumption of 9.5 thousand kwh during this period. Third, the inclusion of the selection correction terms (which are statistically significant) and instrumenting for electricity prices leads to modest reductions in coefficients. All in all though, the point estimates are qualitatively unchanged and remain statistically significant at the 1% level.[41]

With these estimates of the slope of the demand curve for electricity and some assumptions about the shape of the long-run elasticity of electricity supply curve, it is possible to estimate the gain in consumer surplus associated with the adoption of residential AC. Figure 5 illustrates the consumer surplus inferred from shifts in the electricity demand curve due to residential AC that is measured by the parameter β_1 associated with the AC indicator in the regression for electricity demand. Figure 5a depicts the case where the supply curve is perfectly inelastic and here the gain in consumer surplus is the shaded trapezoid *abcd*. With a linear supply curve (Figure 5b) passing through the origin, the consumer surplus is necessarily smaller and is measured by the difference between trapezoid *efgh* and trapezoid p_0p_1gi. We emphasize that these changes in demand and consumer surplus are driven not by changes in primitive properties of consumer tastes but rather by the availability of residential AC.

The lower panel of Table 9 uses the parameter estimates from the residential electricity demand function to develop empirical estimates of the consumer surplus associated with residential air conditioning. To proceed with this calculation, we need to invert the estimated demand equation and solve for p_{is}. Then we compare the consumer surplus in the residential electricity market at observed prices and demand against the consumer surplus in the residential electricity market that would prevail if no AC was available. The complete derivations underlying this calculation are presented in the Appendix.

The estimated gains in consumer surplus are substantial. We estimate that the gain in consumer surplus associated with the adoption of residential AC ranged from $5 to $10 billion (2012$) annually at the 1980 AC penetration rate, depending on the assumptions about the shape of the long run electricity supply curve. This translates into an increase in consumer surplus per U.S. household in 1980 of $120 to $240. These estimates are statistically significant in all but one of the specifications considered.

[40] We also experimented with a specification that allows the effect of AC on electricity demand to depend on the frequency of >90°F days. We found that AC users in warmer places use about 500 additional kwh per year, although the estimate is not statistically significant.
[41] Nevertheless, the selection correction terms enter the equation statistically significantly

Some complementary statistics help to interpret these estimates. First, these gains in consumer surplus are calculated at the 1980 AC penetration rate and it will naturally be larger in later years as AC proliferated. For example, our interpolation procedure suggests that AC penetration rates were at 85% nationally in 2004, relative to 53% in 1980. This higher rate of penetration would suggest a gain in consumer surplus of roughly $15 to $17 billion with perfectly elastic supply and about $8 billion with linear supply. Second, it is instructive to compare the gain in consumer surplus to the total expenditures on electricity in the residential sector in 1980, which were 90 billion ($2012). Third, the present value in 1960 of the consumer surplus associated with the introduction of residential AC is $83 to $186 billion ($2012), with a 5% discount rate. This is calculated with each year's AC adoption rate through 2004 and then that is assumed to hold constant for the indefinite future.[42]

There are several caveats to these calculations. First, the consumer surplus calculation does not account for the capital costs of AC. Second, the calculations are not adjusted for the social costs of greater electricity consumption, primarily local pollution (Chen et al. 2013) and greenhouse gas emissions (Greenstone and Looney 2012). Third, climate change is causing higher temperatures around the world and that is increasing the demand for AC—these estimates do not account for this increase in demand for electricity (Deschenes and Greenstone 2011). Fourth, these calculations will understate the welfare gains from residential AC because they exclude producer surplus in electricity and/or air conditioning markets. Further, there may be interdependencies or externalities in consumption and production that depend on residential AC penetration that are not captured in household demand for electricity. For example, it is often argued that AC made the South hospitable to a much wider share of the population and that this in turn may have created a cultural and economic boon for the South (Gordon (2000), Holmes (1998)). And, of course, these estimates of the value of residential AC do not account for the productivity benefits of AC in the workplace (Cooper 2002).

VI. Interpretation

The paper's mortality results can be interpreted in several lights. Perhaps the most straightforward is to turn these changes in mortality rates into more readily economically interpretable

[42] Greenwood, Seshardri, and Yorukoglu (2005) estimate that the introduction of household technologies, like washing machines and vacuum cleaners, that helped to increase women's labor supply increased U.S. GDP by over 25 percent and led to even larger welfare gains. The source of the increase in female labor supply is a topic of considerable debate with the role of the pill, social norms, and (the potentially endogenous to technology changes) increases in educational opportunities for women likely all having some claim on the truth.

measures. During the 1931-1959 period, the United States population was 144.1 million and the typical American experienced 1.06 days per year where the temperature exceeded 90° F and 24.1 days in the 80-89° F range. Taking the estimates in Table 3 Panel A literally, there were approximately 12,442 premature fatalities annually due to these high temperature days in this period. The available data do not allow for a precise calculation of the loss in life expectancy, but, due to the choice of the specification, these were not gains of a few days or weeks and were all a minimum of two months. It seems reasonable to presume that the loss of life expectancy for infants (recall Table 7) was substantially longer than two months, perhaps even full lives.

By comparison during the 1960-2004 period, there were an average of 232.2 million Americans and they faced an average of 1.47 days with temperatures above 90° F and 21.7 days in the 80-89° F range. The analogous calculation using the estimates in Table 3 Panel suggests that there were roughly 6,000 premature fatalities annually due to high temperatures in this period. If the earlier period's mortality impact of hot days prevailed over 1960-2004, the annual number of premature fatalities would have been about 20,000.

What role did air conditioning play in this dramatic reduction in vulnerability to hot temperature days? Using the by-age category estimates of the protective effect of residential AC on hot days from Table 7, we find that the diffusion of residential AC during the 1960-2004 period reduced premature fatalities by about 17,000 annually. In light of the sampling errors, it is apparent that we cannot reject that, the widespread adoption of residential air conditioning explains the entire reduction in hot day mortality.

How much was this reduction in mortality worth? We estimate this as the sum of the products of the average annual lives saved and the value of a statistical life (VSL) in different age categories. Among the roughly 17,000 lives that were saved annually between 1960 and 2004, 684 were in the 0-1 age category, 803 in the 1-44 age group, 1225 in the 45-64 category, and 14326 in the 65+ age groups.[43]

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[43] The average annual number of saved lives due to residential AC in each age category was calculated in the following way. For the > 90° F days, let y_{stk} denote the annual mortality rate in state s, year t, and age group k, $\delta^{90}_{AC,k}$ represent the estimated protective effect of AC on >90°F mortality for age group k (from Table 7), AC_{st} denote the average residential AC ownership rate in state s in year t, and $TMEAN^{90}_{st}$ represent the realized number of >90°F days in state s and year t. Then, the avoided deaths on >90°F temperature days due to AC in state s, year t, and age group k is given by:

$$(5)\ \mathrm{AVOID}^{90}_{\mathrm{stk}} = y_{stk} \times \hat{\delta}^{90}_{AC,k} \times AC_{st} \times TMEAN^{90}_{st}$$

The left hand side is summed across all 50 states for each year in the 1960-2004 period and we then take the average across all years. This exercise was then repeated for the 80-89° F days .

Using Ashenfelter and Greenstone's (2004) estimate of the VSL of $2.4 million ($2012) and applying Murphy and Topel's (2006) method for deriving age group-specific VSLs, we find that residential AC generated hot day mortality reductions that were worth roughly $7.4 billion annually on average over the period 1960-2004.

The relevant VSL is very likely a function of the remaining life expectancy and this has implications for the estimation of the willingness to pay for the mortality reductions that are not reflected in the previous paragraph's calculations. For example, many individuals would value lives that are extended by a few days less than those that are extended by several years. To investigate this issue, we estimated versions of equation (1) that include the number of days in the various temperature categories for the current month and each of the preceding 11 months. Appendix Figures 2 A and B plot cumulative estimated impacts of days above >90° F and in the 80-89° F range separately for exposure windows of 1 through 12 months, respectively.[44]

Both figures reveal evidence of harvesting, such that the estimated impact of a hot day declines with the amount of time that the day is allowed to influence the mortality rate. Although the effect of a >90° F day declines as its impact is calculated over longer time periods, it still increases the mortality rate by 1% even when its impact is allowed to emerge over 12 months. It is evident that these days led to the death of individuals with substantial remaining life expectancy. In contrast, we cannot reject that the effect of a 80-89° F day is zero when the estimate is summed over 6 months or longer, suggesting that these days hasten the death of individuals with relatively short (i.e., less than 6 months) remaining life expectancy. An alternative, and extreme, measure of willingness to pay for the health improvements from residential AC would continue to use the above approach for the >90° F days and assign zero value to the 80-89° F days. Such an approach suggests that the residential AC generated hot day mortality reductions were worth roughly $1 billion annually in the 1960-2004 period.

Before proceeding, it is worth noting that these back-of-the-envelope VSL-based valuation approaches involve several assumptions. Further, we have ignored the statistical uncertainty in these estimates, based on the standard errors of the estimated coefficients (including of the VSL). Even with these limitations in mind, it seems reasonable to conclude that the mortality benefits account for a substantial share of the estimated gain in consumer surplus due to the adoption of residential air conditioning.

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[44] Since everyone dies eventually, the estimate coefficient will equal zero when the cumulative dynamic estimate is calculated over a long enough time frame.

A second way to interpret these results is through the lens of climate change and the degree to which currently available technologies can be deployed to limit the damages of climate change and amplify the benefits. State of the art climate change models with business as usual scenarios predict that the United States will have 38.0 additional days per year where the temperature falls into 80-89°F and 42.3 additional days per year where the temperature exceeds 90° F by the end of the century (see e.g., Deschenes and Greenstone 2011). If residential AC adoption were at the 1960 rate of adoption and population was at 2004 levels, then the 1960-2004 Table 6 estimates suggest that the increase in 80-89°F and >90° F days would cause an additional 68,000 deaths annually at the end of the century. However at 2004 rates of residential AC adoption, the null hypothesis that additional 80-89°F and >90° F days would have no impact on mortality cannot be rejected. It is apparent that air conditioning has positioned the United States to be well adapted to the high temperature-related mortality impacts of climate change.

However, many other countries, especially poor ones in the tropics, are currently quite vulnerable to temperature related mortality. As just one measure of the stakes, the typical Indian experiences 33 days annually where the temperature exceeds 90 °F, but this is projected to increase by as many as 100 days by the end of the century (Burgess et al. 2014). Indeed using data from 1957-2000, Burgess et al. (2014) find that one additional day above 90 °F, compared to a day in the 60-69° F range, increases the annual mortality rate in India by about 1% which is roughly 20 times the corresponding response in the United States during essentially the same period.

Are this paper's results instructive for today's poor countries who will need to adapt to climate change? It is challenging to apply results from one country and period to another one in a different period when culture, technology, and many other factors differ. However, climate change is regarded as the biggest global health threat of the 21 century (Costello 2009) and it is critical to develop effective and efficient adaptation strategies, especially for today's poor countries.

In an earlier version of this paper, we showed that there are some striking similarities between the United States before 1960 and developing countries today (Barreca et. al 2012). For example, life expectancy at birth in the United States in 1940 was 63, compared to 65 and 68 in India and Indonesia now, respectively. Infant mortality rates per 1,000 are also comparable, with the US at 47 in 1940, and India and Indonesia at 50 and 27, respectively.

Further, the levels of the three 'modifiers' in the historical United States are comparable to today's developing countries. The fraction of the residential population with electricity was 74% in 1940 in the United States, compared to approximately 65-66% in both India and Indonesia today. The number of physicians per 1000 population was higher in the 1940 United States than in India or Indonesia today; however, the medical technologies were likely worse in the 1940s United States compared to modern day developing countries. Perhaps most importantly given this paper's results, it is striking that no individual had access to residential AC in the United States in 1940, which is qualitatively similar to rural India and Indonesia today and is home to 72% of Indians and 54% of Indonesians.

Given the large benefits of AC for the US population found in this paper, it may be surprising that AC adoption rates are so low in developing countries. One important difference is the electric grid—many Indians lack electricity and those who have it face frequent blackouts and brownouts. But a broader explanation is that adoption of many technologies follows an S-curve, and developing countries like India and Indonesia may not yet be into the middle of that curve. Even in the U.S., AC adoption was not complete almost 50 years after AC became available. An important question for future research is how tradeoffs between health investments like air conditioning and other expenditures occur in developing countries where incomes and the value of health may be lower than in countries like the U.S.

The similarity between the United States before 1960 and many developing countries today suggests that the greater use of air conditioning in these countries would significantly reduce mortality rates both today and in the future. Consequently, a primary finding of this paper is that the wider use of residential air conditioning should be near the top of the list of adaptation strategies to consider in response to climate change-induced warming of the planet.

At the same time, it is probable that the greater use of residential air conditioning will speed up the rate of climate change because fossil fuels (e.g., coal and natural gas) that cause climate change are the most inexpensive sources of energy. Further the abundant supply of coal and dramatic increase in the supply of inexpensive natural gas in the last few years due to advances in unconventional drilling mean that in the absence of a significant *global* price on greenhouse gas emissions, they are likely to remain the cheapest source of energy for the foreseeable future. It therefore seems that residential AC is both the most promising existing technology to help poor countries mitigate the temperature related mortality impacts of climate change and a technology whose proliferation will speed up the rate of climate change. In many respects, this underscores the complicated nature of trying to mitigate the rate of climate change when any solution requires reductions in greenhouse gas emissions by countries with very different income levels.

VII. Conclusion

Using the most comprehensive set of data files ever compiled on mortality and its determinants over the course of the 20th century in the United States or any other country, this paper makes two primary discoveries about mortality during the 20th century. First, we document a remarkable decline in the mortality effect of temperature extremes: The impact of days with a mean temperature exceeding 80° F has declined by about 70% over the course of the 20th century in the United States, with almost the entire decline occurring after 1960. The result is that there are about 14,000 fewer fatalities annually than if the pre-1960 impacts of mortality still prevailed.

Second, the empirical results point to air conditioning as a central determinant in the reduction of the mortality risk associated with high temperatures during the 20th century. Specifically, the diffusion of residential air-conditioning after 1960 is related to a statistically significant and economically meaningful reduction in the temperature-mortality relationship at high temperatures. Indeed, the adoption of residential air conditioning explains essentially the entire decline in the relationship between mortality and days with an average temperature exceeding 80 °F. In contrast, we find that electrification (represented by residential electrification) and access to health care (represented by doctors per capita) are not statistically related to changes in the temperature mortality relationship.

The final part of the analysis aims to develop a measure of the welfare consequences of residential AC adoption. Specifically, we estimate that AC adoption leads to a $5 to $10 billion (2012$) annual increase in consumer surplus at the 1980 AC penetration rate, depending on the assumptions about the shape of the long run electricity supply curve. The present value of US consumer surplus from the introduction of residential AC in 1960 (the first year where we measure the AC penetration rate) ranges from $83 to $186 billion ($2012) with a 5% discount rate. It is noteworthy that the monetized value of the mortality improvements account for a substantial fraction of this gain in consumer surplus.

Adaptation is going to be a critical part of the world's climate strategy. This study has documented that there are tremendous opportunities available to mitigate climate change's impacts on mortality through the use of an existing technology. There are surely meaningful opportunities to deploy existing technologies in many other domains to limit climate damages and this is an urgent area for research. Also of great importance is research into the development of new technologies that have value in a changed climate. Adaptation of both forms offers great promise but it should not be lost that it requires resources that could be used for other purposes. Ultimately, it is a cost of climate change too.

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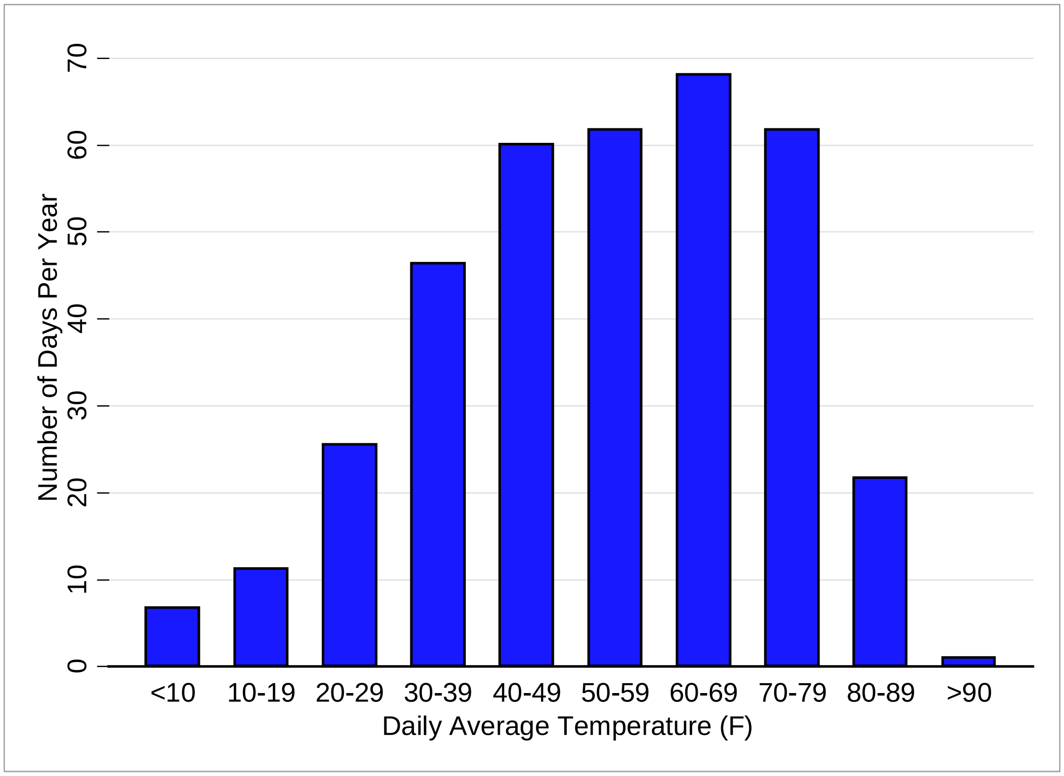
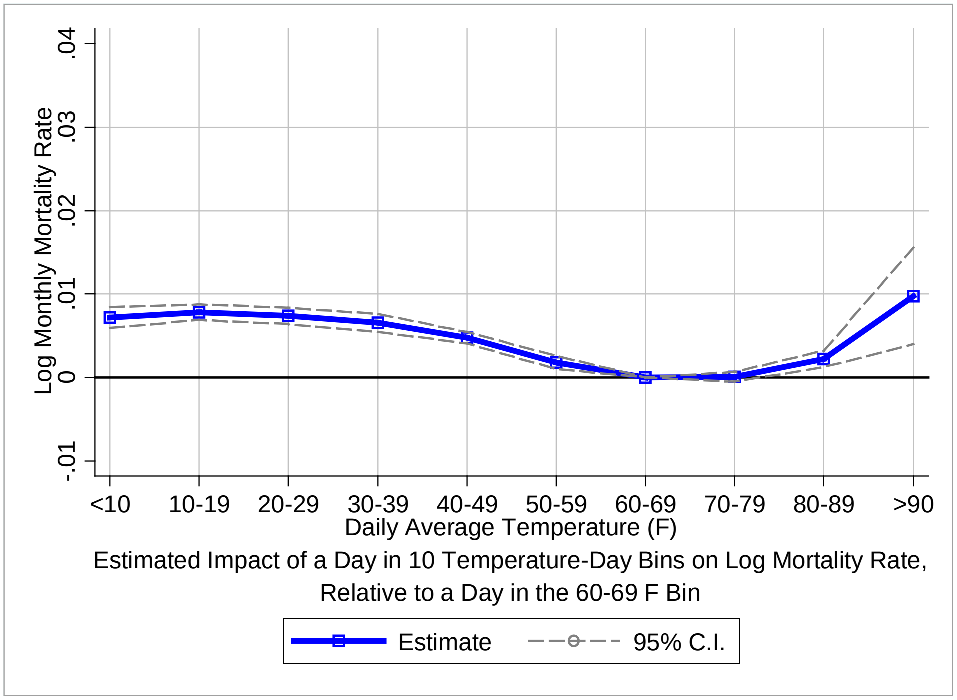
Figure 1: Distribution of Daily Average Temperatures, 1900-2004



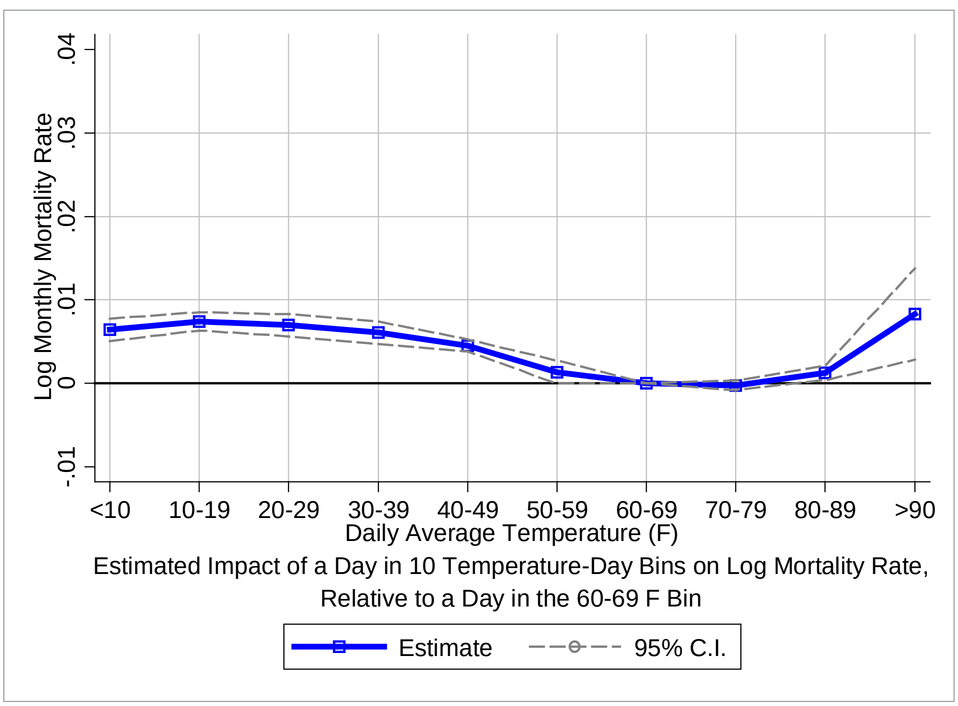
Notes: Figure 1 shows the historical average distribution of daily mean temperatures across 10 temperature-day bins. Each bar represents the average number of days per year in each temperature category over 1900-2004, weighted by the total population in a state-year. See the text for more details.

Figure 2: Estimated Temperature-Mortality Relationship

(a) 1900-2004



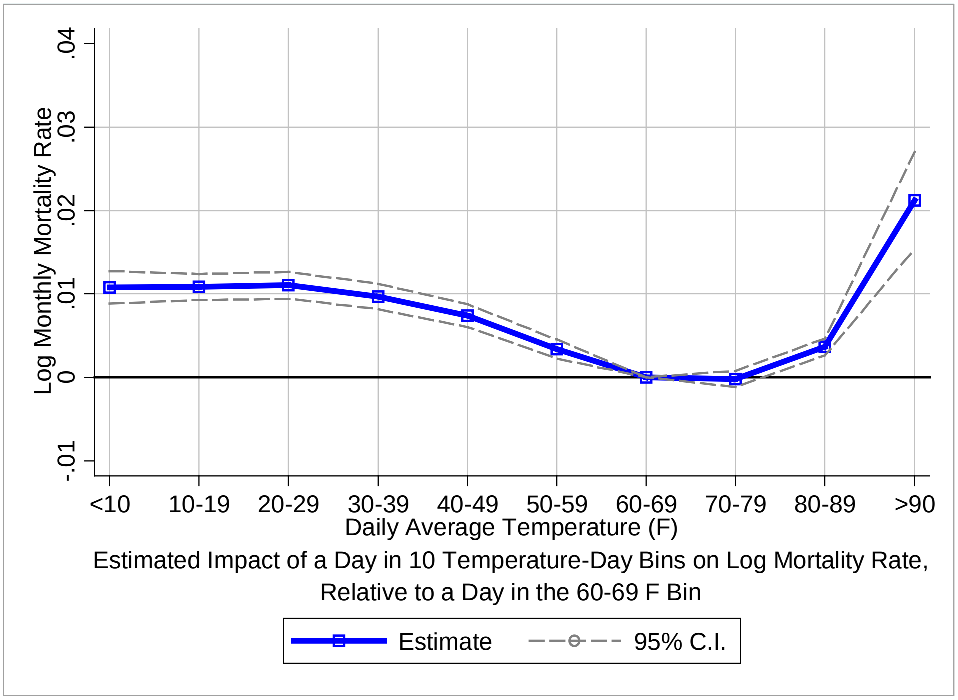
(b) 1931-2004, including controls for log per capita income



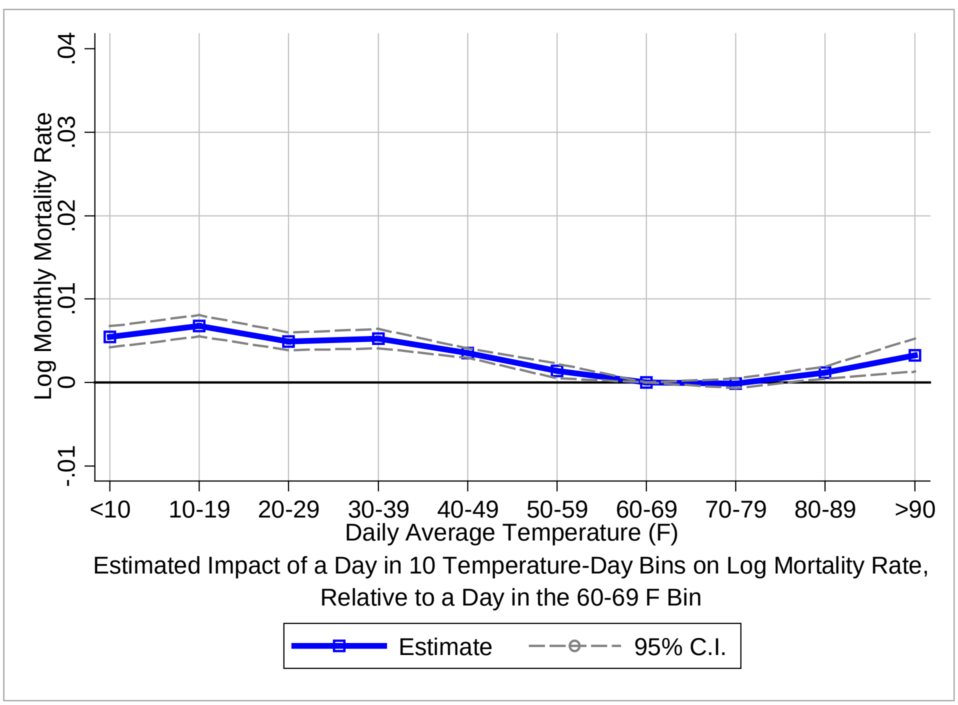
Notes: at end of Figure 2 (d)

Figure 2: Estimated Temperature-Mortality Relationship (Continued)

(c) 1931-1959, including controls for log per capita income



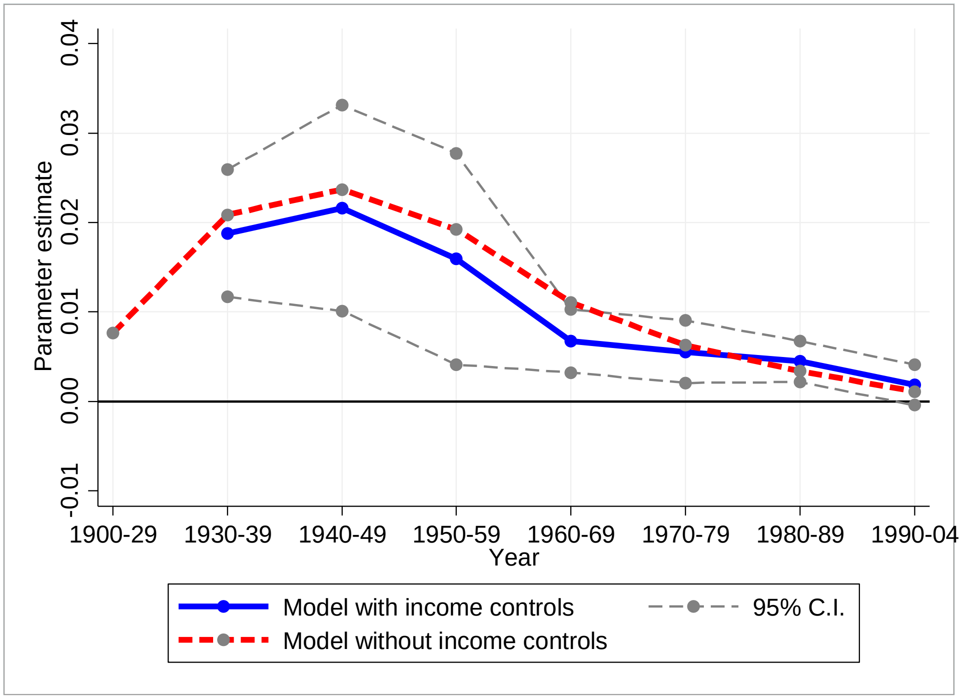
(d) 1960-2004, including controls for log per capita income



Notes: Figure 2 plots the response function between log monthly mortality rate and average daily temperatures, obtained by fitting equation (1). The response function is normalized with the 60°-69° F category set equal to zero so each estimate corresponds to the estimated impact of an additional day in bin j on the log monthly mortality rate relative to the mortality rate associated with a day where the temperature is between 60°-69° F. The dependent variable is the log monthly mortality rate. Temperature exposure window defined as 2 months and 9 temperature-day bin variables are included in the model. Cumulative dynamic estimates are reported. All regressions are weighted by the relevant population. The estimates underlying Figures 2 (b), (c), and (d) include the baseline set of covariates. The estimates underlying Figure 2 (a) are based on same specification, but exclude month×log per capita income interactions. Standard errors clustered on state.

Figure 3: Estimated Temperature-Mortality Relationship, by 10 Year Period

(a) Temperature-days above 90° F



(b) Temperature-days in 80-89° F

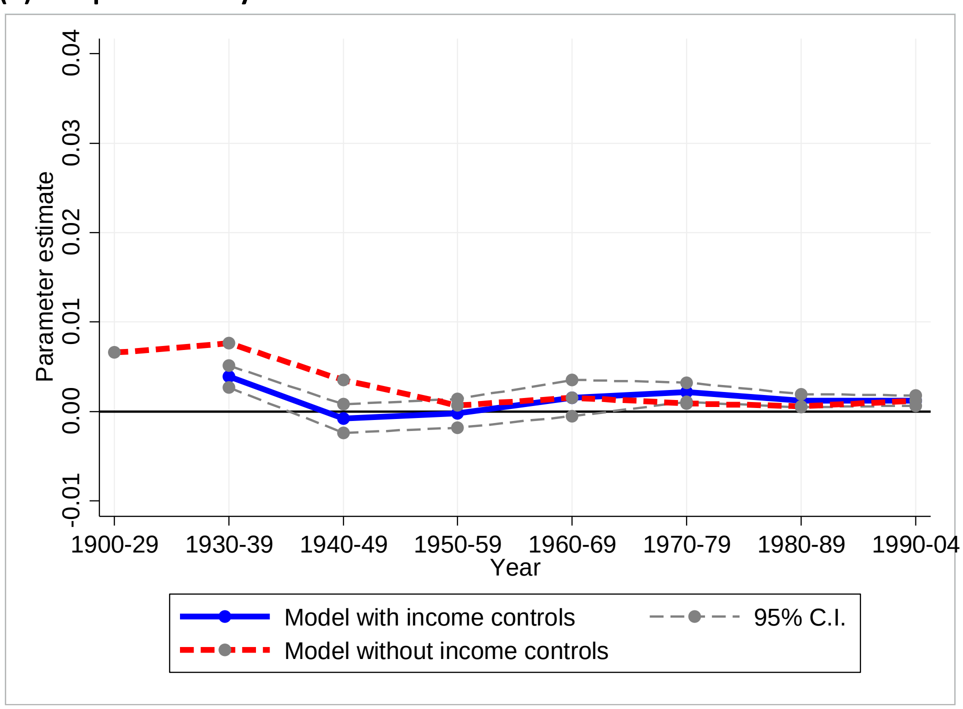
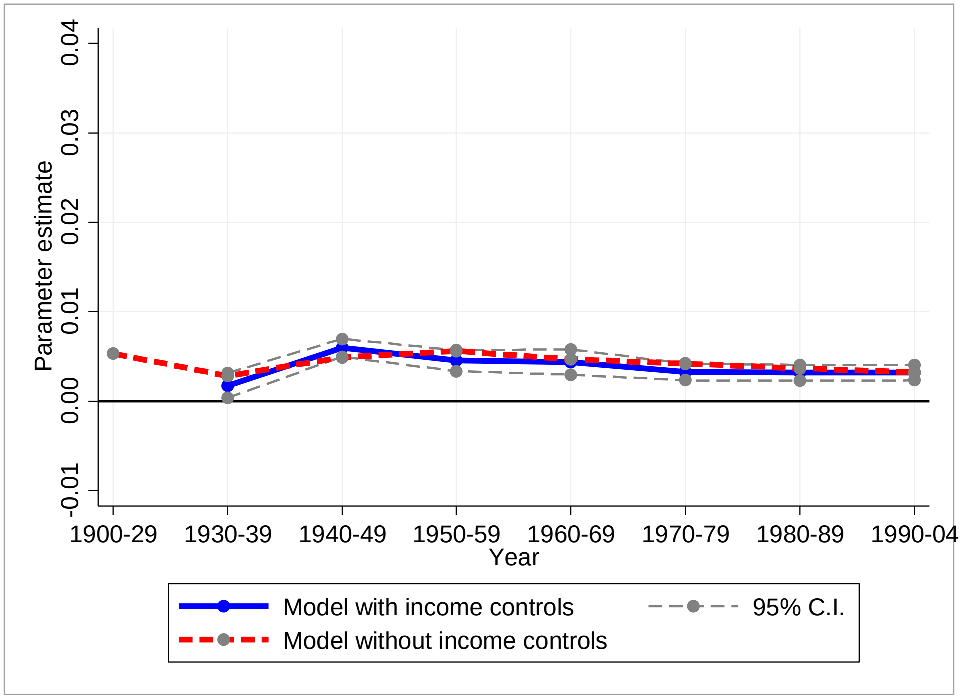


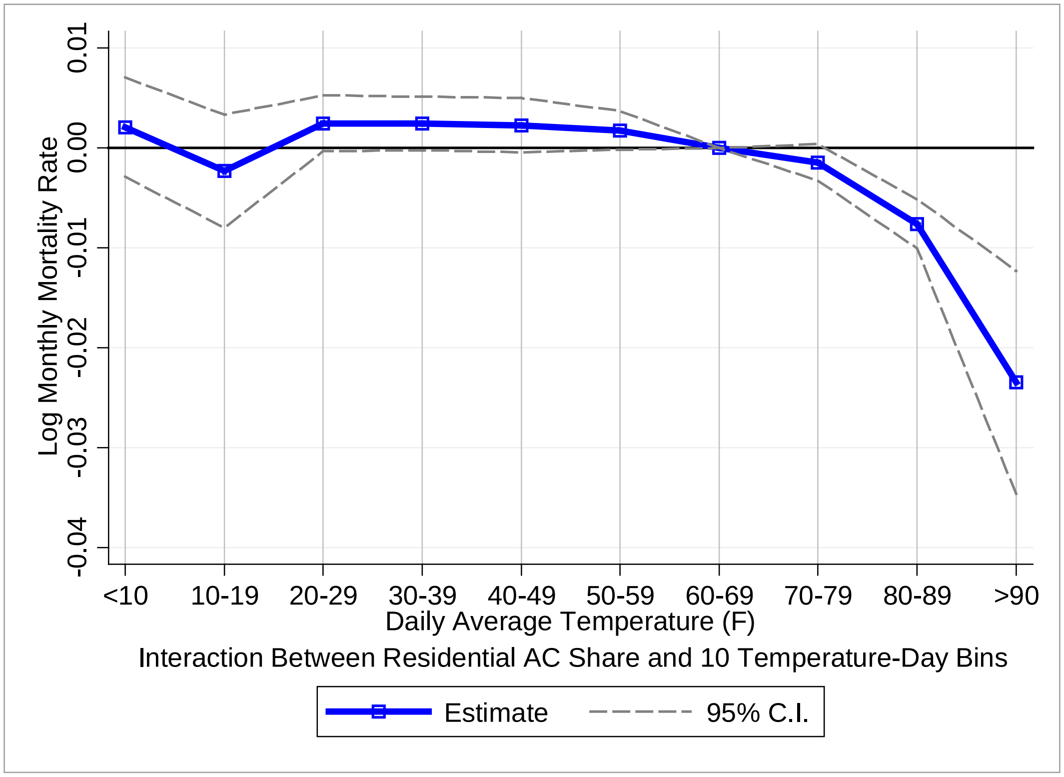
Figure 3: Estimated Temperature-Mortality Relationship, by 10 Year Period (continued)

(c) Temperature-days below 40° F



Notes: Dependent variable is log monthly mortality rate. Temperature exposure window defined as 2 months and 3 critical temperature bins (<40°F, 80-89°F, and >90°F) are included in the model. Estimates for period 1900-29 are pooled to increase precision. Otherwise, all estimates are for 10 year periods listed on the horizontal scale. Estimates denoted by the red (blue) dashed line are based on models that exclude (include) month*log per capita income interactions. Otherwise, baseline set of covariates is included in both regressions. All regressions are weighted by the relevant population. Standard errors clustered on state. See the text for more details.

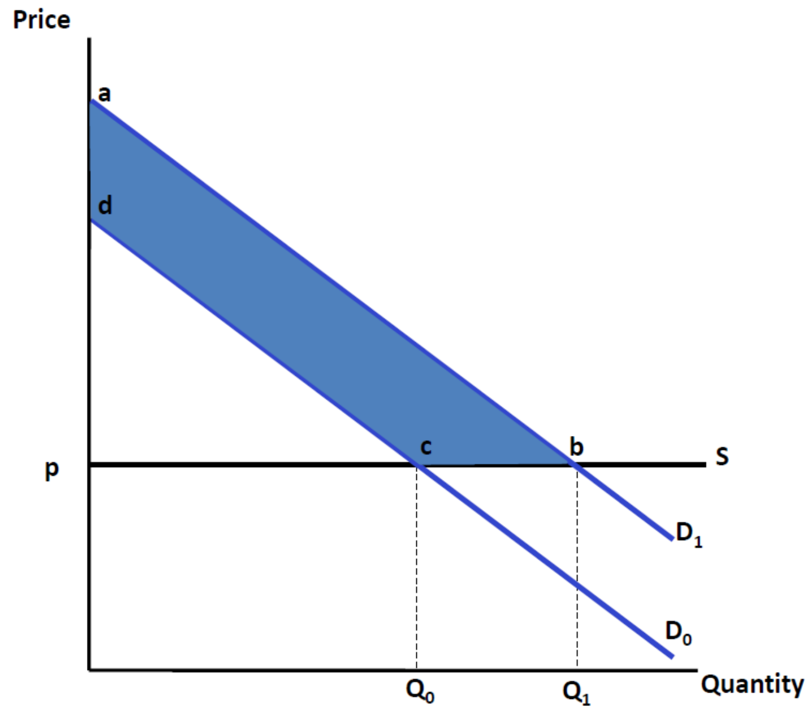
Figure 4: Impact of Residential Air Conditioning on the Mortality-Temperature Relationship, 1960-2004



Notes: Figure 4 plots the δ_j's coefficients associated with the interactions between the share of the population with residential AC and the 9 temperature-day bin variables from the fitting of equation (2) to 1960-2004 data. The dependent variable is the log monthly mortality rate and the specification includes the baseline set of covariates. Standard errors are clustered on state. See the text for additional details.

Figure 5: Consumer Surplus Associated with Shift in Electricity Demand Functions

(a) Perfectly inelastic long-term supply curve



(b) Linear long-term supply curve

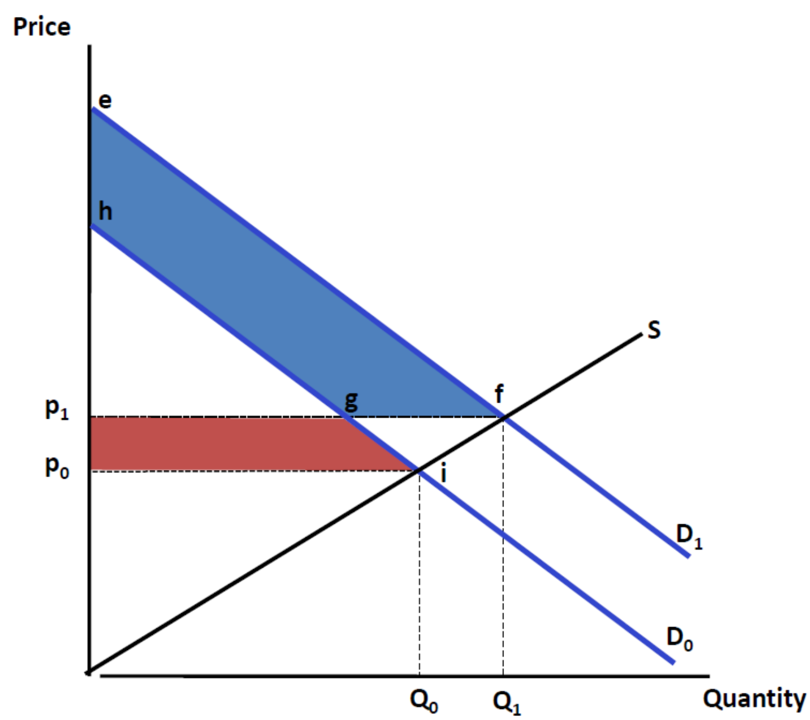


Table 1: Summary Statistics on Vital Statistics and Exposure to Temperature Extremes

	All-Age Mortality Rate:		Annual Days With Mean Temperature:					
			<40° F	<40° F	80-89° F	80-89° F	> 90° F	> 90° F
	1900-59	1960-04	1900-59	1960-04	1900-59	1960-04	1900-59	1960-04
A. National Estimate:	1,110.5	885.8	85.6	73.7	23.3	26.0	0.54	1.14
A. By U.S. Climate Region								
1. Northeast	1,242.8	950.8	110.8	106.6	8.0	9.0	0.1	0.1
2. Central	1113.6	946.6	97.4	100.7	18.7	13.9	0.4	0.1
3. East North Central	1038.9	874.4	141.5	139.5	8.0	5.6	0.1	0.0
4. West North Central	946.4	903.1	141.3	139.2	11.5	9.3	0.5	0.1
5. Northwest	997.4	821.2	76.7	67.3	1.6	2.1	0.0	0.0
6. West	1060.8	748.5	9.1	7.1	9.8	15.0	1.0	2.4
7. Southwest	1036.7	701.6	95.1	74.5	17.7	30.5	3.4	14.1
8. South	945.9	849.9	32.7	29.9	70.7	73.4	2.2	2.0
9. Southeast	1013.8	906.0	33.6	31.2	44.9	53.8	0.1	0.1

Notes: All statistics are weighted by the relevant population. Mortality rate per 100,000 population. US climate regions are defined as follows: Northeast = CT, DE, ME, MD, MA, NH, NJ, NY, PA, RI, VT; Central = IL, IN, KY, MO, OH, TN, WV; East North Central = IA, MI, MN, WI; West North Central = MT, NE, ND, SD, WY; Northwest = ID, OR, WA; West = CA, NV; Southwest = AZ, CO, NM, UT; South = AR, KS, LA, MS, OK, TX; Southeast = AL, FL, GA, NC, SC, VA.

Table 2: Summary Statistics on the Modifiers of the Temperature-Mortality Relationship and Electricity Consumption in 1980

	Number of Doctors Per 1000 Population			Share of Households With With Electricity			Share of Households With Residential Air Conditionning			Electricity Consumption and Prices, 1980		
	1930	1960	2004	1930	1960	2004	1960	1980	2004	Consumption (HH with AC)	Consumption (HH w/o AC)	Prices ($2012) (per kWh)
A. National Estimate:	1.24	1.33	2.90	0.69	1.00	1.00	0.12	0.55	0.87	10.6	8.1	0.14
A. By U.S. Climate Region												
1. Northeast	1.36	1.74	3.90	0.90	1.00	1.00	0.10	0.45	0.76	7.6	6.3	0.17
2. Central	1.25	1.19	2.67	0.66	1.00	1.00	0.12	0.60	0.99	11.1	8.7	0.12
3. East North Central	1.23	1.06	2.69	0.73	1.00	1.00	0.06	0.42	0.80	7.9	7.7	0.13
4. West North Central	0.95	1.17	1.93	0.49	1.00	1.00	0.12	0.51	0.82	10.4	9.7	0.10
5. Northwest	1.41	1.15	2.70	0.81	1.00	1.00	0.05	0.18	0.36	20.0	18.7	0.06
6. West	1.78	1.62	2.59	0.96	1.00	1.00	0.05	0.41	0.77	7.6	5.6	0.14
7. Southwest	1.56	1.71	2.52	0.63	1.00	1.00	0.13	0.52	0.88	9.2	7.3	0.14
8. South	1.03	1.03	2.47	0.37	1.00	1.00	0.26	0.80	1.00	12.1	7.0	0.12
9. Southeast	0.93	0.94	2.81	0.36	1.00	1.00	0.13	0.71	1.00	13.8	9.6	0.13

Notes: All statistics are weighted by the relevant population. US climate regions are defined as follows: Northeast = CT, DE, ME, MD, MA, NH, NJ, NY, PA, RI, VT; Central = IL, IN, KY, MO, OH, TN, WV; East North Central = IA, MI, MN, WI; West North Central = MT, NE, ND, SD, WY; Northwest = ID, OR, WA; West = CA, NV; Southwest = AZ, CO, NM, UT; South = AR, KS, LA, MS, OK, TX; Southeast = AL, FL, GA, NC, SC, VA. Residential electricity consumption in thousand kilowatt hour per year. Residential electricity price in $2012 per kWh.

Table 3: Estimates of the Impact of High and Low Temperatures on Log Monthly Mortality Rate

	Sample:		
	1931-2004	**1931-1959**	**1960-2004**
	(1)	(2)	(3)
A. Daily Average Temperature			
Number of Days Above 90°F	0.0092**	0.0216***	0.0034***
	(0.0028)	(0.0029)	(0.0009)
Number of Days Between 80-89°F	0.0015***	0.0037***	0.0012***
	(0.0003)	(0.0004)	(0.0003)
Number of Days Below 40°F	0.0041***	0.0057***	0.0033***
	(0.0004)	(0.0007)	(0.0003)
B. Daily Minimum and Maximum Temperature			
Daily Minimum Temperature			
Number of Days Above 80°F	0.0025	0.0208**	0.0010
	(0.0023)	(0.0077)	(0.0007)
Number of Days Between 70-79°F	0.0011	0.0034***	0.0006
	(0.0006)	(0.0007)	(0.0005)
Number of Days Below 30°F	0.0036***	0.0051***	0.0027***
	(0.0006)	(0.0009)	(0.0004)
Daily Maximum Temperature			
Number of Days Above 100°F	0.0038***	0.0052***	0.0015*
	(0.0005)	(0.0012)	(0.0006)
Number of Days Between 90-99°F	0.0002	0.0002	0.0005
	(0.0003)	(0.0004)	(0.0003)
Number of Days Below 50°F	0.0015**	0.0021**	0.0014***
	(0.0005)	(0.0007)	(0.0004)
Observations	43,464	17,004	26,411

Notes: Dependent variable is log monthly mortality rate. Temperature exposure window defined as 2 months. Cumulative dynamic estimates are reported. Regressions are weighted by the relevant population. All regressions include baseline set of covariates. Standard errors clustered on state. Asterisks denote p-value < 0.05 (*), <0.01 (**), <0.001 (***).

Table 4: Estimates of the Impact of High and Low Temperatures on Log Monthly Mortality Rate, By US Climate Regions

	Number of Days Above 90°F		Number of Days Between 80-89F°		Number of Days below 40°F	
	1931-1959	1960-2004	1931-1959	1960-2004	1931-1959	1960-2004
	(1a)	(1b)	(2a)	(2b)	(3a)	(3b)
By U.S. Climate Region						
1. Northeast	0.0540	0.0129	0.0042***	0.0025***	0.0038***	0.0025***
	(0.0288)	(0.0146)	(0.0008)	(0.0007)	(0.0007)	(0.0004)
2. Central	0.0337***	0.0183**	0.0036***	0.0019**	0.0043***	0.0024***
	(0.0036)	(0.0067)	(0.0006)	(0.0006)	(0.0009)	(0.0004)
3. East North Central	0.0898***	-0.0316	0.0041***	0.0051***	0.0018*	0.0015***
	(0.0229)	(0.0160)	(0.0007)	(0.0007)	(0.0009)	(0.0002)
4. West North Central	0.0347***	0.0524***	0.0066***	-0.0015*	0.0021**	0.0010*
	(0.0040)	(0.0049)	(0.0012)	(0.0006)	(0.0006)	(0.0005)
5. Northwest	0.0316	0.0987*	0.0039	0.0138***	0.0068***	0.0042***
	(0.2493)	(0.0425)	(0.0070)	(0.0013)	(0.0010)	(0.0006)
6. West	0.0259	0.0056***	0.0049*	0.0037***	0.0225***	0.0160***
	(0.0212)	(0.0005)	(0.0024)	(0.0006)	(0.0034)	(0.0041)
7. Southwest	0.0062**	0.0013*	-0.0013	-0.0012	0.0039**	0.0024
	(0.0021)	(0.0005)	(0.0034)	(0.0009)	(0.0013)	(0.0012)
8. South	0.0166***	0.0026*	0.0027***	0.0008*	0.0083***	0.0052***
	(0.0017)	(0.0011)	(0.0007)	(0.0004)	(0.0019)	(0.0014)
9. Southeast	0.0453	0.0402**	0.0027***	0.0000	0.0114***	0.0053***
	(0.0386)	(0.0138)	(0.0006)	(0.0002)	(0.0014)	(0.0009)

Notes: The dependent variable is the log monthly mortality rate. Temperature exposure window defined as 2 months. Cumulative dynamic estimates are reported. Regressions weighted by the relevant population. All regressions include the baseline set of covariates. US climate regions are defined in the notes of Table 1. Standard errors clustered on state. Asterisks denote p-value < 0.05 (*), <0.01 (**), <0.001 (***). See the text for more details.

Table 5: Estimated Mortality Impact of Temperature-Days Above 90°F, Alternative Samples and Specifications

	Number of Days Above 90°F			Number of Days Between 80-89°F		
	1931-1959	1960-2004	Pre/Post Diff P-Value	1931-1959	1960-2004	Pre/Post Diff P-Value
	(1)	(2)	(3)	(4)	(5)	(6)
1. Baseline (Table 3, Panel A)	0.0216***	0.0034***	0.004	0.0037***	0.0012***	<0.001
	(0.0029)	(0.0009)		(0.0004)	(0.0002)	
2. Exposure Window of 4 Months	0.0211***	0.0024***	<0.001	0.0024**	0.0005	<0.001
	(0.0029)	(0.0006)		(0.0008)	(0.0003)	
3. Log Real Per Capita Income Below Median	0.0220***	0.0041***	<0.001	0.0036***	0.0013***	0.021
	(0.0030)	(0.0008)		(0.0004)	(0.0003)	
4. Log Real Per Capita Income Above Median	0.0199***	0.0025*	0.003	0.0040***	0.0010***	0.016
	(0.0032)	(0.0011)		(0.0007)	(0.0003)	
5. Including Fraction Black, Fraction Living on Farm	0.0218***	0.0036***	0.005	0.0037***	0.0011***	<0.001
Fraction Movers as Additional Controls	(0.0029)	(0.0009)		(0.0004)	(0.0003)	
6. Including Temperature*Rainfall Interactions	0.0196***	0.0040***	0.003	0.0041***	0.0013***	<0.001
	(0.0029)	(0.0009)		(0.0004)	(0.0003)	

Notes: Dependent variable is log monthly mortality rate. Unless noted otherwise, temperature exposure window is defined as 2 months. Cumulative dynamic estimates are reported. Regressions are weighted by the relevant population. All regressions include the baseline set of covariates. Standard errors clustered on state. Asterisks denote p-value < 0.05 (*), <0.01 (**), <0.001 (***). The entries in columns (3) and (6) are the p-values for the test of equality of the pre-1960 coefficients and the post-1960 coefficients.

Table 6: Interaction Effects Between Modifiers and Number of Temperature-Days Between 80-89°F and Above 90°F

	[A] Sample: 1931-1959			[B] Sample: 1960-2004		
	(1a)	(2a)	(3a)	(1b)	(2b)	(3b)
<u>Temperature Above 90°F</u>						
Number of Days Above 90 °F ×	0.0059	---	0.0077	-0.0022	---	-0.0007
Log Doctors Per Capita	(0.0058)		(0.0066)	(0.0025)		(0.0030)
Number of Days Above 90 °F ×	---	0.0225	0.0237	---	---	---
Share with Residential Electricity		(0.0114)	(0.0129)			
Number of Days Above 90 °F ×	---	---	---	---	-0.0223***	-0.0217**
Share with Residential AC					(0.0056)	(0.0067)
<u>Temperature in 80-89°F</u>						
Number of Days in 80-89 °F ×	0.0005	---	0.0007	-0.0026*	---	0.0005
Log Doctors Per Capita	(0.0011)		(0.0010)	(0.0010)		(0.0006)
Number of Days in 80-89 °F ×	---	-0.0019	-0.0024	---	---	---
Share with Residential Electricity		(0.0016)	(0.0019)			
Number of Days in 80-89 °F ×	---	---	---	---	-0.0066***	-0.0070***
Share with Residential AC					(0.0011)	(0.0012)

Notes: Each column corresponds to a separate regression. Dependent variable is log monthly mortality rate. Temperature exposure window defined as 2 months. Cumulative dynamic estimates are reported. Number of temperature-day variables for days < 40°F, 80-90°F, and >90°F and their interactions with log doctors per capita, share with residential electricity, and share of residential AC are included. All regressions include the baseline set of covariates. Standard errors clustered on state. Asterisks denote p-value < 0.05 (*), <0.01 (**), <0.001 (***).

Table 7: Effect of Residential Air Conditioning on Heat-Related Mortality, By Age, Race, and Cause of Death, 1960-2004

	(1)	(2)	(3)	(4)	(5)
A. By Age Group					
	Infants (Age 0-1)	**Age 1-44**	**Age 45-64**	**Age 65+**	
Number of Days Above 90 °F ×	-0.0230	0.0000	-0.0141**	-0.0273**	
Share with Residential AC	(0.0170)	(0.0172)	(0.0046)	(0.0093)	
Number of Days in 80-89 °F ×	-0.0083*	-0.0026	-0.0013	-0.0050***	
Share with Residential AC	(0.0034)	(0.0024)	(0.0019)	(0.0010)	
B. By Race					
	White	**Black**			
Number of Days Above 90 °F ×	-0.0197***	-0.0474***			
Share with Residential AC	(0.0054)	(0.0124)			
Number of Days in 80-89 °F ×	-0.0056***	-0.0036			
Share with Residential AC	(0.0012)	(0.0020)			
C. By Cause of Deaths					
	Cardiovascular Disease	**Respiratory Diasease**	**Motor-Vehicle Accidents**	**Infectious Disease**	**Neoplasm**
Number of Days Above 90 °F ×	-0.0221***	-0.0556*	-0.0098	-0.0249	-0.0094***
Share with Residential AC	(0.0047)	(0.0263)	(0.0162)	(0.0253)	(0.0024)
Number of Days in 80-89 °F ×	-0.0058***	-0.0231***	-0.0031	0.0101	-0.0020
Share with Residential AC	(0.0015)	(0.0033)	(0.0034)	(0.0081)	(0.0017)

Notes: Each entry is from a separate regression. Dependent variable is log monthly mortality rate. Temperature exposure window defined as 2 months. Cumulative dynamic estimates are reported. Number of temperature-day variables for days < 40°F, 80-90°F, and >90°F and their interactions share of residential AC are included. All regressions include the baseline set of covariates. Standard errors clustered on state. Asterisks denote p-value < 0.05 (*), <0.01 (**), <0.001 (***).

Table 8: Robustness Analysis of the Effect of Residential Air Conditioning on the Temperature-Mortality Relationship, 1960-2004

	(1)	(2)	(3)	(4)	(5)
Number of Days Above 90 °F ×	-0.0223***	-0.0239***	-0.0317*	-0.0461***	-0.0223*
Share with Residential AC	(0.0056)	(0.0063)	(0.0147)	(0.0060)	(0.0106)
Number of Days Between 80-89 °F ×	-0.0066***	-0.0051***	-0.0057*	-0.0094***	-0.0052*
Share with Residential AC	(0.0011)	(0.0010)	(0.0022)	(0.0016)	(0.0020)
Number of Days Below 40 °F ×	0.0004	-0.0007	0.0027	0.003	0.0001
Share with Residential AC	(0.0009)	(0.0008)	(0.0023)	(0.0015)	(0.0015)
Baseline controls	yes	yes	yes	yes	yes
State-month cubic time trends	no	yes	no	no	no
Two year window around census years	no	no	yes	no	no
Temperature*year trends	no	no	no	yes	no
Exposure window = 4 months	no	no	no	no	yes
Observations	26,411	26,411	4,704	26,411	26,264

Notes: Each column is from a separate regression. Dependent variable is log monthly mortality rate. Temperature exposure window defined as 2 months. Cumulative dynamic estimates are reported. Number of temperature-day variables for days < 40°F, 80-90°F, and >90°F and their interactions share of residential AC are included. The specification of the regression follows the description at the bottom of the table. See the text for more details. Standard errors clustered on state. Asterisks denote p-value < 0.05 (*), <0.01 (**), <0.001 (***).

Table 9: Estimates of the Electricity Demand Function, and Implied Estimates of National Consumer Surplus Associated with Residential Air Conditioning

	(1)	(2)	(3)	(4)	(5)
Electricity price	-92.29***	-88.97***	-62.77***	-54.16***	-53.56***
	(15.89)	(21.27)	(11.43)	(11.48)	(11.35)
Air conditioning	2.45***	3.44	1.26***	1.24***	1.11***
	(0.39)	(2.60)	(0.15)	(0.16)	(0.14)
Electricity price × air conditioning	---	-7.31	---	---	---
		(17.54)			
Air conditionning × above median annual 90° F days	---	---	---	---	---
Full set of controls	no	no	yes	yes	yes
Electricity price instrumented	no	no	no	yes	yes
Selection ccrrection terms	no	no	no	no	yes
Implied National Consumer Surplus from AC (Billion $2012 Per Year)					
Perfectly elastic supply case	10.89***	9.34**	8.63***	9.82***	8.37***
	(2.78)	(2.92)	(1.78)	(2.37)	(2.41)
Inelastic supply case (linear supply curve)	4.88**	3.17	4.57***	5.57***	4.88**
	(1.57)	(3.45)	(1.11)	(1.52)	(1.61)

Notes: Each column is from a separate regression. Number of observations = 3,699,613. The dependent variable is the annual household-level electricity consumption in 1980, measured in thousand kWh. Electricity price is the state-level residential sector electricity price (from SEDS) in $2012 per kwh. Air conditioning is an indicator variable equal to 1 if the household owns a central or room air conditioning. Full set of controls include climate variables, indicators for household size, household income, homeownership, number of rooms, age of structure, and number of units in the structure. Electricity price is instrumented using U.S. census division indicator variables (columns 4 and 5). The selection correction terms in column 5 follow from Dubin and McFadden (1984). Derivation of national consumer surplus explained in the text. Standard errors clustered on state. Asterisks denote p-value < 0.05 (*), <0.01 (**), <0.001 (***).

APPENDIX --- FOR ONLINE PUBLICATION

Details from Application of Discrete-Continuous Model (Section V.)

This appendix describes an approach to using the residential electricity market to estimate the consumer surplus from AC. Including selection terms in the model described in the main approach gives

$$q_{is} = \beta_0 + \beta_1 AC_{is} + \beta_2 p_{is} + X_{is}\gamma + \beta_3 \left[AC_{is} \left(\frac{\hat{P}_{is0} ln\hat{P}_{is0}}{1 - \hat{P}_{is0}} + ln\hat{P}_{is1} \right) + (1 - AC_{is}) \left(\frac{\hat{P}_{is1} ln\hat{P}_{is1}}{1 - \hat{P}_{is1}} + ln\hat{P}_{is0} \right) \right]$$

Solving for prices gives:

$$p_{is} = \frac{q_{is} - \beta_0 - \beta_1 AC_{is} - X_{is}\gamma - \beta_3 \left[AC_{is} \left(\frac{\hat{P}_{is0} ln\hat{P}_{is0}}{1 - \hat{P}_{is0}} + ln\hat{P}_{is1} \right) + (1 - AC_{is}) \left(\frac{\hat{P}_{is1} ln\hat{P}_{is1}}{1 - \hat{P}_{is1}} + ln\hat{P}_{is0} \right) \right]}{\beta_2}$$

Assuming that the quantity supplied at $P = 0$ is zero, the (inverse) electricity supply function is $P^S(q) = \frac{P^*}{Q^*} q$, where P^* and Q^* are observed equilibrium price and quantity. So if residential AC did not exist, the new equilibrium quantity $Q^{*'}$ would be given by:

$$Q^{*'} = \frac{-\beta_0 - X_{is}\gamma - \beta_3 \left\{ \overline{AC} \left[\frac{\hat{P}_{is0} ln\hat{P}_{is0}}{1 - \hat{P}_{is0}} + ln\hat{P}_{is1} \right] + (1 - \overline{AC}) \left[\frac{\hat{P}_{is1} ln\hat{P}_{is1}}{1 - \hat{P}_{is1}} + ln\hat{P}_{is0} \right] \right\}}{\frac{P^*}{Q^*}\beta_2 - 1}$$

where $\overline{AC}$ is the population share with AC in the data. If AC did not exist, the equilibrium price would be:

$$P^{*'} = \frac{\left(-\beta_0 - X_{is}\gamma - \beta_3 \left\{ \overline{AC} \left[\frac{\hat{P}_{is0} ln\hat{P}_{is0}}{1 - \hat{P}_{is0}} + ln\hat{P}_{is1} \right] + (1 - \overline{AC}) \left[\frac{\hat{P}_{is1} ln\hat{P}_{is1}}{1 - \hat{P}_{is1}} + ln\hat{P}_{is0} \right] \right\} \right) \frac{P^*}{Q^*}}{\left(\frac{P^*}{Q^*}\beta_2 - 1 \right)}$$

Note that in all these calculations, the equilibrium price P^* is the mean observed price, and the equilibrium quantity Q^* is given by:

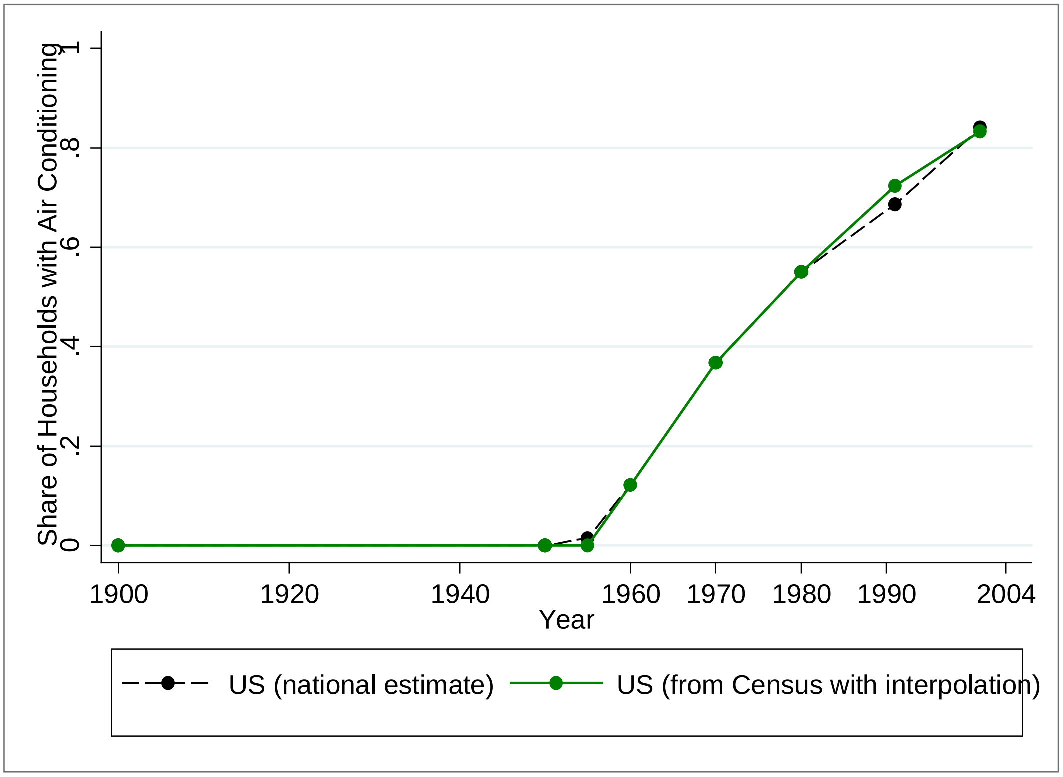
$$Q^* = \beta_0 + \overline{AC}\,\beta_1 + \beta_2 \bar{p} + \bar{X}\gamma + \overline{AC}\beta_3 \overline{\left[\frac{\hat{P}_{\iota s0} ln\hat{P}_{\iota s0}}{1 - \hat{P}_{\iota s0}} + ln\hat{P}_{\iota s1} \right]} + (1 - \overline{AC}\,)\beta_3 \overline{\left[\frac{\hat{P}_{\iota s1} ln\hat{P}_{\iota s1}}{1 - \hat{P}_{\iota s1}} + ln\hat{P}_{\iota s0} \right]}$$

To calculate the consumer surplus from air conditioning, we compare the consumer surplus in the electricity market at observed prices and demand (CS) against the consumer surplus that would prevail if no AC was available (CS'). Then we get the following consumer surplus under cases where air conditioning is and is not available:

$$CS = \frac{1}{2}\left(\overline{AC}\,\frac{-\beta_0-\beta_1-\bar{X}\gamma-\beta_3\overline{\left[\frac{\hat{P}_{\iota s0}ln\hat{P}_{\iota s0}}{1-\hat{P}_{\iota s0}}+ln\hat{P}_{\iota s1}\right]}}{\beta_2}+(1\overline{-AC})\,\frac{-\beta_0-\bar{X}\gamma-\beta_3\overline{\left[\frac{\hat{P}_{\iota s1}ln\hat{P}_{\iota s1}}{1-\hat{P}_{\iota s1}}+ln\hat{P}_{\iota s0}\right]}}{\beta_2}-\bar{p}\right)$$
$$\times\left(\beta_0+\beta_1\overline{AC}+\beta_2\bar{p}+\bar{X}\gamma+\overline{AC}\beta_3\overline{\left[\frac{\hat{P}_{\iota s0}ln\hat{P}_{\iota s0}}{1-\hat{P}_{\iota s0}}+ln\hat{P}_{\iota s1}\right]}+(1-\overline{AC})\beta_3\overline{\left[\frac{\hat{P}_{\iota s1}ln\hat{P}_{\iota s1}}{1-\hat{P}_{\iota s1}}+ln\hat{P}_{\iota s0}\right]}\right)$$

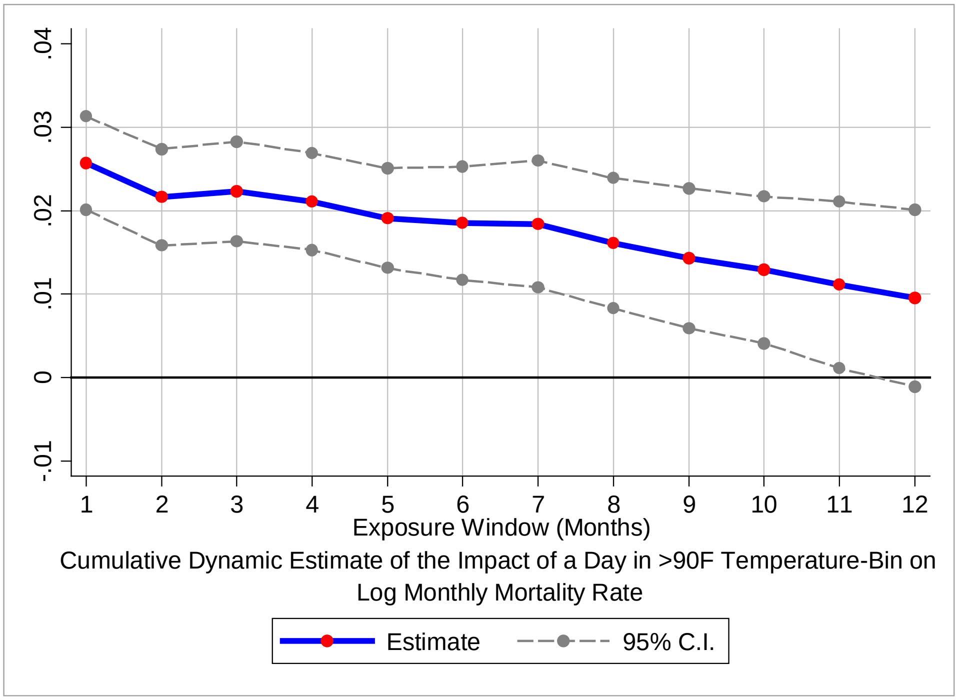
$$CS' = \frac{1}{2}\left(\frac{-\beta_0-\bar{X}\gamma-\beta_3\left\{\overline{AC}\,\overline{\left[\frac{\hat{P}_{\iota s0}ln\hat{P}_{\iota s0}}{1-\hat{P}_{\iota s0}}+ln\hat{P}_{\iota s1}\right]}+(1-\overline{AC})\overline{\left[\frac{\hat{P}_{\iota s1}ln\hat{P}_{\iota s1}}{1-\hat{P}_{\iota s1}}+ln\hat{P}_{\iota s0}\right]}\right\}}{\beta_2}\right.$$
$$\left.-\frac{\left(-\beta_0-\bar{X}\gamma-\beta_3\left\{\overline{AC}\,\overline{\left[\frac{\hat{P}_{\iota s0}ln\hat{P}_{\iota s0}}{1-\hat{P}_{\iota s0}}+ln\hat{P}_{\iota s1}\right]}+(1-\overline{AC})\overline{\left[\frac{\hat{P}_{\iota s1}ln\hat{P}_{\iota s1}}{1-\hat{P}_{\iota s1}}+ln\hat{P}_{\iota s0}\right]}\right\}\right)\frac{P^*}{Q^*}}{\left(\frac{P^*}{Q^*}\beta_2-1\right)}\right)$$
$$\times\left(\frac{\left(-\beta_0-\bar{X}\gamma-\beta_3\left\{\overline{AC}\,\overline{\left[\frac{\hat{P}_{\iota s0}ln\hat{P}_{\iota s0}}{1-\hat{P}_{\iota s0}}+ln\hat{P}_{\iota s1}\right]}+(1-\overline{AC})\overline{\left[\frac{\hat{P}_{\iota s1}ln\hat{P}_{\iota s1}}{1-\hat{P}_{\iota s1}}+ln\hat{P}_{\iota s0}\right]}\right\}\right)}{\frac{P^*}{Q^*}\beta_2-1}\right)$$

Appendix Figure 1: Comparison of interpolated and nationally representative estimates of AC ownership rate

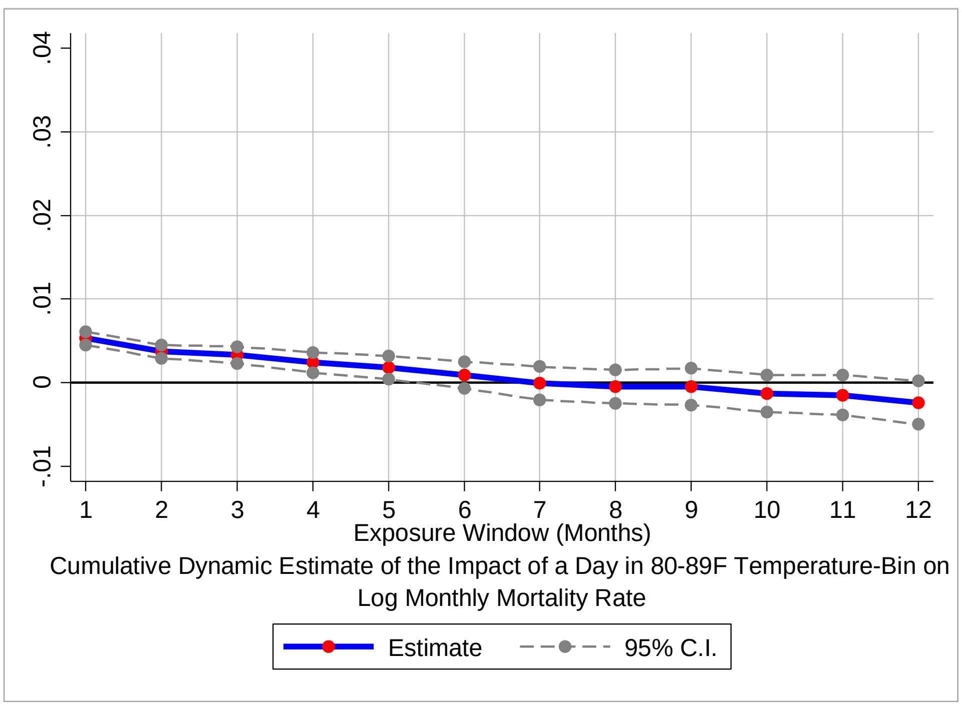


Appendix Figure 2: Cumulative Estimated Impact of 80-89°F and >90°F Temperatures on Log Monthly Mortality Rate, By Length of Exposure Window (Lags)

(a) Impact of >90°F Temperatures on Log Monthly Mortality Rate, 1931-1959



(b) Impact of 80-89°F Temperatures on Log Monthly Mortality Rate, 1931-1959



Notes: Appendix Figure 2 plots the estimated cumulative dynamic estimates of the effect of >90°F and 80-89°F temperature on log monthly mortality as a function of the exposure window. For example, the model with a 1 month exposure window only controls for current month temperature, while the model with a 12 month exposure controls separately for the last 12 months of temperature. In all cases, the estimate reported in the figure corresponds to the sum of the coefficients attached to each month's temperature over the exposure window. Three critical temperature bins (<40°F, 80-89°F, and >90°F) are included in the model and the specification includes the baseline set of covariates. Standard errors are clustered on state.

Appendix Table 1: Year of Entry of States in Vital Statistics Registration System

	State	U.S. Climate Region	Entered sample
1	Connecticut	Northeast	1900
2	District of Columbia	Northeast	1900
3	Indiana	Central	1900
4	Maine	Northeast	1900
5	Massachusetts	Northeast	1900
6	Michigan	East North Central	1900
7	New Hampshire	Northeast	1900
8	New Jersey	Northeast	1900
9	New York	Northeast	1900
10	Rhode Island	Northeast	1900
11	Vermont	Northeast	1900
12	California	West	1906
13	Colorado	Southwest	1906
14	Maryland	Northeast	1906
15	Pennsylvania	Northeast	1906
16	South Dakota	West North Central	1906
17	Washington	Northwest	1908
18	Wisconsin	East North Central	1908
19	Ohio	Central	1909
20	Minnesota	East North Central	1910
21	Montana	West North Central	1910
22	North Carolina	Southeast	1910
23	Utah	Southwest	1910
24	Kentucky	Central	1911
25	Missouri	Central	1911
26	Virginia	Southeast	1913
27	Kansas	South	1914
28	South Carolina	Southeast	1916
29	Tennessee	Central	1917
30	Illinois	Central	1918
31	Louisiana	South	1918
32	Oregon	Northwest	1918
33	Delaware	Northeast	1919
34	Florida	Southeast	1919
35	Mississippi	South	1919
36	Nebraska	West North Central	1920
37	Georgia	Southeast	1922
38	Idaho	Northwest	1922
39	Wyoming	West North Central	1922
40	Iowa	East North Central	1923
41	North Dakota	West North Central	1924
42	Alabama	Southeast	1925
43	West Virginia	Central	1925
44	Arizona	Southwest	1926
45	Arkansas	South	1927
46	Oklahoma	South	1928
47	Nevada	West	1929
48	New Mexico	Southwest	1929
49	Texas	Southwest	1933

Appendix Table 2: Interaction Effects Between Modifiers and Number of Temperature-Days Below 40°F

	[A] Sample: 1931-1959			[B] Sample: 1960-2004		
	(1a)	(2a)	(3a)	(1b)	(2b)	(3b)
Number of Days Above 40 °F ×	-0.0018	---	-0.0010	-0.0013**	---	-0.0014*
Log Doctors Per Capita	(0.0009)		(0.0007)	(0.0005)		(0.0005)
Number of Days Above 40 °F ×	---	-0.0066*	-0.0056*	---	---	---
Share with Residential Electricity		(0.0026)	(0.0024)			
Number of Days Above 40 °F ×	---	---	---	---	0.0004	0.0008
Share with Residential AC					(0.0009)	(0.0010)

Notes: Each column corresponds to a separate regression. Dependent variable is log monthly mortality rate. Temperature exposure window defined as 2 months. Cumulative dynamic estimates are reported. Number of temperature-day variables for days < 40°F, 80-90°F, and >90°F and their interactions with log doctors per capita, share with residential electricity, and share of residential AC are included. All regressions include the baseline set of covariates. Standard errors clustered on state. Asterisks denote p-value < 0.05 (*), <0.01 (**), <0.001 (***).