PRELIMINARY DRAFT: NOT FOR CIRCULATION

"Adapting to Climate Change: Evidence from Long-Run Changes in the Temperature-Mortality Relationship in the 20th Century United States"

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Introduction

The accumulation of greenhouse gases (GHGs) in the atmosphere threatens to fundamentally alter our planet's climate in a relatively short period of geological time. There are three possible approaches to confronting this defining challenge. The first is mitigation, which involves a coordinated reduction in emissions by countries around the globe. The prospects for such a policy do not look highly likely in at least the next decade, due to the failure of the Copenhagen climate conference to produce such action and the continued failures by the United States and several other large emitting countries to institute programs of verified emissions reductions. The second is to undertake a program of geo-engineering or climate engineering that involves the deliberate manipulation of the Earth's climate to counteract the greenhouse gas induced changes in the climate. These solutions remain scientifically unproven and involve a host of international governance issues that appear at least as challenging as reaching agreement on reducing emissions. For example, which country gets to set the desired global change in temperature?

The third approach is adaptation and in light of the practical difficulties of the first two it is the only one guaranteed to be part of the world's climate strategy. 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). Ultimately, climate change's impacts will depend on the sensitivity of our well-being to changes in climate and on the cost of adapting to climate change. However, knowledge on the ability to adapt to large-scale climate or environmental changes and its costs is poor for several reasons, not the least of which is an absence of real-world data. As such, identifying strategies that can help reduce the human health costs of climate change through adaptation is now recognized as global research priority of the 21st century (WHO 2008). This need is especially great in developing countries where high temperatures can cause dramatic changes in life expectancy (Burgess et al. 2011).

This paper provides the first large-scale empirical study of the long-run adaptation strategies that can be implemented to reduce the human health costs of climate change. We proceed in two steps. First, we document the dramatic changes in the temperature-mortality relationship in the United States over the past 100 years using state-year-month mortality data and daily temperature data. We focus on the United States because it is the only country for which high quality vital statistics data are available for such a long time period and at a highly disaggregated level.[1] The long time period is an important contribution of this paper because most studies on this topic rely on data covering at most two or three decades (see e.g, Deschenes and Greenstone 2011).

Second, we quantify the extent to which three health-related innovations in the 20th century United States have contributed to reducing the mortality effect of temperature extremes. Specifically, we examine the role of residential electricity, increased access to health care, and the introduction of residential air conditioning (AC) in muting the temperature-mortality relationship. These three innovations – which we refer to as 'modifiers' of the temperature-mortality relationship – were chosen because the channels that link them to health is itself modified by ambient temperature, especially high temperatures. For example, the introduction of residential AC allowed individuals to reduce the stress on their thermoregulatory systems in periods of extreme heat. In addition we chose these three factors because they are currently available with limited access to a substantial fraction of the world's poor. Climate change is projected to have large negative impacts on human health (see NIEHS 2010) and these effects are likely to begin to emerge in developing countries in the next few decades. An important contribution of this paper thus is to highlight the identification of successful adaptation strategies can begin to moderate negative health impacts in the medium term.

Empirically, the paper brings together the most comprehensive set of data files on mortality and its determinants over the course of the 20th century in the United States or any other country. We estimate flexible models of the temperature-mortality relationship based on monthly mortality rates at the state level and daily temperature records for the period 1900-2004. The baseline specification includes state, state-by-month, and year-by-month fixed effects. Consequently, the temperature variables are identified from the unpredictable and presumably random month-to-month variation in the local temperature distribution, so concerns about omitted variables bias are unlikely to be important.

The basic finding is striking: The impact of a day with a mean temperature exceeding 90° F (relative to a day in the 60°-70° F range) on monthly mortality rates has declined from roughly 2.4% to 0.6% over the course of the 20th century. Almost the decline occurred after 1960. Cumulative dynamic estimates that control for current and past exposure to temperature and generate estimated impacts that are robust to short-term mortality displacement or 'harvesting' confirm the basic finding of a fourfold decline in the mortality effect of very high temperatures exposure. These results are derived

[1] Carson et al. (2006) document the changes in the temperature-mortality relationship in a single location (London) during the 20th century, but do not empirically identify the cause of the changes.

from models that include a rich set of fixed effects that control for aggregate changes in the level and seasonality of health, permanent differences in the level and seasonality of health across states, and (parametrically) control for changes over time in the level and seasonality across states. Further, inclusion of controls for log per capita income or rural/urban population shares does not lead to meaningful changes in the estimated effects.

In the second part of the paper, we set out to examine the role of increased in access to health care, electrification and the diffusion of residential AC (i.e the "modifiers") in reducing the mortality effect of high temperature days. We find that over the 1960-2004 period the diffusion of residential AC lead to a statistically and economically significant reduction in the temperature-mortality relationship. Our estimates indicate suggest that each 10 percentage points increase in residential AC ownership decreased the high temperature mortality effect by 17-21%. More broadly our results indicate that increased access to health care and to residential AC could dramatically reduce the health effects of high temperature days in countries that are expected significant warming in the coming years and where access is currently at very low levels.

The paper proceeds as follows. Section I 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 II describes the data sources and reports summary statistics. Section III presents the econometric models, and Section IV describes the results. Section V interprets our estimates in the context of guiding adaptation policies to reduce the health impacts predicted to occur in developing countries under global climate change. Section VI concludes the paper.

I. Conceptual Framework

A. Background

Temperature-Mortality Relationship. The human body's thermoregulatory function enables us to cope with exposure to high and low temperatures. Specifically, high and low temperatures generally trigger an increase in the heart rate in order to increase blood flow from the body to the skin, leading to the common thermoregulatory responses of sweating in hot temperatures and shivering in cold temperatures. These responses allow individuals to pursue physical and mental activities without endangering their health within certain ranges of temperature. Exposure to temperatures outside of these ranges poses dangers to human health and can result in premature mortality.

An extensive literature has documented a relationship between high temperatures and mortality (see e.g., Basu and Samet 2002 for a review). These excess deaths are generally concentrated among causes related to cardiovascular, respiratory, and cerebrovascular diseases. The need for body temperature regulation imposes additional stress on the cardiovascular and respiratory systems. In terms of specific indicators of body operations, elevated temperatures are associated with increases in blood viscosity and blood cholesterol levels. Exposure to cold days is also a risk factor for mortality (Deschenes and Moretti 2009). Exposure to very cold temperatures causes cardiovascular stress due to changes in blood pressure, vasoconstriction, and an increase in blood viscosity (which can lead to clots), as well as levels of red blood cell counts, plasma cholesterol, and plasma fibrinogen (Huynen et al. 2001). Thus the analysis we present below will focus on exposure to both very high and low daily temperatures.

B. Technological Advances that Might Alter the Temperature-Mortality Relationship

Access to Health Care. Health care had two inter-related effects on heat-related mortality. The first was to strengthen the most vulnerable populations – the young, the sick, and the old. For example, in the early twentieth century, physician-led vaccination and public health campaigns, helped maintain a healthier population.[2] In later periods, more effective drug and other medical interventions existed. Many of these served to strengthen the relevant populations by managing diseases, such as cardiovascular disease, diabetes, and kidney disease (Davis et al 2003). Stronger populations were more likely to tolerate the additional stress posed by periods of high heat.

The second was to address heat-related issues as they happened. Here it is important to recognize that historically and even today not everyone who died of heat related illness sought medical intervention prior to death. For example, heart attacks and CVD more broadly are the leading cause of death during heat waves many of whom die before reaching a hospital or health care center (Kovats et al 2004).

For individuals who did seek medical care, before the late 1930s physicians and hospitals had limited scope for addressing heat-related mortality. In selected cases, health care might have mitigated

[2] Vaccination campaigns involved smallpox, polio, diphtheria, and whooping cough. Public health campaigns involved hookworm, malaria, and pasteurization of milk.

heat stroke or heat exhaustion. Hospitals had air conditioning much earlier than homes or other locations and greater access to ice. But more commonly the stress of the heat exacerbated underlying health conditions causing a heart attack, stroke, kidney failure, or the spread of a bacterial infection. Medicine of the time had few tools to address these illnesses. To make matters worse, individuals who went to the hospital often contracted other diseases.

Breakthroughs relevant for heat-related mortality proceeded condition by condition. In the late 1930s, sulfa drugs become available and other antibiotics become available in the 1940s. This gave doctors tools to address bacterial infections (Jayachandran et al 2010). IV rehydration was available from fairly early on, although the composition of the IV and cleanliness of the procedure changed over time to make it more effective. Oral rehydration began to be widely available and effective in the 1950s. Breakthroughs in the treatment of heart disease would follow from results of the Framingham study, which began in 1948, and the development of effective blood pressure medication in the late 1950s and beta blockers in the 1960s. In hospital mortality from heart attacks has been falling since the 1970s, as a result of a variety of factors including improvements in treatment protocol (Rosamond et al 1998). Treatment of strokes followed similar trajectories.

Access to Electricity. Residential access to electricity can modify the impact of temperature extremes on health in several ways. First, electricity facilitated indoor plumbing, thereby allowing indoor toilets, showers, and faucets. Historians have linked outdoor toilets (“privies”) to hookworm, dysentery, typhoid, and enteritis (Brown 1979). These infectious conditions can spread more rapidly during heat.[3] Piped water also let families use sinks for washing hands, which could help prevent the spread of bacteriological and viral conditions which also spread more rapidly during heat. Increasing the accessibility of drinking water could also decrease dehydration episodes during heat. This is particularly important since dehydration is a common cause of morbidity associated with infectious disease, especially for the young.

[3] Electricity was required to pump water into indoor pipes. Brown (1998, p. 68) writes:

> Many observers felt electrical service would be necessary to overcome the poor state of rural health in the United States. Improper sanitary conditions associated with the use of the outhouse, or `privy,’ and the water well were significantly responsible for the higher infant-mortality rate and the higher mortality and morbidity rates of the rural population. The high rate of hookworm infestation, often reaching 30 to 40 percent in southern states, was linked directly to the lack of indoor bathrooms. Without cold storage for preserving foods, meals tended to be monotonous and lacked the variety commensurate with a balanced diet. Among the poorer families, the seasonal scourage of pellagra commonly emerged each year after a prolonged winter diet short of B vitamins.

Second, electricity allowed refrigeration of food. Refrigeration postponed spoilage and associated food poisoning during heat. This is more important during high temperatures, when bacterial growth and spoilage occur most quickly. In 1940, 56 percent of urban homes with electricity and a third of REA customers had a refrigerator (Kline 2002, p. 336). Refrigeration also permitted households to expand their diets in ways which may have provided better nutrition and more variety. For example, sharecroppers in the early 20th century South frequently ate fatback, cornmeal, and molasses. This diet may have contributed to pellagra and to undernourishment of pregnant women and infants. The refrigeration that electricity provided may have increased the vitamin, iron, and protein content of diets (Brown 1980).

Third, electricity initially permitted artificial temperature control by fans and electric heaters. Fans provided an early alternative to air conditioning for hot days. Electric heating also provided a clean alternative to coal, gas, or oil-fired heaters, with no associated household pollution.[4] Moreover, electric heating pads for cold and for treating illness experienced rapid sales growth during urban electrification in the 1920s (Tobey 1996). Starting in the late 1950s, residential electricity (which had reached a penetration rate of close to 100% by then) also paved the way to the introduction of residential air conditioning. We return to a discussion of residential AC below. By allowing for better inside thermal control during cold and hot spells electrification may have contributed to lowering excess morality associated with both extremes of the temperature distribution.[5]

Residential Air Conditioning. 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. A rise in the temperature of the blood by less than 1°C activates actives heat receptors that begin the process of thermal regulation by increasing blow 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, often as a result of increased ambient temperature. Due to the strong connection between ambient temperature and heat-related illness, air conditioning is

[4] Electric water heaters and air conditioners became common after 1955, once most households already had electricity (Tobey 1996).

[5] Electricity facilitated smokeless lighting. Upon connection to the electric grid, most households replaced kerosene lamps and candles with incandescent lights. REA materials state that fires killed about 3,500 people annually on US farms in the US, and that many fires were due to oil lamps and candles (REA 1936). Heat only increased the risk and spread of fire. Finally, most households connected to the electric grid purchased a radio—in 1940, 88 percent of REA households and 81 percent of all US homes with electricity owned one (Kline 2002, p. 336). Weather forecasts are among the most popular news broadcasts, and advanced notice of extremely high or low temperatures could help people modify dress and activities accordingly.

probably the most prominent modern technology that can lower the risk of heat-related illness since it allows individuals to recuperate and reduce the heat stress on their thermoregulatory systems in periods of extreme heat. Indeed, 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.

C. Welfare Consequences of Technological Advances that Alter the Temperature-Mortality Relationship

The estimation of the full welfare impacts of these advances in technology is a topic of considerable interest. Following the canonical Becker-Grossman health production model (Grossman (2000)), this would require information on how these technological advances impact mortality and morbidity rates, as well as the monetized value of changes in behavior and defensive investments (e.g., the availability of medical care might allow individuals to work outside on hot days). This paper will provide evidence on a subset of these benefits—namely the impact on mortality in response to hot days. For this reason, it will only provide a partial estimate of the benefits of these technologies and cannot be used in isolation to conduct a cost-benefit analysis of whether particular regions should invest in electricity, hospitals, or air conditioners as a strategy to adapt to climate change.

II. Data and Summary Statistics

This paper is based on the most comprehensive date file ever compiled on mortality and its determinants over the course of the 20th century in the United States or any other country. This section briefly describes these data and reports summary statistics. More details on the data sources are provided in the Appendix.

A. Data Sources

Vital Statistics Data. The data used to construct mortality rates at the state-year-month level for the period 1900-2004 is from multiple sources. Data on mortality counts or rates for the United States is not systematically available in machine readable format before 1959. For the years prior to 1959, we assembled the sample of state-year-month death counts from volumes of the Mortality Statistics of the United States from the National Center for Health Statistics (NCHS) archives. States began reporting mortality statistics for the first time at different points over this period. 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. The final sample consists of all valid state-year-month observations on mortality rates for the continental United States.[6]

From 1959 to 2004, we use the annual Multiple Cause of Death files that contain state and month of death of all deaths in the United State in a given calendar year. Notably, geographic information on state of residence in not available in the public domain files starting in 2005, which explains why the sample stops in 2004. From these data we obtain an unbalanced panel of state-year-month death counts for 1900-2004. We then combine these data with annual population counts to derive an all-age monthly mortality rate (per 100,000 population) to be used in the analysis below. Two caveats should be noted on this data source. First, to the best of our knowledge, there is consistent source of data on mortality counts by state-year-month and age group for the period 1900-2004. As a result all our analyses are based on a crude all-age mortality rate, although we control for the population shares in 4 age groups in all our regression models. Second, there is no data available at state-year-month level that identifies vital events separately for rural and urban populations.

Weather Data. The weather station data are drawn from the National Climatic Data Center (NCDC) Global Historical Climatology Network-Daily (GHCN-Daily), 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.[7] Unfortunately, it is impossible to derive a consistent high-frequency set of daily humidity data, in particular no weather station measured relative humidity prior to 1980. Baracca (2012) shows that including controls for humidity leads to smallest changes to the estimated temperature-mortality relationship in the US over the 1968-2002 period. As such, this is not an important concern here, although we also consider models where precipitation and temperature are interacted.

To construct our annual measures of weather from the daily records we select weather stations that have non-missing records for all days 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

[6] There is no vital statistics reported in 1930.

[7] 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).

the early 1900s and around 2,000 stations by the end of the century. The station-level data is then aggregated at 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 its squared distance to the county centroid so that more distant stations are given less weight. Finally, since the analysis is currently done at the state level, the county-level variables are aggregated at the state level by taking a simple average of all counties in a state.

Doctors Per Capita and Hospital Beds Data. We have collected the state by decade counts of physicians and nurses from the decennial censuses from 1900 to 2000.[8] The 1900, 1980, and 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 and nurses per 1,000 by dividing the physician and nurse counts by population.[9] Finally, we linearly interpolate the rates across the census years.

We are also in the process of collecting and compiling comparable data on short-term hospital beds per capita at the state level over the period 1920-2000. Short-term hospital beds correspond to beds in local or community hospitals and exclude psychiatric beds, tuberculosis beds, long-term hospital beds, and federal beds.[10] We are collecting these data from publications of the American Medical Association and from the American Hospital Association.

Electrification Data. We combine two data sources, each measuring the share of US households with electricity to form our main measure of access to electricity. The first are reports of the Censuses of Electrical Industries (CEI), conducted every five years between 1902 and 1937. For each state-year, these volumes report the number of customers with electricity. Second is the decennial US Census of Population, which we access through the data files produced by Haines (2005). We use these censuses to calculate the denominator for other data sources—the number of households, farm households, rural-urban population balance, and dwellings. In the years 1945, 1950, and 1954, the census records the share of farm households with electricity. We compile state-year measures of electrification from the CEI every 5 years from 1902 through 1927. We measure rural electrification using the 1945, 1950, and 1954 population censuses. We linearly interpolate urban electrification rates in these three later years from the CEI.

[8] We accessed these data through IPUMS.

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

[10] By far the largest excluded category was beds in mental hospitals. For much of the first half of the twentieth century, the number of beds in mental hospitals exceeded the number of beds in general (short-term) hospitals.

Residential AC Data. Available spatially delineated data on residential AC ownership in the US is limited. The most spatially disaggregated data source is the US Census of Population, which can be used to derive residential AC ownership rates at the county level from 1960-1980. We use these data in the regression analysis below and test if access to residential AC contributed to the decline of the mortality effect of high temperature days.[11] We also supplement the aggregate (national) summary statistics on AC adoption by using data reported in Biddle (2008) and in various American Housing Surveys for the 1990s and 2000s.

B. Summary Statistics

Weather and Mortality Rate Statistics. Figure 1 shows the average annual mortality rate over the 1900-2004. Even though the data underlying the estimation of the regression models is at the state-year-month level we report average mortality rates calculated at the state-year level for better comparability with other studies and with official published statistics. Unless noted otherwise, all statistics reported in the paper are weighted by the total population in a state-year so they correspond to the exposure of the average American over the 1900-2004 period. The main point of Figure 1, as is well known, is that with the exception of the significant spike associated with 1918-19 Influenza pandemic, the decline in the mortality rate has been steady over the last 100 years.

The leftmost panel Table 1 reports national and regional averages of mortality rates and of various high temperature variables measures over the period 1900-2004. The first row of Table 1 reports averages for all states, while the following four rows are for the four U.S. Census regions (Northeast, Midwest, South, and West).[12] To help highlight any differences over time in these averages, we report them separately for 1900-59 and 1960-04. 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 between 1960-2004. Geographical variation in the mortality rate is highlighted by entries for the 4 regions. The Northeast region has the highest mortality rates in both periods, and the South and the West have the lowest mortality rates.

[11] We construct a balanced data series on average annual AC coverage by state by linearly interpolating from 1960 to 2004, except for 1960, 1970 and 1980 where we use the actual reports from the Census. Figure 4 below compares the out of sample interpolations to independent estimates from other national surveys.

[12] The US census regions are defined as follows: Northeast = CT, MA, ME, NH, NJ, NY, PA, RI, VT; Midwest = IA, IL, IN, KS, MI, MN, MO, ND, NE, OH, SD, WI; South = AL, AR, DC, DE, FL, GA, KY, LA, MD, MS, NC, OK, SC, TX, VA, WV; West = AZ, CA, CO, ID, MT, NM, NV, OR, UT, WA, WY. Appendix Figure 2 displays the geographic concordance between states and US regions.

The bars in Figure 2 depict the average annual distribution of daily mean temperatures across ten temperature-day categories over the 1900-2004 period. 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 that the average person is exposed to in each bin. This represents a population-weighted average across all state-year realizations. Exposure to high temperatures is measured by the frequency of the upper two bins (i.e. days with average temperature between 80 and 89°F and above 90°F). Based on this, the average person is exposed to about 20 days per year with mean temperatures between 80°F and 89°F and 0.7 days per year where the average temperature exceeds 90°F.[13] As Table 1 shows below, this national average masks substantial heterogeneity in the exposure to high temperatures, especially the very high temperatures (i.e. warmer than 90°F).

These ten bins form the basis for a simple semi-parametric modeling of temperature in equations for mortality rates that we use in the rest of this paper. The only substantive restriction is that the temperature-days bins restrict the marginal effect of temperature on mortality to be constant within 10F ranges. Further, the binning of the data preserves the daily variation in temperatures, which is important given the considerable nonlinearities in the temperature-mortality relationship (Deschenes and Greenstone 2011). As we explain below, we also consider more parsimonious models of exposure that rely on a smaller number of temperature-day bins.

Returning to Table 1, the remaining columns reports summary statistics on exposure to high temperatures over the 1900-2004 period. The right-hand panel shows the average number of days per year in the upper two temperature categories from Figure 2, in addition to the number of days per year below 40°F (this is obtained by summing the days in the lowest 4 temperature bins). As we show below, these are the temperature ranges where the mortality impacts are more pronounced.

The first entries document the frequency of cold days, where the mean temperature is 40°F or less. Nationally, the average is about 90 days per year in 1900-59 and 80 days per year after 1960. There is also a great degree of variation across Census regions. The Northeast and Midwest are exposed to about 120 days per year of below 40°F average days, while such days are 3 times less frequent in the South and in the West. The average number of exposure days with daily average temperature ranging from 80-89°F is 22.2 in 1900-59 and 22.9 in 1960-04. As expected, there is sizable geographical variation around this national average. The average exposure in the South is about 48 days per year but only 5 for

[13] Days where the daily average temperature exceeds 90°F are indeed hot. The average minimum and maximum daily temperature on such days are 80°F and 106°F, respectively.

the Northeast region. More the most, the means for this temperature range are stable across the two time periods, although the West region experiences an increase of 4 days in exposure.

The patterns for the number of temperature-days in excess of 90°F are generally similar, except that exposure to this extreme high temperature is much less frequent. The population weighted national average increased from 0.5 to 0.8 day per year in the early and later parts of the sample. The limited exposure to extreme temperature days for the average person highlights that identifying its effect on mortality is empirically challenging. Again, there are significant geographical differences in average exposure. For instance, there is essentially no exposure in Northeast, while the average exposure in the West region doubled from 1.4 to 2.8 days per year before and after 1960. As such identification of the effect 90°F+ temperature-days will be driven mostly by the South and West regions. In fact, Arizona (22), California (2), Nevada (4), Oklahoma (3) and Texas (2) are the only states that experience more than 2 days per year where the average daily temperature exceeds 90°F. In fact we hope to estimate more disaggregated models reflecting this local variation in the next version of this paper.

Finally it worth noting that the "warming" suggested by comparing the 1900-59 and the 1960-04 averages may reflect many factors, including the changing in the location of weather stations over time, the geographical mobility of the population to warmer states such as Arizona and Nevada, and of course general warming of the climate.

Modifiers of the Temperature-Mortality Relationship.

(i) Doctors Per Capita

Over much of the twentieth century, access to health care was increasing. Through the 1930s, the number of physicians per capita actually fell as the medical profession focused on training fewer individuals to a higher standard. As Figure 3 illustrates, the number of physicians per capita was relatively constant through 1960, at which point it began to rise (Blumenthal 2004). The current average is 2.9 doctors per 1,000 population.

(ii) Electrification

Figure 4 reports estimates of the share of US households with access to electricity from the early 1900s to 2000. We report two independent estimates. The first is from the "Historical Statistics of the United States" publication which reports only national means. These data are reported in the black line. The second source is the state-year data we use in the analysis and described earlier (i.e. from the CEI) which we linearly interpolate to fill in the years in which there are no surveys. The green line displays the national means derived from these data. Apart from some minor level differences the two lines essentially show the same adoption curve. The key point in Figure 3 is that after the early 1960s, essentially all households in the US had access to electricity, and so the effect of electricity access alone in reducing the mortality effects of extreme temperature exposure should be concentrated in the pre-1960 period.

(iii) Residential Air Conditioning Adoption

Figure 5 shows the fraction of households with residential AC in the United States (black line), based on data from Biddle (2008), our tabulations from the US Census files for 1960-80, and various American Housing Surveys for the 1990s and 2000s. The green line shows the actual measure of average AC ownership rates derived from the 1960-1980 US Census files (assumed to be 0 prior to 1960 and linearly interpolated to 2004). It is clear from these two data series that the linear interpolation does not appear to introduce any significant bias in the estimation of residential AC coverage in non-census years and past 1980.[14]

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. At the same time, many office buildings, movie theaters and shops offered AC to their patrons, so knowledge about this technology and its comfort and possible health benefits was known to a large share of the population. In 1960 about 10% of US households had access to residential AC (either through the form of central AC or room AC). By 2000, more than 80% of US household lived in homes with AC. Figure 4 also shows that at the aggregate level, the diffusion of AC evolved at a very steady rate over time.

The steady increase in aggregate share of AC households hides significant regional variation in the extent and speed of adoption. Indeed, Biddle (2008) concludes that differences in income and electricity prices across SMSAs are strongly related to the adoption of central AC. This is in addition to the rise in AC coverage that was the result of changes standard methods of residential construction during the 1950s and the result of a 1957 regulatory change at that allowed central AC systems to be included in FHA-approved mortgages (Ackermann 2002).

[14] In addition, any error introduced by the linear interpolation will be independent of the shocks to the local temperature distributions that identify our models.

Figure 5 also highlights some of the key geographical differences in residential AC adoption by comparing the adoption curve of households located in Texas (red line) and Pennsylvania (blue line).[15] It is clear that adoption rates in Texas have always exceeded those of Pennsylvania, and of the national average. In 1980, the share of household with residential AC is 0.8 in Texas, 0.4 in Pennsylvania, and 0.55 nationally. The difference between Texas and Pennsylvania may be attributable to income, tastes or electricity price differences, as well as the obvious difference in climate. Residential AC is more likely to offer indoor comfort and possibly health benefits to a resident of Texas than to a resident of Pennsylvania. For the purpose of our analysis, we take the state-year average AC ownership rate as well as the difference trends in adoption across areas as given. Its possible endogeneity (due say to income differences) is addressed by controlling for rich fixed effects by state*month and year*month in the regression models. Further, it is unlikely that the unobserved determinants of adoption which could bias the analysis are correlated with month-to-month weather shocks that identify the models.

III. Empirical Approach

A. Regression Models

The regression models are identified by historical year-to-year random variation in temperature in each state. Under the reasonable assumption that year-to-year variation in temperature within a state is independent of unobservable determinants of health, this research design allows us to causally attribute variation in mortality outcomes to exposure to extreme ambient temperatures. The baseline estimating equation of the form:

$$(1)\ \log(Y_{sym}) = \sum_j \theta_j TMEAN_{symj} + \pi_L LOWP_{sym} + \pi_H HIGHP_{sym} + X_{sym}\beta + \alpha_s + \gamma_y + \delta_m + \varepsilon_{sym}$$

where $\log(Y_{sym})$ is the log of the monthly mortality rate in state s, year y, and month m. 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 annual fluctuations in temperature and are defined as the number of days in a state-year-month where the daily mean temperature is in the jth of the ten bins

[15] Appendix Figure 3 further documents the geographical differences in AC adoption between 1960 and 1980 by displayed county-level averages. It is evident than southern and warmer states are more likely to have AC in their homes.

used in Figure 2. The only 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 degree intervals. The choice of ten temperature bins represents an effort to allow the data, rather than parametric assumptions, to determine the mortality-temperature relationship, while also obtaining estimates that are precise enough that they have empirical content.

In some models below 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 temperature-day variables: the number of days below 40°F, the number of days between 80-89°F and the number of days above 90°F. This choice of degree-days base is informed by the estimated response function linking mortality and the 10 temperature-day bins. The simpler regression model takes the form of:

$$\textbf{(2)}\ \log(Y_{sym}) = \theta_{40} DAYS40_{sym} + \theta_{8089} DAYS8089_{sym} + \theta_{90} DAYS90_{sym} + \pi_L LOWP_{sym} + \pi_H HIGHP_{sym} + X_{sym}\beta + \alpha_s + \gamma_y + \delta_m + \varepsilon_{sym}$$

In both specifications the variables LOWP and HIGHP are indicators for unusually high or low amounts of precipitation in a state-year-month. More specifically, these are defined as indicators for realized monthly precipitation that is less than the 25th (LOWP) or more than the 75th (HIGHP) percentiles of the 1900-2004 average monthly precipitation in a given state-month. While interesting in their own right, these variables are treated as control variables and so we do not report their estimated coefficients in order to keep the number and size of tables reasonably small.

The specifications in equations (1) and (2) also includes a full set of state, year and month fixed effects, although the preferred specification will also include state*month fixed effects and year*month fixed effects, as well state*month linear trends. The monthly fixed effects are included to absorb the strong seasonality in mortality (which is the largest in the winter months and is the smallest in the summer months). By interacting the month fixed effects with state and year fixed effects, the model allows for the seasonality of mortality to across states and to change over time in a manner common to all states. The state*month linear trends also allow the state-specific seasonality to change differentially across states, albeit in a parametric manner. The year*month fixed effect will control for trends in mortality outcomes and control for time-varying factors related to health and that are common across state (e.g., for example the introduction of the Medicare program). Finally, the state fixed effects will absorb all unobserved state-specific time invariant determinants of the mortality rate. So, for example, differences in permanent hospital quality or the overall healthiness of local populations will not confound the weather variables.

There are additional issues with the econometric approach that bear noting. First, we report standard errors that are clustered at the state level. This allows the errors within states to be arbitrarily correlated over time (across years and month). Second, we estimate equation (1) as a GLS, where the weights correspond to the square root of the state population (i.e., the denominator for the mortality rate) for two complementary reasons. The estimates of mortality rates from large population state are more precise, so it corrects for heteroskedasticity associated with these differences in precision. Further, the results reveal the impact on the average person, rather than on the average state, which we believe is more meaningful. Finally, since age is an important correlate of health, we control for each state's population share in 4 age groups: infants (0-1), 1-44, 45-64 and 65+. Further, since the effect of temperature extremes on health might vary across age groups we also estimate models where the temperature variables are interacted with the population shares in the 4 age groups.

Another important empirical issue that needs discussion is the possibility of temporal advancement of mortality or 'harvesting'. Harvesting or short-term mortality displacement refers to the temporal advancement of death among persons who are already ill or at high risk of dying. Empirically, this implies that periods of unusually high temperature lead to spikes in daily or weekly mortality rates that followed by several days of below trend mortality rates. Therefore examining the day-to-day correlation between mortality and temperature will overstate the substantive effect of temperature on life expectancy. In addition, the possibility of delayed effects -- the case where the effect of temperature shocks on health takes several days or weeks to manifest themselves – can also possibly confound the day-to-day temperature mortality association. In both cases, the key point is that the full impact of a given day's temperature may take several days to manifest fully. The solution to both types of problems is to design empirical models that examine intermediate- and long-term effects, rather than only short-term effects, either through appropriate time aggregation of the data (as in Deschenes and Greenstone 2011) or through the use of distributed lag models (as Deschenes and Moretti 2009). The baseline model we consider below includes an exposure window of 1 month. We also report cumulative estimates that are derived from models with an exposure window of 3 months.

B. Modifiers of the Temperature-Mortality Relationship

In order to quantify the contribution of each specific innovation or 'modifier' played in changing the temperature-mortality relationship, we augment the models in (1) and (2) with interactions between the temperature variables with time-varying measures of access to health care (measured by log doctor per capita in a state-year), electrification (measured by the fraction of households with electricity in state-year), and residential AC (measured by the fraction of households with residential AC in state-year). Naturally, we also include main effects for these variables. We consider augmented specifications where the modifiers and their interactions with the temperature variables are introduced one modifier at the time. We also estimate the full model with all modifiers and interactions at the same time.

We posit that the coefficients on the interaction terms will be negative at the extreme temperature categories. A negative coefficient would be interpreted as evidence that the adoption of a particular modifier contributed to reduce the mortality effect of exposure to temperatures in the range associated with the interaction term. In particular, for reasons discussed earlier, we expect the modifier variables would play a key role in dampening the mortality effects of high temperatures (e.g. days>90° F).

An important issue for the interpretation of the interaction coefficients between temperature extremes and the modifiers is the process by which these modifiers were diffused across geography and time. Namely, it is ideal if these innovations are implemented locally based on factors that are independent of the component of individual health that is influenced by temperature extremes. In that case, the interpretation of the interaction term as evidence of a modifier muting the mortality effects of high temperatures is correct. Alternatively, one can view the adoption of these innovations at the local level as the outcome of a basic technology adoption model. Suppose that willingness-to-pay for a technology is time-invariant in a location, but varies across location. As the cost of adoption for each innovation declines over time, the adoption rate should follow the standard "s-curve" as we documented in Figure 4 and 5 for electricity and residential AC. Thus the diffusion process should be exogenous to health conditional on the state fixed effects and one the various time fixed effects.[16]

IV. Results

[16] The process of electricity diffusion in the US reflected costs (population density for cheap transmission; proximity to coal reserves and hydropower) and demand (wealth, heavy manufacturing industry). Although it plays a role in demand, health is unlikely to be the primary driver of electrification.

A. Estimates of the Temperature-Mortality Relationship

Figure 6 (a) presents the estimates of the temperature-mortality relationship using the full panel of state-year-month data for 1900-2004 and based on the preferred specification of equation (1) that includes state*month fixed effects and year*month fixed effects, as well state*month linear trends. Specifically, the figure plots the regression coefficients associated with the temperature-day bins (i.e. the θ_j) under a zero normalization for the 50-59°F temperature bin.[17] As a result each coefficient measures the estimated impact of an additional day in temperature bin j on the log monthly mortality rate, relative to the impact of a day in the 50-59° F range.

The figure confirms that mortality risk is highest at the coldest and especially at the highest temperatures. For example, exposure to a single day in the >90°F category increases the mortality rate by approximately 1.6% (i.e. 0.016 log mortality points), while exposure to the 80-89°F category increases the mortality rate by about 0.2%. It is also evident that cold temperatures lead to excess mortality: the coefficients associated with the lowest 3 temperature bins range from 0.4% to 0.6%. All estimates associated with temperature bins exposures above 80°F and below 40°F are statistically significant at the 5% level. This is hardly a new finding (see Deschenes 2012 and NIEHS 2010 for reviews of the literature), however, this is the first estimate of the temperature-mortality relationship based on data going back to as early as 1900. The estimates in Figure 6 also motivate the more parsimonious approach we take below and that models the full range of exposure with number of temperature-days below 40°F, temperature-days between 80-89°F and temperature-days exceeding 90°F.

Figure 6 (b) and (c) provide the first opportunity to assess if the temperature-mortality has changed over time. To this end, we estimate the model separately for the 1900-1959 and 1960-2004 periods. The “breakpoint” at 1960 is illustrative only, but it does correspond to the point in time where electrification in the United States reached 100% and when residential AC begins to spread and potentially contribute to reduce the health burden of extreme heat**.** Two key results emerge from Figure 6 (b) and (c): First, there is a sharp decline in the mortality impact of high temperature days (especially those above 90°F after 1960). In particular, the coefficient associated with the hottest temperature range declined by a factor of 4 after 1960, i.e. from 2.4% to 0.6%. Similarly, the impact of exposure in the 80-89°F range declined from 0.4% to 0.1%. At the same time, there is a much lesser decline in the

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

extent of cold-related mortality. For example the coefficient associated with the 10-19°F temperature range changed from 0.6% to 0.5% in the two time periods.

Figure 7 further documents the changing nature of the high-temperature mortality relationship over time. Specifically, it estimates the temperature-mortality relationship based on the 10 bins and preferred specification of equation (1) for 20 year periods: 1900-1919, 1920-1939, 1940-1959, 1960-1979, 1980-04. Figure 7 (a) shows the coefficient associated with temperature-days exceeding 90°F and Figure 7 (b) shows the coefficients for days 80-89°F, along with the 95% confidence intervals.

Qualitatively, the patterns in Figure 7 (a) and (b) tell a slight different story. The effect of extreme high temperature (days where the average temperature exceeds 90°F) remains roughly constant at around 0.02 log mortality points (so about 2% effect on the mortality rate) from 1900 to 1959, and then begins to decline over the period 1960-2004. The point estimate for 1960-79 is 0.0156 and 0.0051 for 1980-2004. The effect of exposure to 80-89°F temperature-days shows a threefold decline between the first two periods (1900-19 and 1920-39), but then remains relatively constant from 1940 to 1980 at about 0.0025. Finally, this effect essentially vanishes after 1980 as the estimated coefficient drops to 0.0002. This qualitative difference in the time patterns of the "very high" and "high" temperature exposure effects on mortality rates suggest that the factors that contributed to the decline in these effects did not alter the temperature-mortality relationship uniformly.

Table 2 reports the regression coefficients estimates associated with the upper and lower parts of the temperature distribution from a more parsimonious version of equation (1). In particular, we focus on 3 temperature-day variables: the number of days below 40°F, the number of days between 80-89°F and the number of days above 90°F. This simpler functional form is motivated by the estimates in Figure 6. Panel [A] in Table 2 includes temperature controls for the current month only. Panel [B] reports cumulative dynamic estimates based on models that control for 3 months of temperature exposure, that is, the current month, and the prior two. The cumulative dynamic estimates are the sum of the coefficients associated with any temperature-day bins over the course of the 3 months. These cumulative estimates are robust to near-term mortality displacement up to at least 90 days.[18] All estimates in Table 2 are derived from the preferred specification of equation (1) that includes state*month fixed effects and year*month fixed effects, as well state*month linear trends. The three columns of Table 2 correspond to the 3 different estimation periods: 1900-04, 1900-59, and 1960-04.

[18] Most papers in the epidemiology literature consider displacement windows of less than 3 weeks. Deschenes and Moretti (2009) use a window of 3 months while Deschenes and Greenstone (2011) implicitly use a window of up to 1 year.

The results in Panel A of Table 2 confirm the evidence in Figure 6. Very high daily average temperature exposure (>90°F) leads to significant and large excess mortality, with an effect of 1.7% per exposure day. This estimated impact substantially declines in the pre and post 1960 samples, from 2.6% to 0.7%, and is statistically significant in both sample periods. Exposure to temperature-days between 80-89F and temperature-days below 40F also leads to statistically significant increases in mortality, but the effects are much smaller, ranging from 0.2% to 0.6% across the various sample periods. The decline in the mortality impact of exposure to "extreme" temperatures is also notable for those 2 ranges of the daily temperature distribution.

Panel B further confirms the findings by establishing that the excess mortality associated with exposure to temperature extremes documented in Figure 6 and panel A of Table 2 is not a mere artifact of near-term mortality displacement. The estimates in Panel B are generally slightly smaller in absolute terms, indicative of some degree of near-term displacement. At the same time, the corresponding estimates in Panels A and B are generally within standard errors of each other, and so one would fail to reject the null hypothesis of no displacement effect. Nevertheless, the magnitudes of the key >90°F temperature-day exposure on mortality remains large and all but one of the estimates in Panel are statistically significant at the 5% level. Based on this evidence, we proceed with the simpler 1 month exposure model and ignore near-term mortality displacement or harvesting in the rest of the paper.

Table 3 probes the extent of geographical differences in the impact of high and low temperatures on mortality. This investigation is motivated by the important regional differences in the frequency of high and low temperature days documented in Table 1. As a result, the population of these regions may have adapted differently as technologies permitted. Specifically, we estimate the more parsimonious version of equation (1) that includes the number of days below 40°F, the number of days between 80-89°F, and the number of days above 90°F. We continue to report separate estimates for the 1900-59 and 1960-04 sample periods.

There is substantial heterogeneity in the estimated effects of extreme temperatures on mortality. For example, the impact of temperature-days exceeding 90°F and between 80-89°F is largest in the Northest and Midwest regions, where exposure is the lowest. Likewise, exposure to cold temperature days leads to larger mortality effects in West and South regions, where again exposure is lowest. This evidence is consistent with physical acclimatization or climate-specific investments in mitigation technologies, such as air conditioning. The estimates in Table 3 also show that across all regions, there is a notable decline in the mortality effect of extreme temperature days before and after 1960, as was previously shown.

Table 4 presents a robustness analysis on the estimated effect of very high temperature days (>90°F) on mortality. We consider additional control variables, subsamples, and included fixed effects. The estimates are derived from the full 1900-04 sample. The first column reports the estimated coefficient while the second reports the sample size, as the sample is not fixed across alternative specifications. Estimates in Table 4 are based on the models with a one month exposure window, as in Panel A of Table 2.

The first row reproduces the baseline estimate of 0.0170 (se = 0.0027) from Table 2.[19] In row 3 we report the estimate produced when the regression also controls for log real per capita income by state-year. These data, taken from the Bureau of Economic Analysis, are available from 1929 onwards, and so the sample size is smaller than in row 1. Adding this control does not lead to a meaningful change in the estimated effect, as expected since the many fixed effects included in the baseline specification are likely to capture the impact of average economic wellbeing on mortality.

Rows 4-7 break the sample down by median per capita income and by median share of rural population and estimates the mortality effects specific to these subgroups. 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. Rows 4 and 5 show that the mortality effect of very high temperature days falls disproportionately on the lower income populations. The point estimate for below median per capita income states is about 2.5% as opposed to 0.6% for the above median per capita income states. Rows 6 and 7 further show that the mortality effects are slightly larger for urban populations instead of rural populations.

Finally, the row 8 specification adds interactions between the temperature variables and the precipitation variables (*LOWP* and *HIGHP*) and reports the marginal effects evaluated at the sample means. This addresses the possibility of temperature effects that depend on the degree of humidity, as warmer and wetter days are generally humid. However, this simple specification of modification by humidity does not lead to a meaningful change in the point estimate.

Taken together the evidence in Tables 2-4 clearly shows that exposure to extreme temperatures raise mortality. This confirms the similar findings reported in many prior studies. The mortality effects of high temperature days is not limited to mere near-term displacement, the effect of shocks statistically persists for at least 90 days. The key finding reported in this section is the large decline of the mortality

[19] In this baseline specification, the coefficient associated with 'low' monthly precipitation (deviation from state-month average in the lowest tercile) is statistically significant at 0.0027 (se = 0.0007). The coefficient on 'high' monthly precipitation is smaller and statistically insignificant (-0.0003).

impact of high temperature days over the course of the 20^{th} century in the United States. For instance, we show a fourfold reduction in the mortality associated with temperature days in excess of 90°F. Further, we also document that this decline is observed across all regions in the United States, although the 'level' effects differ across regions. Finally, we consider simple alterations to the baseline specification and generally this fails to lead to a meaningful change in the estimates of the effect of extreme temperatures on mortality. The one notable exception is that the temperature-mortality effects are concentrated in the segment of the population with income per capita less than the median.

Tables 5 and 6 report the interaction effects between each of the modifiers and the three daily temperature variables that are analyzed in Tables 2 and 3. For brevity we only report the interactions associated with temperature-days in excess of 90°F since those are the main focus of the paper. The estimating equations are the same as in Panel A of Table 2, with the exception that the main effect and interactions associated with each modifiers are now included. Table 5 is based on the full sample of 1900-2004.

Column (1) reproduces the main estimate from Table 2, i.e. that a single additional day in excess of 90F increases the monthly mortality rate by 0.017 log points. Columns (2) – (4) are based on specifications that introduce each modifier individually, while column (5) is based on the specification where all modifiers and included jointly. The basic finding in columns (2)-(4) is that all modifiers have the expected negative sign, indicating that increasing access to each of them individually leads to a reduction in the mortality effect of temperature days in excess of 90°F, although the interaction coefficient on share of households with electricity access is not statistically significant. The interactions coefficients are large in magnitude, sometimes as large as the temperature main effect. For instance, the interaction between days >90°F and log doctors per capita is -0.03. Thus a 10% increase in log doctors per capita is predicted to reduce the mortality effect of very high temperature days by about 16%. Similarly an increase in fraction of households with residential AC of 10 percentage points is predicted to lower the mortality effect of very high temperature days by about 10%. However, when all modifiers of the temperature-mortality relationship are included in the same regression model (column (5)), only the impact of log doctors per capita remains statistically and economically significant.

Table 6 reports similar estimates that are derived from the pre- and post-1960 samples (Panels A and B). The cutoff date of 1960 was chosen because it corresponds to the point in time when virtually all households in the United States had access to electricity and also the point in time that marks the beginning of the diffusion of residential AC. For this reason, the estimated modifying effect of electrification is only reported in Panel A (sample years 1900-1959), and the estimated modifying effect of residential AC is only reported in Panel B (sample years 1960-2004). Like in Table 5, we consider the effect of each modifier individually, (columns 1a-2b), as well as jointly (columns 3a and 3b).

Column (1a) and (1b) report the interaction effect for log doctors per capita estimated individually in each sample. In both cases it is negative as expected, and it is larger in magnitude and statistically significant at the 6% level in the 1960-2004 sample. The larger impact in the post 1960 sample possibly reflects the increase in access to care during the 1960s (recall Figure 3), and also the improvements in medical technology for treating heat-related diseases, such as better IV technologies. Columns (2a) and (3a) report the interaction effect of electrification individually (2a) and jointly with doctors per capita for the period 1900-1959. Neither of those factors appears to have contributed to reducing the mortality effects of high temperature days.

Panel B reports estimates specific to the 1960-2004 period. Since electrification was complete by 1960, it is excluded from the Panel. The mitigating effects of health care access (as proxied by doctors per capita) and residential AC are clearly documented. All interactions effects have the expected negative sign, with log doctors per capita being marginally significant at the 5% level and with residential AC being both statistically and economically significant. The estimates in columns (2b) and (3b) both show the interaction effect being larger than the main effect on temperature-days >90F and suggest that a 10 percentage point increase in residential AC ownership decrease the high temperature mortality effect by 17-21%.

V. Interpretation

Global climate change is regarded as the biggest global health threat of the 21st century (Lancet 2009). Its impacts on health are far-reaching and connected through multiple causal pathways. It is also generally accepted that the most vulnerable populations are today's poor who live in developing economies, reflecting their lower levels of infrastructure and medical technologies, their weather-dependent economies, and already warm climates. One objective of this paper is to inform health-preserving adaptation policies in those countries to mitigate negative health impacts predicted to occur under global climate change.

Table 7 presents some background information that supports the external validity of our study based on the historical United States for guiding policies in contemporary developing countries. Specifically, the table reports average vital statistics for the United States in 1940, 2004, and for India and Indonesia. The figures in table are from the study sample (United States) and from the World Bank

Global Indicators (India and Indonesia). The table also reports the averages of the 'modifiers' of the temperature-mortality relationship we considered in the analysis.

Without overreaching with these comparisons, the early 20th century United States appears fairly comparable to contemporary India and Indonesia. Life expectancy at birth in the United States in 1940 was 63. It is currently 67 and 68 in India and Indonesia, respectively. Infant mortality rates per 1,000 are also comparable, ranging from 28 to 58, with the US at 47 in 1940. Perhaps even more striking is the similarity between the three 'modifiers'. In 1940, no individual had access to residential AC in the United States. That is essentially the figure that prevails in India and Indonesia. Similarly, the fraction of population with access to electricity was 74% in 1940 in the United States. The corresponding numbers for India and Indonesia is roughly 66%. The number of physicians per 1000 population was higher in the 1940 United States than it is today in India and Indonesia. The similarity between the average vital statistics and average coverage of modifiers of the temperature-mortality relationship in our study sample and two of today's most prominent countries in terms of global climate change health risk gives us confidence that the results of our study can be of some value to help guiding the adaptation policies debates in these and other similar countries.

The 2 most significant factors that contributed to reducing the mortality burden of extreme temperature days are increases in physician per capita and access to residential AC. Residential AC has been especially effective in reducing the mortality effect on high temperature days since the late 1950 when it was introduced. For instance our estimates suggest that each 10 percentage points increase in the fraction of households with residential AC has contributed to a 17% decrease in the mortality associated with temperature-days in excess of 90°F. Thus our results indicate that increased access to health care and to residential AC could dramatically reduce the health effects of high temperature days in countries that are expected significant warming in the coming years and where access is currently at very low levels. Further, it is clear that increasing access to health care, residential AC, and electrification would produce substantial benefits that go well beyond reducing the health burden of temperature extremes. Our paper cannot quantify these benefits.

VI. Conclusion

Adaptation will certainly be part of our response to the global health threat posed climate change, yet we have very little real world evidence on its potential. This paper brings together a comprehensive data file with over 1 century of observations on monthly mortality, daily temperatures, and several other key determinants of mortality to address this question. Specifically, the paper provides the first empirical evidence on the potential for adaptation to mitigate the mortality effects of the increased extreme temperature in today's developing countries.

The paper first document the remarkable decline in the mortality effect of temperature extremes: The impact of a day with a mean temperature exceeding 90° F on mortality rates has declined by a fourfold factor over the course of the 20th century in the United States, with almost the decline occurring after 1960. We find this result to be robust to dynamic models that account for near-term mortality displacement, and to the inclusion of controls for log per capita income and rural/urban population shares. Our analysis of three key health-related innovations that may have contributed to reducing the mortality burden of high temperature days indicates that the arrival of residential AC in the late 1950s played a key role in this remarkable decline. Our estimates suggest that each 10 percentage point increase in the residential AC ownership rate reduced high temperature mortality effect by at least 17%.

There are some limitations to this research that bear noting. First, the empirical models are identified by monthly variation in weather, rather than a permanent change in climate. Clearly responses and impacts of monthly temperature shocks will likely be different than the responses and impacts of climate shocks. Absent random assignment of climates across population, there is no empirical research design that can fully address this point. Further, three observations support this analysis in this paper. First, the transition between the 'historical' and 'new' climates will not be discrete. Temperature distributions will converge to their new equilibrium levels through a series of high-frequency or (i.e. monthly or annual) shocks. Second, economic theory suggests that relying on high-frequency shocks to identify the empirical models leads to an overstatement of the projected human health costs of climate change.

Finally concerns about external validity always plague historical studies that seek to inform current policy debates, and so our study is also subject to this limitation. Nevertheless, there are important similarities between the population of the United States in the early part of the 20^{th} century and many of today's developing countries that make this paper's results important for guiding health-preserving policies and help countries adapt to the changes in climate that have already begun to emerge.

References - INCOMPLETE

Barreca, Alan 2012. “Climate Change, Humidity, and Mortality in the United States,” Journal of Environmental Economics and Management.

Basu, Rupa and Jonathan M. Samet. 2002. “Relation Between Elevated Ambient Temperature and Mortality: A Review of the Epidemiologic Evidence.” Epidemiologic Review. 24 (December): 190-202.

Blumenthal, David. 2004. “New Steam from an Old Cauldron – The Physician Supply Debate.” New England Journal of Medicine 350: 1780-1787.

Brown, D. Clayton. 1979. “Health of Farm Children in the South, 1900-1950.” Agricultural History 53(1): 170-187.

Brown, D. Clayton. 1980. Electricity for Rural America: The Fight for the REA. Westport, CT: Greenwood Press.

Brown, D. Clayton. 1998. “Modernizing Rural Life: South Carolina’s Push for Public Rural Electrification.” The South Carolina Historical Magazine 99(1): 66-85.

Center for Disease Control. (CDC) 2012. “Ten Great Public Health Achievements -- United States, 1900-1999.” Accessed on August 16, 2012: http://www.cdc.gov/mmwr/preview/mmwrhtml/00056796.htm

Burgess, Robin, Olivier Deschenes, David Donaldson, and Michael Greenstone 2011. "Weather and Death in India: Mechanisms and Implications for Climate Change," Mimeograph, MIT Department of Economics.

Deschenes, Olivier. 2012. “Climate Change, Human Health, and Adaptation: A Review of the Empirical Literature” NBER Working Paper No. 18345

Deschenes, Olivier, and Michael Greenstone. 2011. “Climate Change, Mortality, and Adaptation: Evidence from Annual Fluctuations in Weather in the U.S.” *American Economic Journal: Applied Economics*

Deschenes, Olivier, and Enrico Moretti. 2009. “Extreme Weather Events, Mortality and Migration.” *Review of Economics and Statistics* 91(4): 659-681.

Fishback, Price V. , Werner Troesken, Trevor Kollman, Michael Haines, Paul W. Rhode, Melissa Thomasson. 2011. “Information and the Impact of Climate and Weather on Mortality Rates During the Great Depression.” in *Climate Change Past and Present*. Edited by Gary Libecap and Richard H. Steckel. Chicago: University of Chicago Press.

Grossman, Michael. 2000. “The Human Capital Model.” In Handbook of Health Economics: Volume 1A, edited by Anthony J. Culyer and Joseph P. Newhouse. Amsterdam: North-Holland.

International Panel on Climate Change Working Group II. 2007. Climate Change 2007: Impacts, Adaptation and Vulnerability. Published for the International Panel on Climate Change.

Jayachandran, Seema, Adrianna Lleras-Muney, and Kimberly Smith. 2010. “Modern Medicine and the Twentieth Century Decline in Mortality: Evidence on the Impact of Sulfa Drugs.” American Economic Journal: Applied Economics 2: 118-146,

Kunst, Anton E., Feikje Groenhof, and Johan P. Mackenbach. 1994. “The Association between Two Windchill Indices and Daily Mortality Variation in The Netherlands.” American Journal of Public Health. 84 (November): 1738-1742.

National Institutes of Health 2010: “A Human Health Perspective On Climate Change,” Accessed September 2010. http://www.niehs.nih.gov/health/docs/climatereport2010.pdf

REA. 1936. “Rural Electrification News: A Summary of Rural Electrification Activities.” 1(5): p. 6.

World Health Organization. 2003. Climate Change and Human Health – Risks and Responses. Published by World Health Organization.

World Health Organization (WHO). 2012. “Diarrhoeal disease”. Accessed on August 15, 2012: ttp://www.who.int/mediacentre/factsheets/fs330/en/index.html

Figure 1: Average Annual Mortality Rate Per 100,000

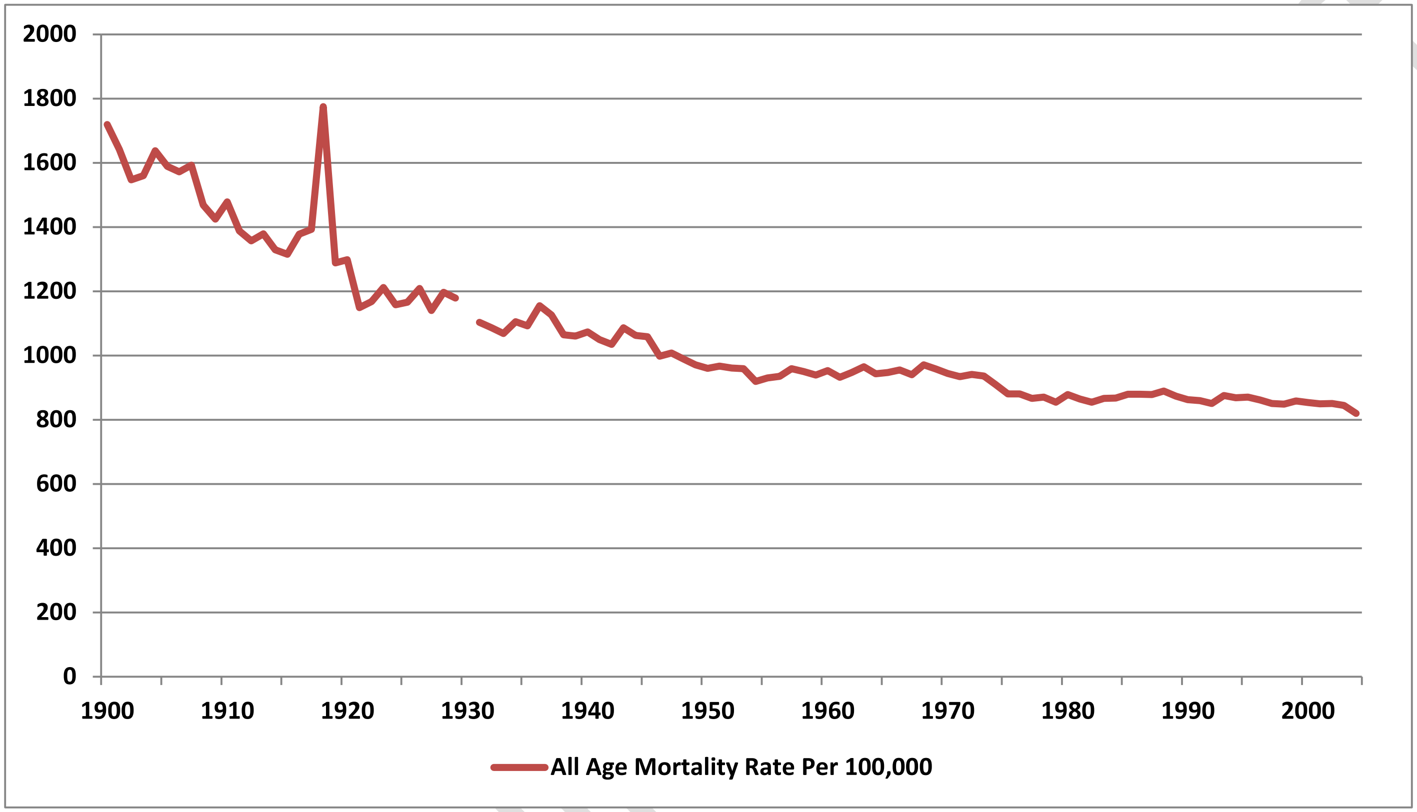


Figure 2: Distribution of Daily Average Temperatures, 1900-2004

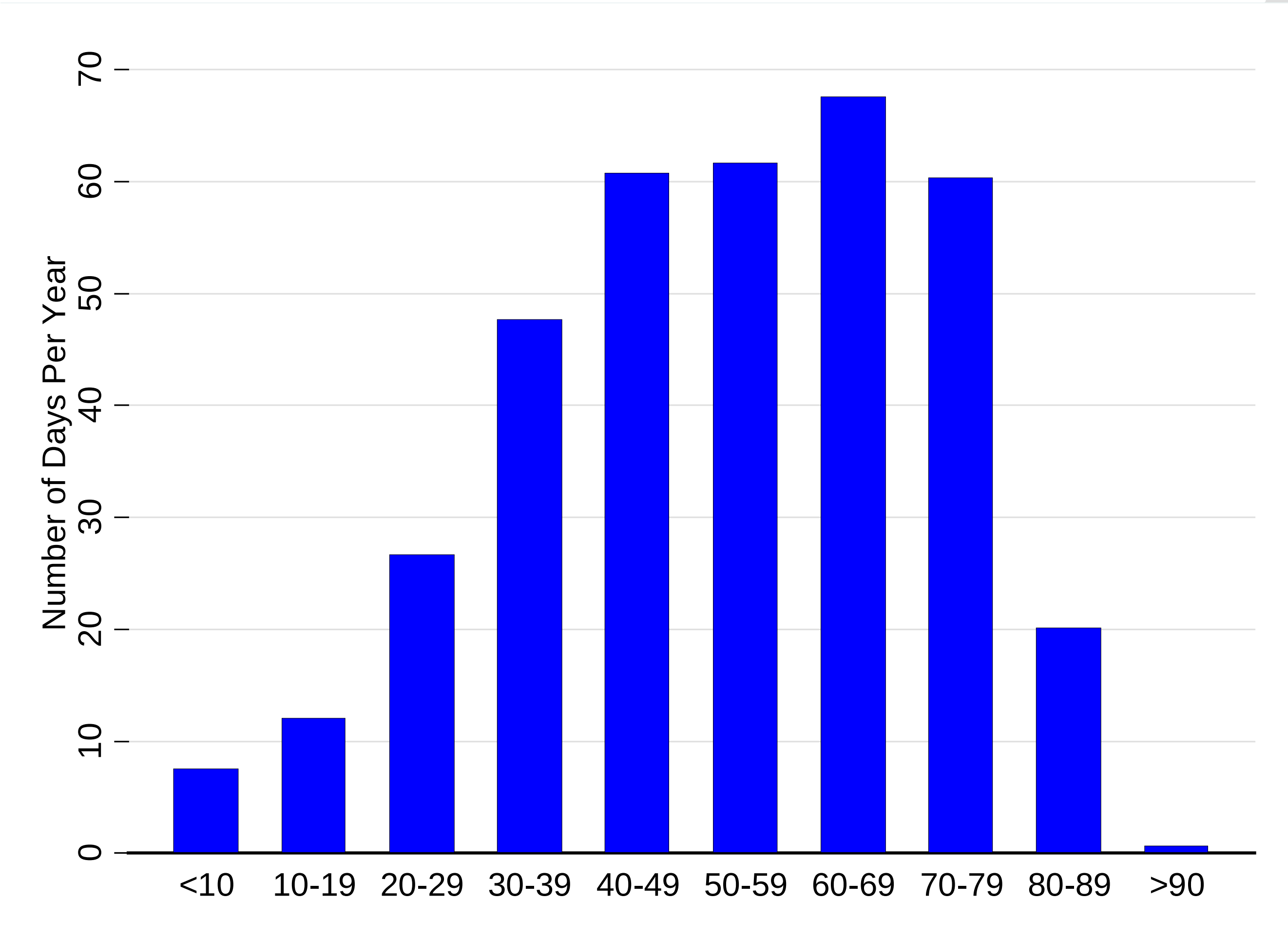


Figure 3: Physicians Per Capita (Per 1,000 inabitants)

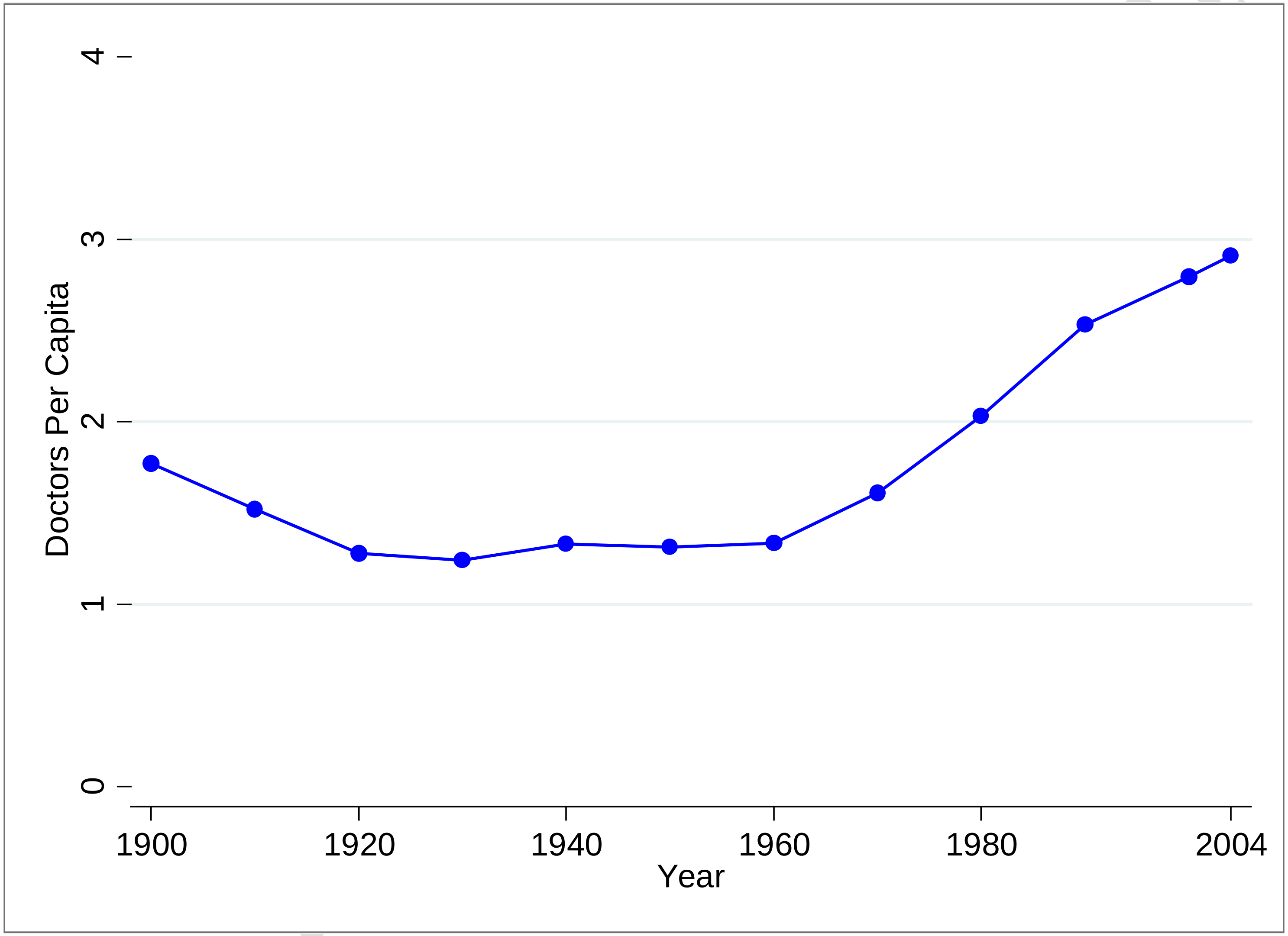


Figure 4: Fraction of US Households with Electricity

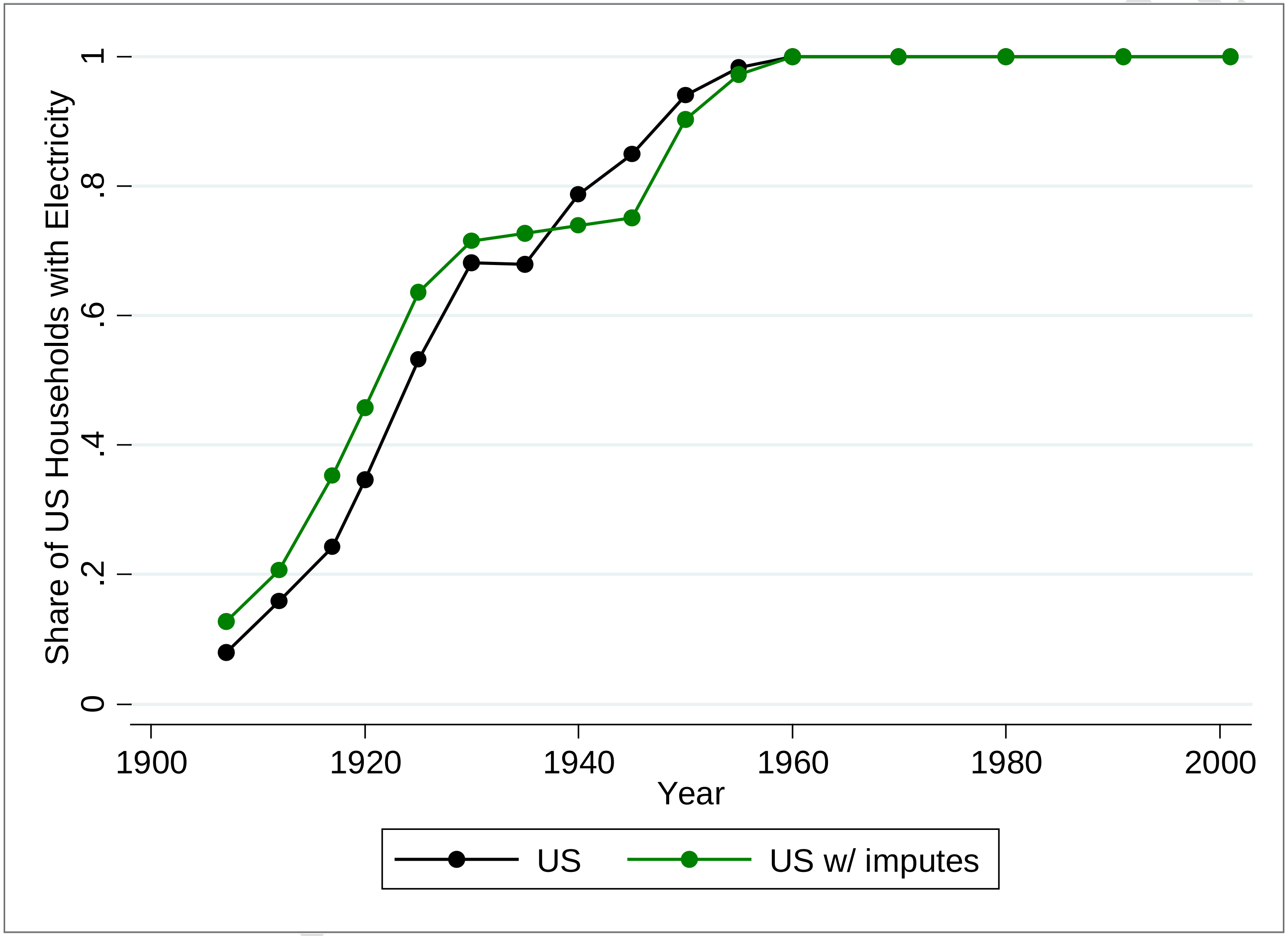


Figure 5: Fraction of US Households with Air Conditioning

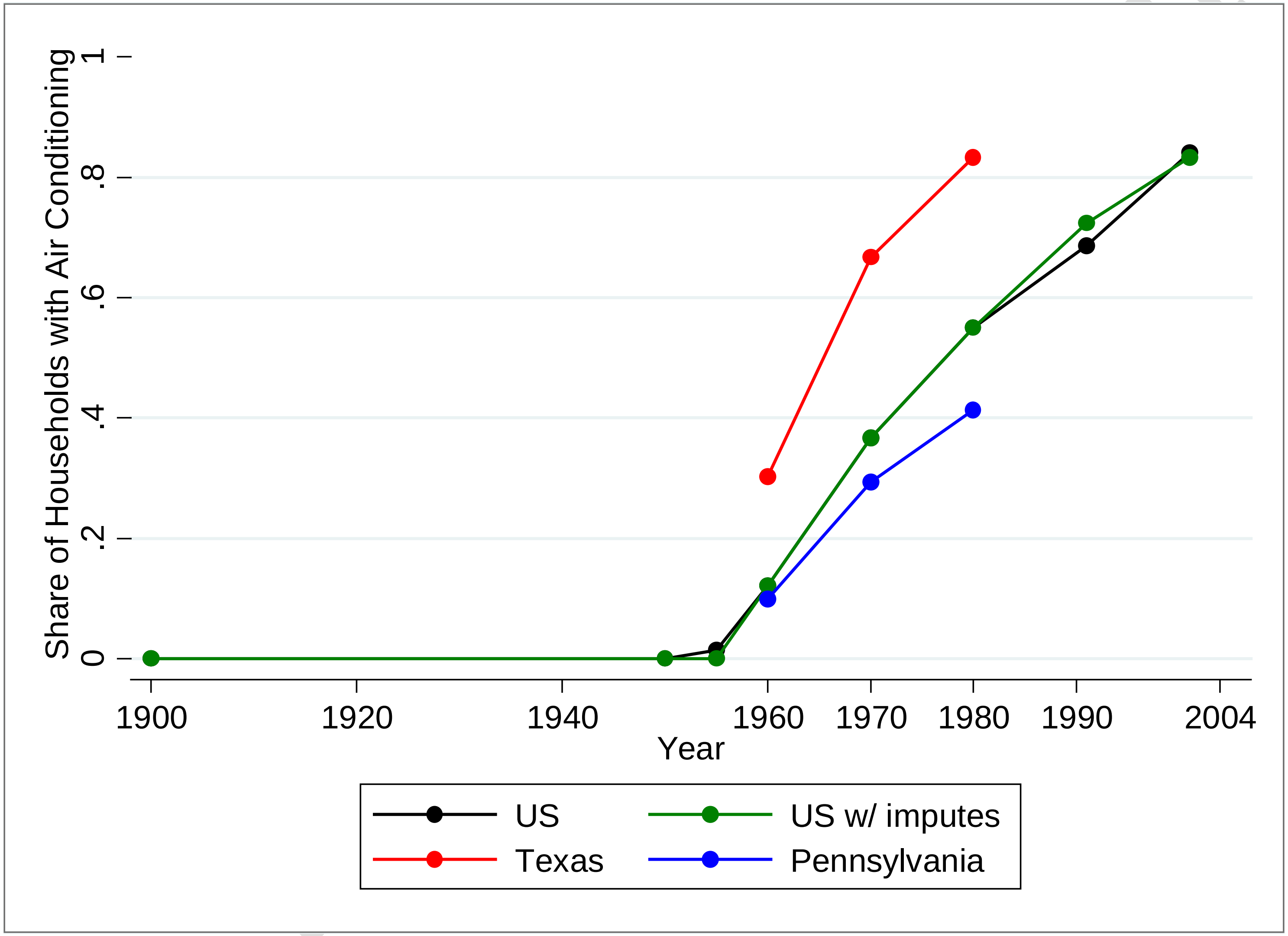


Figure 6: Estimated Temperature-Mortality Relationship

(a) 1900-2004

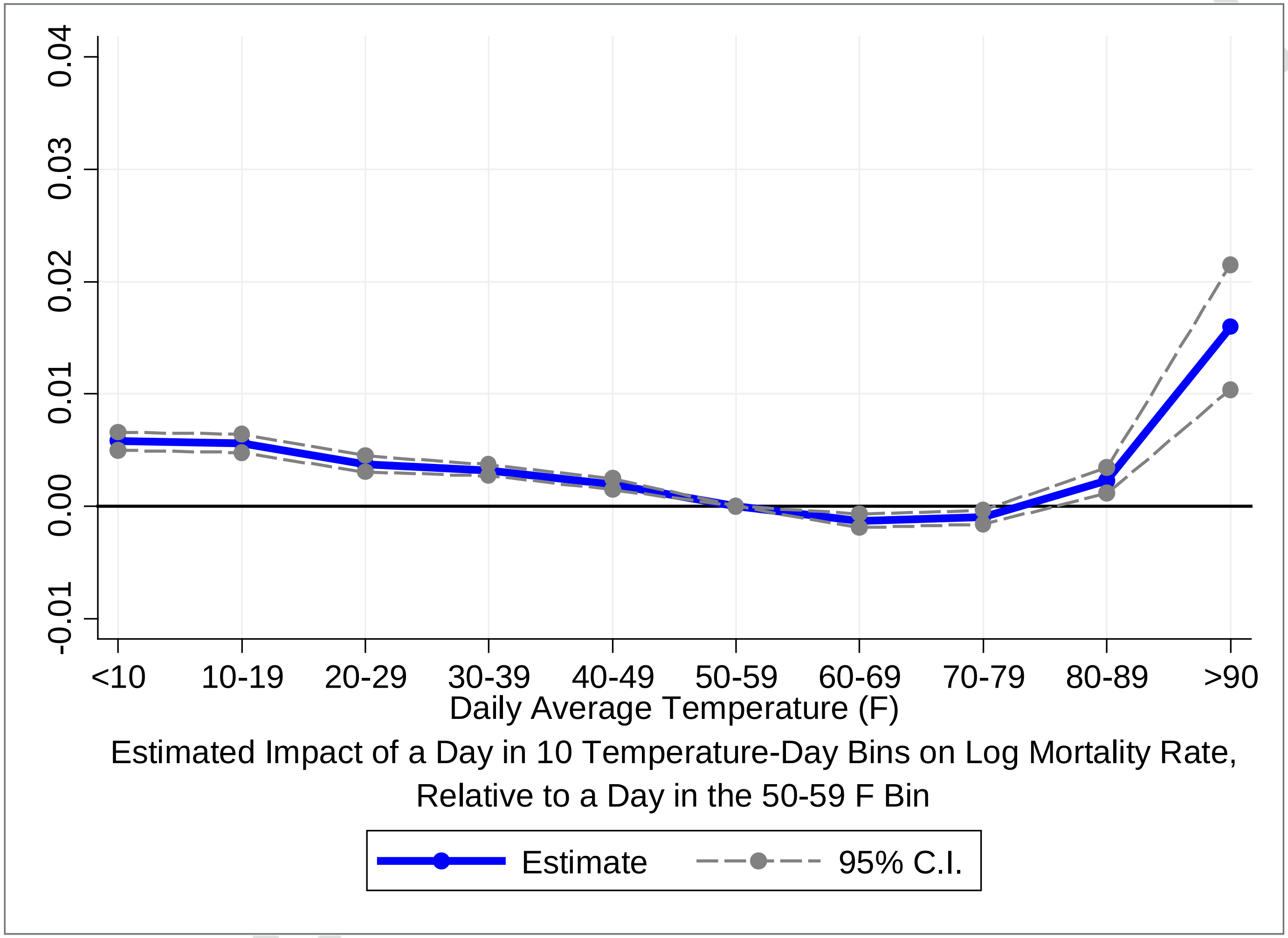


Figure 6: Estimated Temperature-Mortality Relationship

(b) 1900-1959

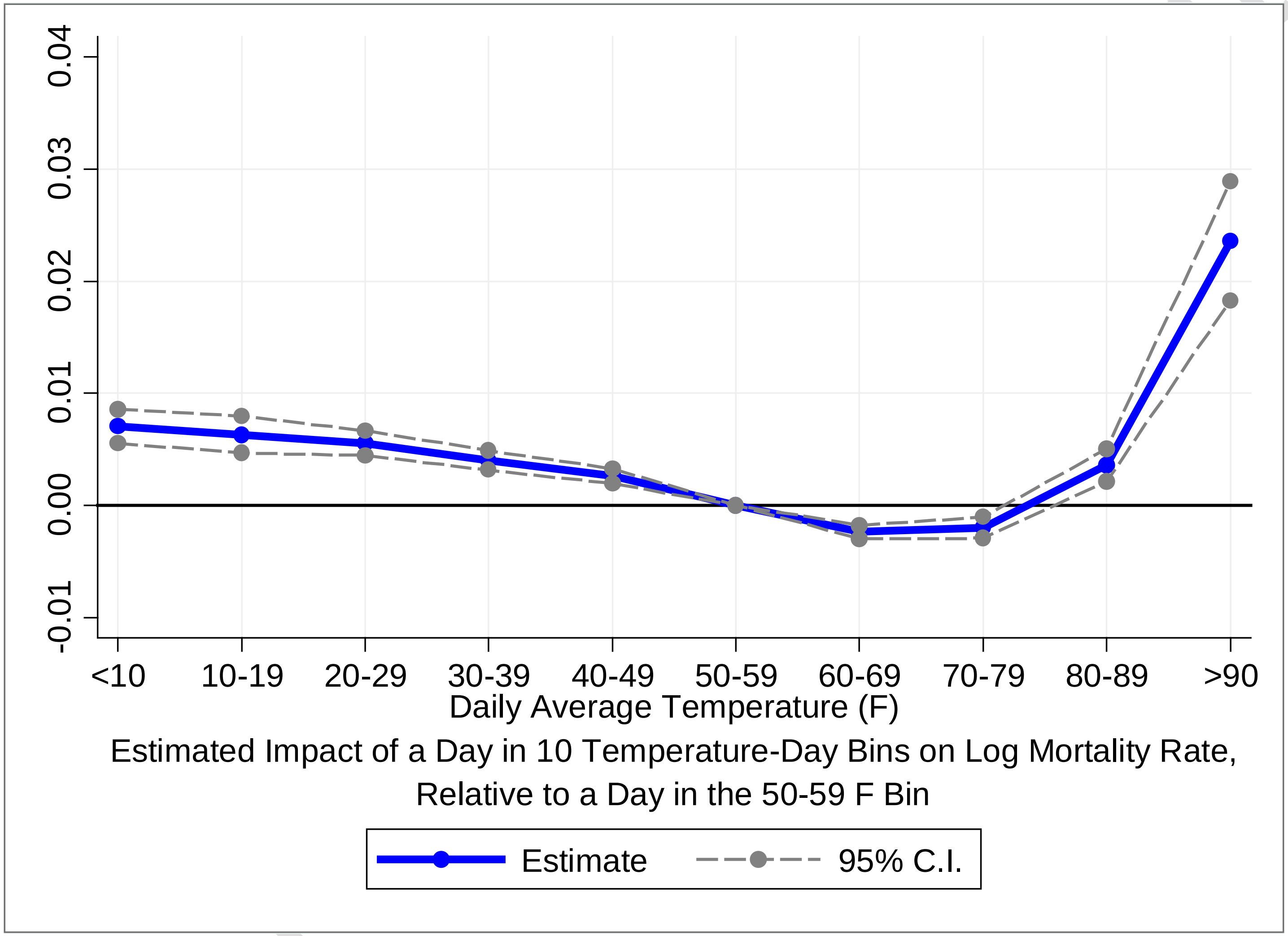


Figure 6: Estimated Temperature-Mortality Relationship

(c) 1960-2004

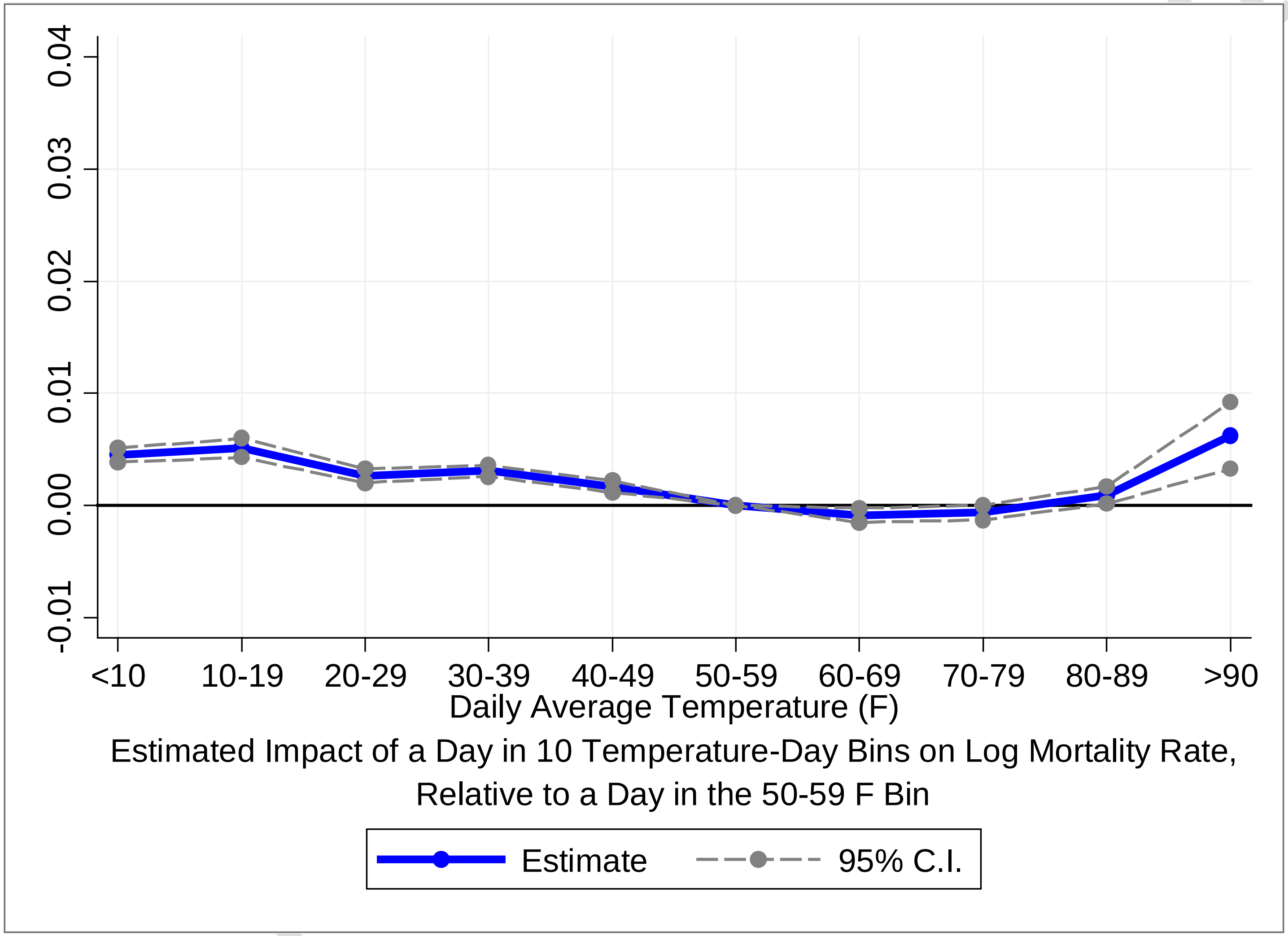


Figure 7: Estimated Impact of High-Temperature Variables on Log Monthly Mortality Rate, By 20 Year Period

(a) Estimated Impact of >90°F Temperature-Days on Log Monthly Mortality Rate, By 20 Year Period

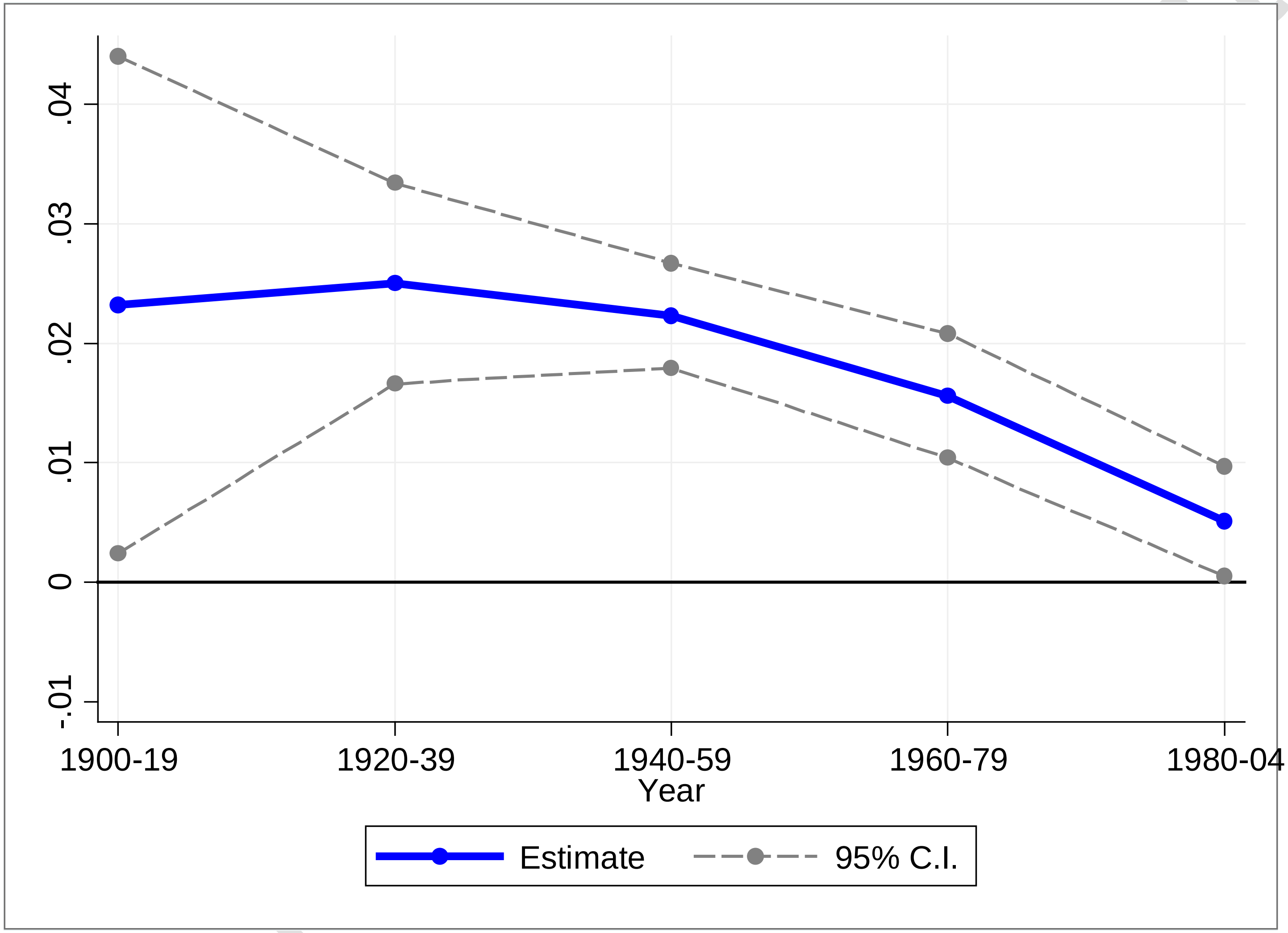


Figure 7: Estimated Impact of High-Temperature Variables on Log Monthly Mortality Rate, By 20 Year Period

(b) Estimated Impact of 80-89°F Temperature-Days on Log Monthly Mortality Rate, By 20 Year Period

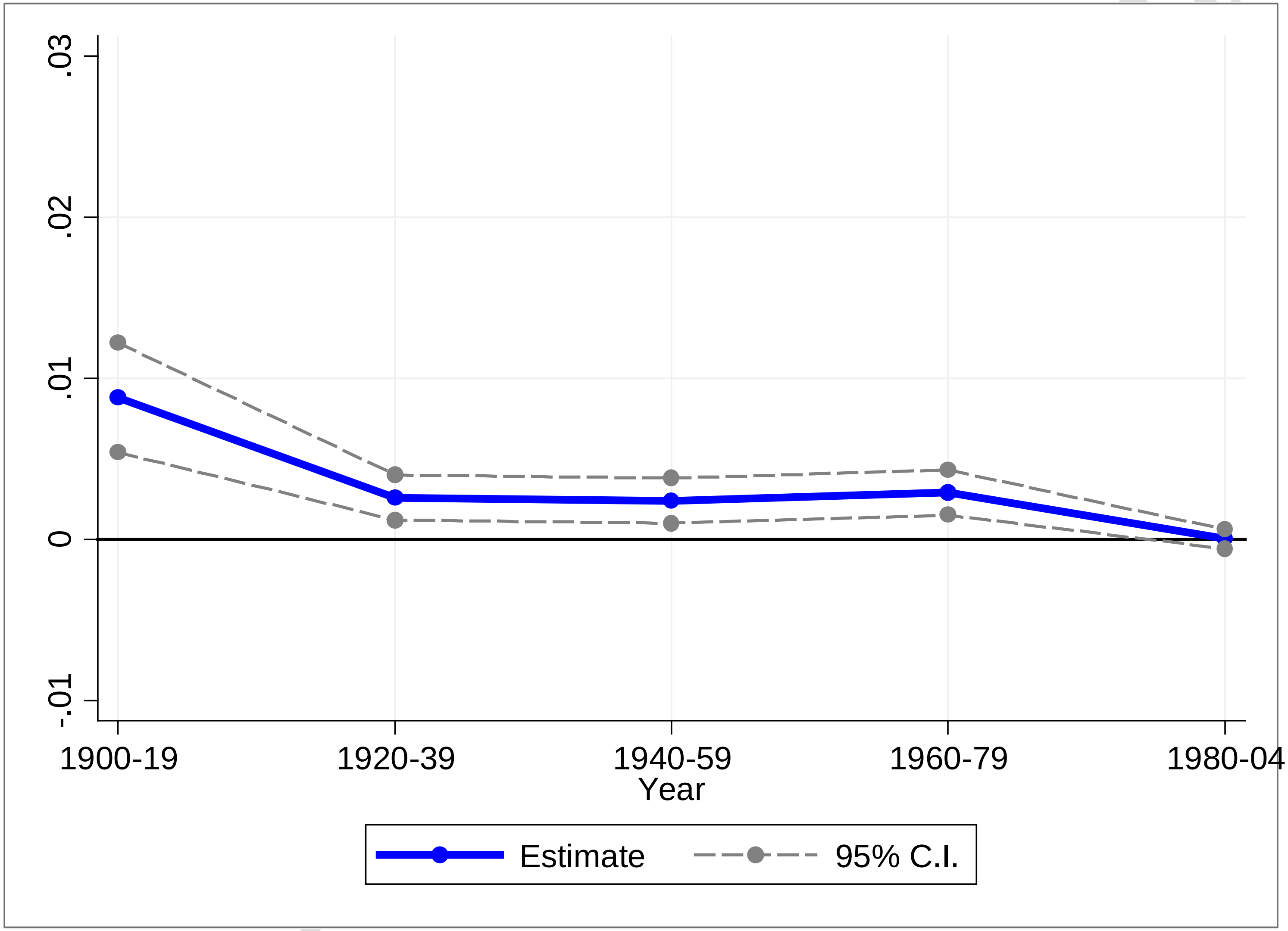


Figure 7: Estimated Impact of High-Temperature Variables on Log Monthly Mortality Rate, By 20 Year Period

(c) Estimated Impact of <40°F Temperature-Days on Log Monthly Mortality Rate, By 20 Year Period

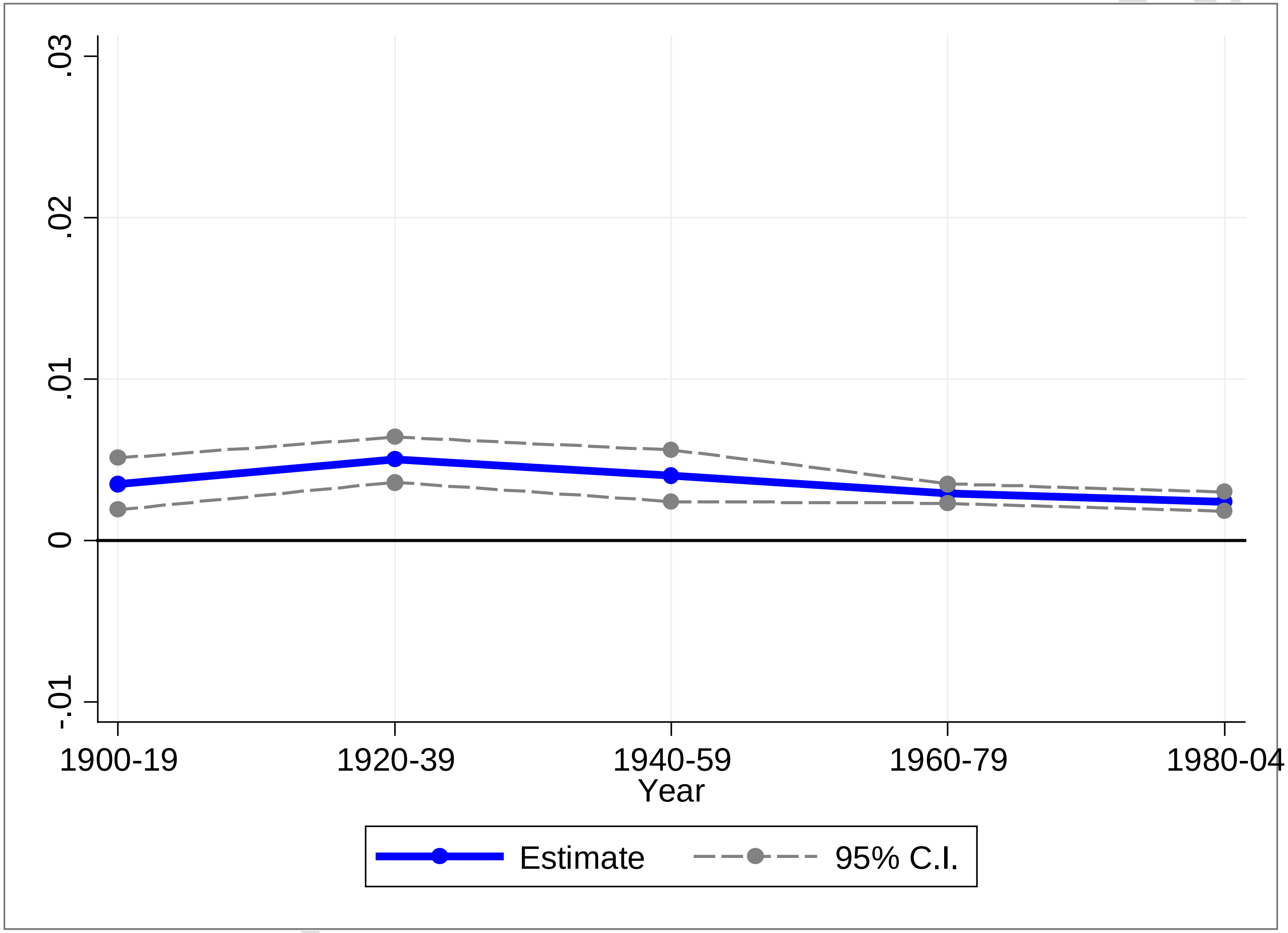


Table 1: Summary Statistics on Vital Statistics and Exposure to Temperature Extremes

	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. All States:	1,111.0	885.8	89.9	80.7	22.2	22.9	0.53	0.75
B. By US Census Region:								
1. Northeast	1,245.0	963.7	122.3	120.6	5.1	4.9	0.02	0.02
2. Midwest	1086.6	915.4	118.7	121.0	15.2	10.7	0.41	0.11
3. South	1,012.9	888.8	41.9	40.3	47.7	48.5	0.80	0.56
4. West	1038.6	754.4	65.2	53.4	10.1	14.4	1.36	2.73

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

Table 2: Estimates of the Impact of High and Low Temperatures on Log Monthly Mortality Rate

	Sample:		
	1900-2004	**1900-1959**	**1960-2004**
	(1)	(2)	(3)
[A] 1 Month Exposure Window			
Number of Days Above 90°F	0.0171*	0.0257*	0.0069*
	(0.0027)	(0.0026)	(0.0014)
Number of Days Between 80-89°F	0.0034*	0.0057*	0.0016*
	(0.0004)	(0.0005)	(0.0002)
Number of Days Below 40°F	0.0030*	0.0039*	0.0026*
	(0.0004)	(0.0007)	(0.0003)
[B] 3 Months Exposure Window (Cumulative Effect)			
Number of Days Above 90°F	0.0123*	0.0197*	0.0052*
	(0.0027)	(0.0031)	(0.0011)
Number of Days Between 80-89°F	0.0025*	0.0044*	0.0003
	(0.0006)	(0.0008)	(0.0003)
Number of Days Below 40°F	0.0043*	0.0065*	0.0031*
	(0.0003)	(0.0007)	(0.0004)
Year*Month Fixed Effects	y	y	y
State*Month Fixed Effects	y	y	y
State*Month Time Trends	y	y	y

Notes: Regression weighted by population. Standard errors clustered on state. See the text for more details.

Table 3: Estimates of the Impact of High Temperatures on Log Monthly Mortality Rate, By US Census Region

	Number of Days Below 40°F		Number of Days Between 80-89°F		Number of Days Above 90°F	
	1900-1959	1960-2004	1900-1959	1960-2004	1900-1959	1960-2004
	(1a)	(1b)	(2a)	(2b)	(3a)	(3b)
[A] 1 Month Exposure Window						
1. Northeast	0.0030*	0.0019*	0.0102*	0.0063*	0.1337*	-0.0416
	(0.0006)	(0.0002)	(0.0015)	(0.0023)	(0.0452)	(0.0210)
2. Midwest	0.0025*	0.0017*	0.0065*	0.0027*	0.0327*	0.0129*
	(0.0005)	(0.0002)	(0.0006)	(0.0005)	(0.0034)	(0.0054)
3. South	0.0057*	0.0033*	0.0048*	0.0011*	0.0193*	0.0062*
	(0.0008)	(0.0004)	(0.0005)	(0.0002)	(0.0010)	(0.0014)
4. West	0.0054*	0.0040*	0.0055*	0.0026*	0.0233*	0.0063*
	(0.0011)	(0.0008)	(0.0013)	(0.0007)	(0.0046)	(0.0014)

Notes: All models include state*month effects, year*month effects, and state*month linear trends. Regression weighted by population. Standard errors clustered on state. See the text for more details.

Table 4: Robustness Analysis

	Number of Days Above 90°F	Observations
1. Baseline (Table 2)	0.0170* (0.0027)	53,076
2. Controls for State*Year Fixed Effects	To come	
3. Controlling for Log Real Per Capita Income	0.0158* (0.0023)	44,028
4. Log Real Per Capita Income Below Median	0.0245* (0.0028)	21,948
5. Log Real Per Capita Income Above Median	0.0064* (0.0016)	22,044
6. Fraction Rural Below Median	0.0124* (0.0031)	30,348
7. Fraction Rural Above Median	0.0226* (0.0027)	22,728
8. Including Temperature*Rainfall Interactions	0.0160* (0.0023)	53,076
Separate Controls for Daily Minimum and Maximum	To come	
Controlling for 'Heatwaves'	To come	
Relative Temperature Exposure	To come	

Notes: All models include state*month effects, year*month effects, and state*month linear trends. Regression weighted by population. Standard errors clustered on state. See the text for more details.

Table 5: Interaction Effects Between 'Modifiers' and Number of Days > 90°F, 1900-2004

	Sample: 1900-2004				
	(1)	(2)	(3)	(4)	(5)
Number of Days Above 90°F	0.0170*	0.0184*	0.0192*	0.0199*	0.0177*
	(0.0027)	(0.0024)	(0.0032)	(0.0024)	(0.0030)
Number of Days Above 90 °F ×	---	-0.0300*	---	---	-0.0249*
Log Doctors Per Capita		(0.0036)			(0.0112)
Number of Days Above 90 °F ×	---	---	-0.0147	---	0.0054
Share with Residential Electricity			(0.0259)		(0.0354)
Number of Days Above 90 °F ×	---	---	---	-0.0197*	-0.0028
Share with Residential AC				(0.0073)	(0.0195)
Observations	53,052	53,052	53,052	53,052	53,052
Year*Month Fixed Effects	y	y	y	y	y
State*Month Fixed Effects	y	y	y	y	y
State*Month Time Trends	y	y	y	y	y

Notes: All models include state*month effects, year*month effects, and state*month linear trends. Also included are main effects for days <40°F and days 80-89°F, as well as their interactions with each modifiers. Regression weighted by population. Standard errors clustered on state. See the text for more details.

Table 6: Interaction Effects Between 'Modifiers' and Number of Days > 90°F, 1900-1959, and 1960-2004

	[A] Sample: 1900-1959			[B] Sample: 1960-2004		
	(1a)	(2a)	(3a)	(1b)	(2b)	(3b)
Number of Days Above 90°F	0.0255*	0.0198*	0.0197*	0.0082*	0.0147*	0.0137*
	(0.0026)	(0.0021)	(0.0020)	(0.0013)	(0.0016)	(0.0017)
Number of Days Above 90 °F ×	-0.0062	---	-0.0061	-0.0122	---	-0.0114
Log Doctors Per Capita	(0.0073)		(0.0070)	(0.0065)		(0.0060)
Number of Days Above 90 °F ×	---	0.0138	0.0149	---	---	---
Share with Residential Electricity		(0.0219)	(0.0230)			
Number of Days Above 90 °F ×	---	---	---	---	-0.0302*	-0.0227*
Share with Residential AC					(0.0039)	(0.0058)
Observations	26,592	26,592	26,592	26,460	26,460	26,460
Year*Month Fixed Effects	y	y	y	y	y	y
State*Month Fixed Effects	y	y	y	y	y	y
State*Month Time Trends	y	y	y	y	y	y

Notes: All models include state*month effects, year*month effects, and state*month linear trends. Also included are main effects for days <40°F and days 80-89°F, as well as their interactions with each modifiers. Regression weighted by population. Standard errors clustered on state. See the text for more details.

Table 7: Comparison of Vital Statistics and Modifiers of Temperature-Mortality Relationship in Historical United States, Contemporary United States, and Contemporary India and Indonesia

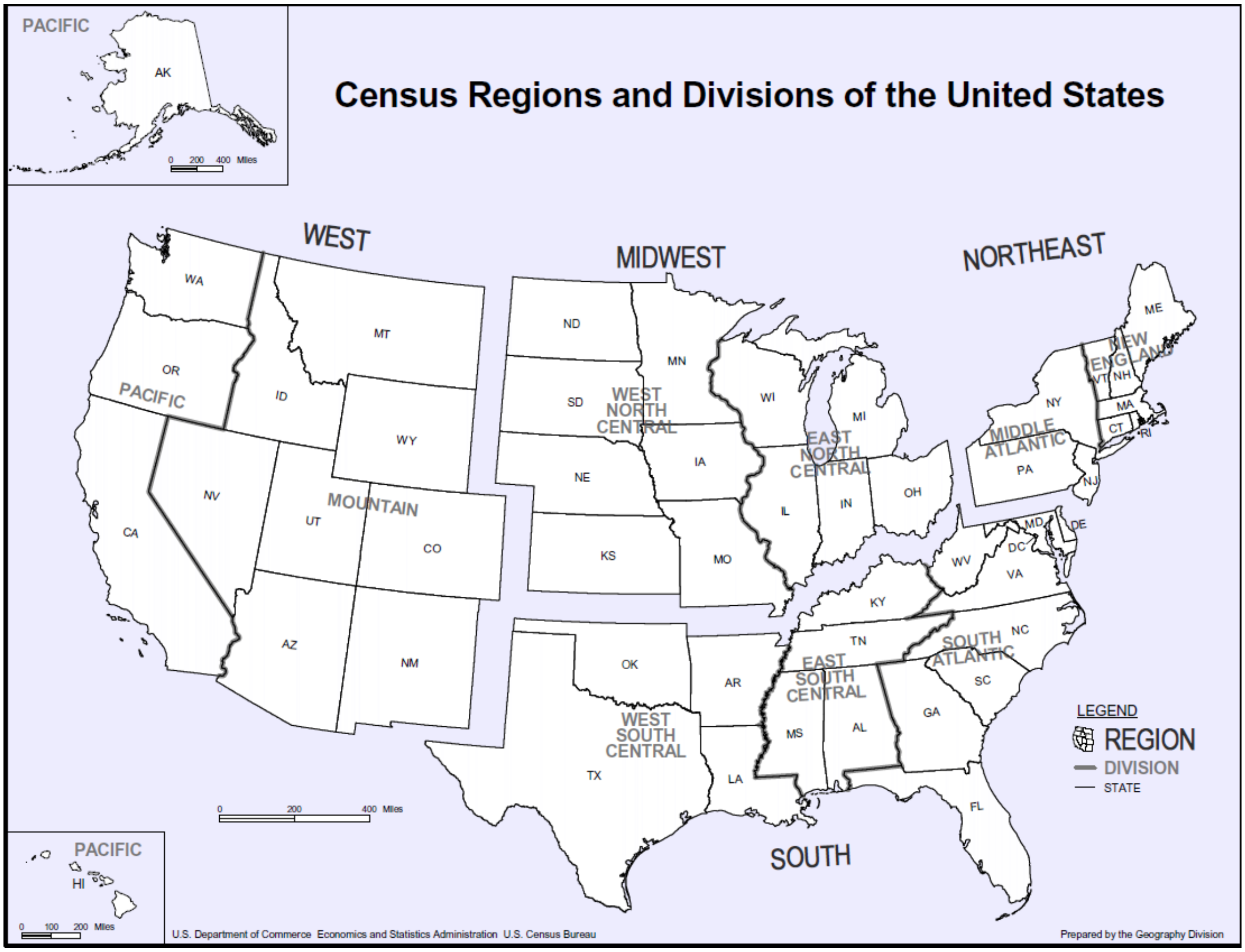
	United States:		India:	Indonesia:
	1940	2004	2004	2004
Basic vital statistics				
Life expectancy at birth	63	80	67	68
Infant mortality rate (per 1,000)	47	7	58	28
All age mortality rate (per 1,000)	11.0	8.0	8.5	6.3
Modifiers of temperature-mortality relationship				
Physicians per 1,000 population	1.3	2.9	0.6	0.1
Fraction of population with access to electricity	0.74	1	0.66	0.67
Fraction of population with residential AC	0	0.85	0.02	?

Source: World Bank Indicators and study data sample.

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

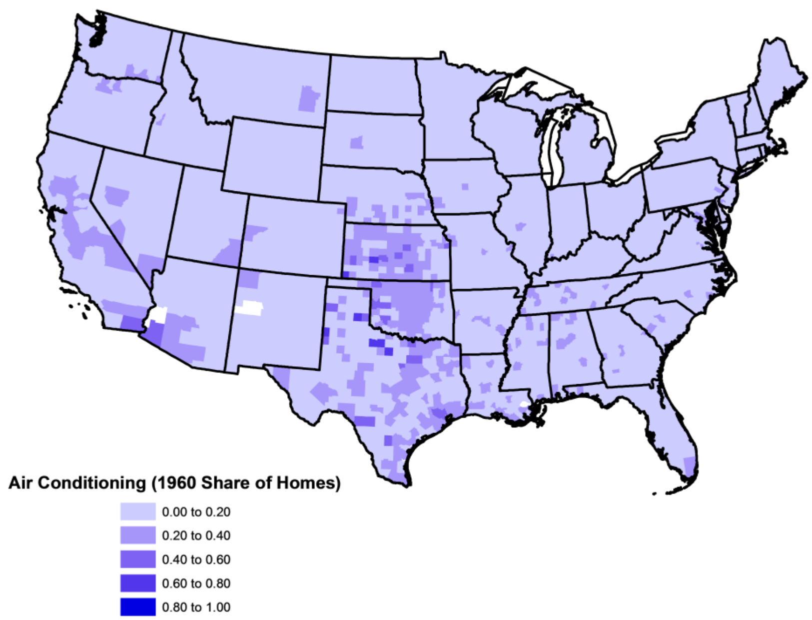
	State	Region	Entered sample
1	Connecticut	Northeast	1900
2	District of Columbia	South	1900
3	Indiana	Midwest	1900
4	Maine	Northeast	1900
5	Massachusetts	Northeast	1900
6	Michigan	Midwest	1900
7	New Hampshire	Northeast	1900
8	New Jersey	Northeast	1900
9	New York	Northeast	1900
10	Rhode Island	Northeast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

Appendix Figure 2: Census Regions and Divisions of the United States

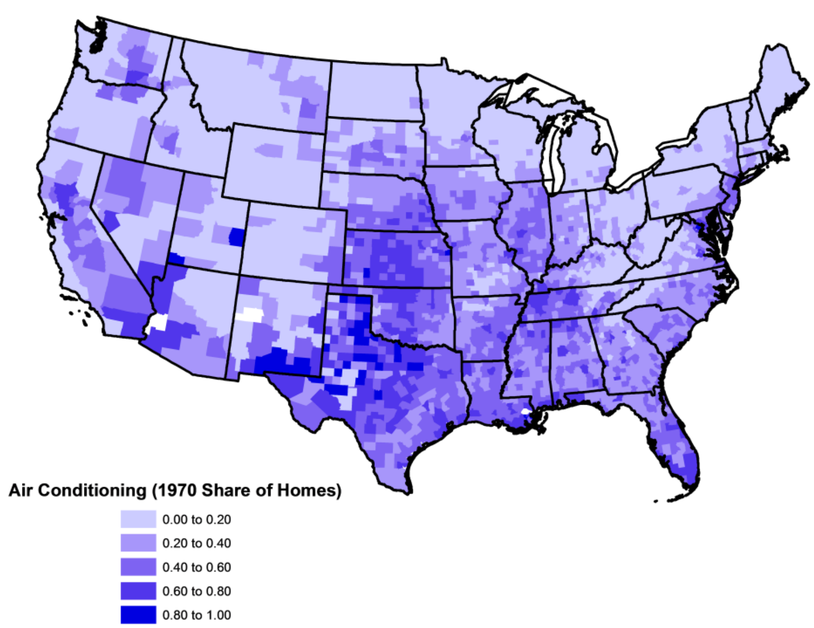


Appendix Figure 3: Fraction of Households with Air Conditioning: By County and Decade

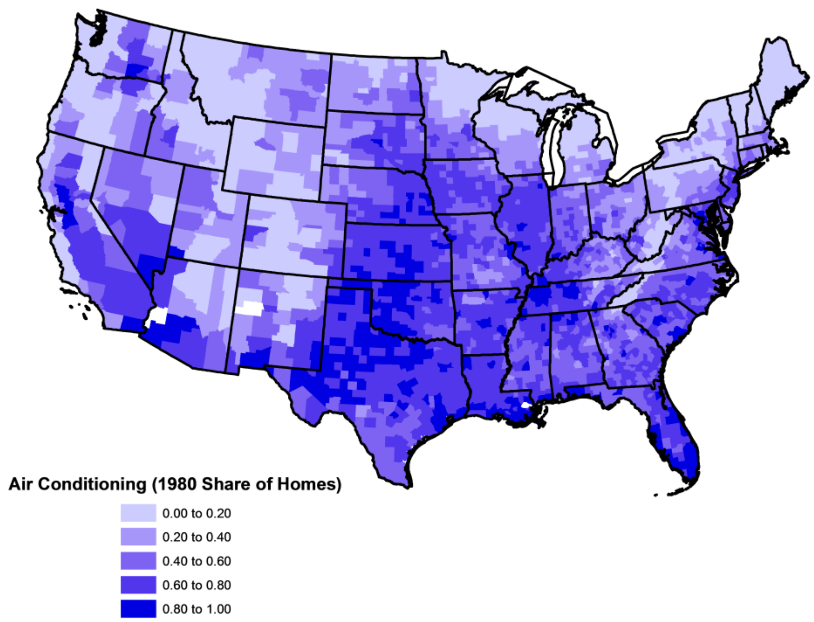
(a) 1960



(b) 1970



(c) 1980


Air Conditioning (1980 Share of Homes)
0.00 to 0.20
0.20 to 0.40
0.40 to 0.60
0.60 to 0.80
0.80 to 1.00