Temperature Variability and Mortality: Evidence from 16 Asian Countries

Olivier Deschenes*

This paper presents an empirical analysis devised to understand the complex relationship between extreme temperatures and mortality in 16 Asian countries where more than 50% of the world's population resides. Using a country-year panel on mortality rates and various measures of high temperatures for 1960–2015, the analysis produces two primary findings. First, high temperatures significantly increase annual mortality rates in Asia. Second, this increase is larger in countries with cooler climates where high temperatures are infrequent. These empirical estimates can help inform climate change impact projections on human health for Asia, which is considered to be highly vulnerable to climate change. The results indicate that unabated warming until the end of the century could increase annual mortality rates by more than 40%, highlighting the need for concrete and rapid actions to help individuals and communities adapt to climate change.

Keywords: Asia, climate change, impact, mortality, temperature
JEL codes: I10, Q54, O13

I. Introduction

Climate change is expected to negatively affect human health in most countries. This ongoing threat is especially significant in South, East, and Southeast Asia (SESA), where more than 50% of the world's population resides and where weather-dependent economic activities such as agriculture remain important contributors to gross domestic product (GDP). Furthermore, the lower levels of income observed in many SESA countries limit opportunities for private and public investment in health-preserving adaptations in response to extreme weather events. While the empirical literature on the predicted health impacts of climate change for the United States (US) and Europe is well developed, the literature for Asia and for lower-income countries is still lacking (see Deschenes 2014 for a review). Most of the existing evidence on climate change impacts for Asia is based on integrated assessment models and other simulation-based approaches rather than data-driven

*Olivier Deschenes: Professor, Department of Economics, University of California; and Research Associate, National Bureau of Economic Research. E-mail: olivier@econ.ucsb.edu. I would like to thank the participants at the Asian Development Review Conference in Seoul in August 2017, the managing editor, and two anonymous referees for helpful comments and suggestions. Levi Marks provided excellent research assistance. ADB recognizes "China" as the People's Republic of China. The usual disclaimer applies.

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empirical estimates (see, for example, ADB 2014, 2017 for a detailed discussion of the results from such quantitative model analyses). This gap in the literature highlights the importance of deriving empirical estimates of climate change impacts based on historical data for Asia.

This paper presents a cross-country panel data analysis of the effects of temperature variability on health in 16 SESA countries.[1] Health data come from the World Development Indicators (WDI) for the period 1960–2015, which includes annual measures of mortality rates across various age groups. An important advantage of using mortality rates as indicators of health is that they are reasonably well measured across many countries for long periods of time. Furthermore, mortality rates are key indicators of a population's ability to smooth consumption; withstand income shocks; and more generally address all changes in health determinants that are driven by weather variability, including effects on human physiology (Burgess et al. 2014).

The empirical results indicate a nonlinear relationship between daily average temperatures (modeled through annual temperature bins) and annual mortality rates. For example, 1 additional day with a mean temperature above 90 degrees Fahrenheit (°F), relative to 1 day with a mean temperature in the 70°F–79°F range, increases the annual mortality rate by roughly 1%. However, given the observed daily average temperature distributions in the sample, such >90°F days are relatively infrequent and concentrated in a handful of countries. A second empirical specification considers cooling degree days as a measure of extreme heat and finds similar evidence for a wider range of SESA countries. In particular, a 10% increase in cooling degree days, with a base of 80°F, leads to a 1.9% increase in the all-age mortality rate. Estimates for infant and adult mortality rates are slightly smaller in magnitude, suggesting that the 65+ population is especially vulnerable to adverse temperature shocks.

The analysis also uncovers important differences across countries in the effects of high temperatures on mortality rates. Countries that experience extreme high temperature events infrequently suffer larger mortality responses compared to countries where high temperatures are more common. This indicates that populations in hotter places may be better adapted to respond to high temperatures than populations in colder places. Importantly, this and all findings in the paper hold true even adjusting for differences in per capita income and other predictors of health and well-being across countries.

The analysis concludes by combining the estimated temperature response functions with output from Global Circulation Models to derive ceteris paribus predictions of the impact of climate change on mortality for the 16 SESA countries

[1]The SESA countries in the sample are Bangladesh, Bhutan, Cambodia, India, Indonesia, Japan, Malaysia, Mongolia, Nepal, Pakistan, the People's Republic of China (PRC), the Philippines, the Republic of Korea, Sri Lanka, Thailand, and Viet Nam. These 16 SESA countries were chosen because data on mortality rates were consistently available in the WDI.

in the sample. It is important to bear in mind that this paper relies on interannual variation in temperature, not on permanent changes in the temperature distributions. This will likely produce an overestimate of the impacts of climate change, because individuals and communities can only engage in a limited set of adaptations in response to interannual variation.

With this caveat in mind, I derive the predicted impacts of climate change on mortality under a business-as-usual scenario from the National Center for Atmospheric Research's (NCAR) Community Climate System Model 3 (CCSM3) Global Circulation Model. The preferred specification suggests that climate change would lead to a 45% increase in the annual mortality rate by the end of the century (i.e., 2080–2099) across the 16 countries in the sample.[2] By comparison, in the near-term future (i.e., 2020–2039), the corresponding estimate is an increase of 4% in the annual mortality rate. Thus, it appears that continued social and economic growth, as well as targeted investments in public health and infrastructure, may help prevent some of the catastrophic predicted increase in the end-of-century mortality rate. A subregional analysis comparing East Asia, Southeast Asia, and South Asia also leads to a similar conclusion: the mortality rate is predicted to increase in all three subregions, ranging from 24% in Southeast Asia to 34% in East Asia.[3] However, two of the three subregional estimates are statistically imprecise and need to be interpreted accordingly. It is also noteworthy that the entire predicted increase in the mortality rate is driven by a change in the temperature distribution, as opposed to a change in the precipitation distribution. This has implications for climate change adaptation policy since ambient temperature (unlike water) is not "storable" and thus cannot be shifted across time periods.

This paper's empirical approach addresses many (though not all) of the empirical challenges that typically make deriving credible estimates of climate change impacts difficult. In general, these challenges arise from the complex nature of the causal link between climate and human health. First, there is a complicated, dynamic relationship between temperature and mortality, which can cause the short-term relationship to differ substantially from the long-term one (Deschenes and Moretti 2009). Second, individuals' locational choices, which determine exposure to local temperature and rainfall distributions, are in part attributable to socioeconomic status and health. This form of locational sorting may confound the effects of temperature, making it difficult to uncover the causal relationship between temperature and mortality. Third, the relationship between temperature and mortality is potentially nonlinear, meaning it may not be well captured by relating mortality rates with average annual temperatures.

[2] As a reference point, a similar exercise suggests that climate change will lead to a roughly 2%–3% increase in the US mortality rate by the end of the century (Deschenes and Greenstone 2011).

[3] The subregion-specific estimates are subregion-specific regression models.

These challenges are addressed as follows. First, estimating regression models for annual mortality rates rather than for daily or weekly mortality rates helps capture the long-term effects of temperature shocks on mortality, as opposed to transitory effects due to near-term mortality displacement or harvesting. Second, the panel constructed from the WDI data permits the inclusion of country fixed effects, year fixed effects, and region-year fixed effects. Accordingly, the temperature variables are identified from unpredictable and presumably random year-to-year variation in weather, and the results account for any permanent differences across countries such as health or socioeconomic status while controlling for yearly shocks at the regional level. Third, relying on daily weather data to construct measures of exposure to extreme temperatures reduces the dependence on functional form assumptions to identify the "temperature–mortality relationship." Fourth, the WDI data allow for the estimation of separate effects for the mortality of specific age groups (including infants) for each country in the sample, which allows for heterogeneity in the estimated temperature–mortality relationship.

There are a few important caveats to these calculations and to the analysis in general that warrant further discussion. First, the country-year panel design used in this paper makes it difficult to control for country-specific shocks. In particular, the main results are not robust to the inclusion of country-specific time trends since those absorb a large component of the underlying variation. Future research may overcome this limitation by using panel data with within-country (e.g., province-level) variation. Furthermore, as discussed above, the estimated climate change impacts likely overstate the mortality costs because the analysis relies on interannual variation in weather, not a permanent change in the distribution of weather. It is possible that individuals and communities would invest in more health-preserving adaptations in response to permanent climate change. On the other hand, climate change is likely to affect many other health outcomes in addition to mortality—for example, it may increase vector-borne diseases such as malaria and dengue that are especially prominent in Asia and the Pacific (ADB 2014, 2017). Finally, climate change will also shift the observed patterns of other climatic variables that may impact health (e.g., changes in monsoon patterns, hurricanes, floods, and other extreme weather events). By focusing only on temperature change, the results reported in this paper could underestimate the overall health costs of climate change for the 16 SESA countries.

II. Literature Review

A. Thermoregulation and the Temperature–Mortality Relationship

The human body's thermoregulation function allows us to cope with extreme high and low temperatures. In particular, exposure to excessive heat triggers an increase in the heart rate in order to increase blood flow from the body to the skin, which reduces body temperature by convection, and increases sweat production, which reduces body temperature by evaporative cooling. These responses allow individuals to pursue physical and mental activities without endangering their health within certain temperature ranges. Temperatures outside of these ranges pose dangers to human health and can result in heat-related illnesses, including heat stroke, seizure, organ failure, and in some cases premature mortality.

A large literature studies the connection between extreme temperatures and mortality, which is sometimes known as the temperature–mortality relationship (see, for example, Basu and Samet 2002, Portier et al. 2010, and Deschenes 2014). A challenge in this literature is that heat-related illness is not part of the International Classification of Diseases that underlies most vital statistics records worldwide. As a result, studies typically relate all-cause mortality rates (or mortality rates for cardiovascular disease) to ambient measures of temperature. Evidence of excess heat-related mortality has been documented in many countries, time periods, and for various subpopulations. Younger and older populations and lower socioeconomic groups generally face higher risks of heat-related mortality. Access to air-conditioning greatly reduces mortality on hot days and the spread of residential air-conditioning in the US explains a large share of the marked reduction in heat-related mortality observed over the 20th century (Barreca et al. 2016).

Empirical studies of the effect of temperature and other environmental insults on mortality need to address the possibility of harvesting or near-term mortality displacement in which the number of deaths immediately caused by a period of very high temperatures is typically followed by a reduction in the number of deaths in the period immediately subsequent to the hot day or days (Basu and Samet 2002, Deschenes and Moretti 2009). This pattern tends to occur because heat shocks firstly affect individuals who are already very sick and would have likely died in the near-term.

Predicting changes in life expectancy due to climate change becomes an important challenge in the presence of harvesting. Studies that correlate day-to-day changes in temperature with day-to-day changes in mortality tend to overstate the mortality effect of climate change, since the dynamics of temperature and mortality are such that episodes of harvesting are generally followed by a reduction in the number of deaths in the period immediately following the temperature shock. The solution to this problem is to design studies that examine intermediate and long-term effects, either through appropriate time aggregation of the data to combine daily temperature shocks with annual mortality rates (Deschenes and Greenstone 2011) or through the use of distributed lag models (Braga, Zanobetti, and Schwartz 2001; Deschenes and Moretti 2009). I follow the former approach in this paper.

In the context of low- and middle-income countries, like most countries in the SESA region, the causal linkages between mortality and high temperatures are even more complex. The relationship not only can reflect the body's physiological thermoregulatory functions, but it is also likely to be driven by socioeconomic factors (e.g., income, nutrition, and access to basic medicines) and biological factors (e.g., vector-borne diseases and infections, including diarrhea) (ADB 2017). The empirical analysis below will therefore also make use of some of the available data on stunting and nutrition deficits in the WDI to shed light on the mechanisms underlying the observed temperature–mortality relationship in SESA countries.

B. Conceptual Framework

The application of the Becker–Grossman model of health production to derive the willingness to pay for improvements in environmental quality, which includes the value of defensive action, is increasingly common in the literature (Deschenes and Greenstone 2011; Graff-Zivin and Neidell 2013; Deschenes, Greenstone, and Shapiro 2017). The formal derivation of the theoretical predictions is presented in these papers and so there is no need to reproduce them here. The key result is that the mortality-related social cost of climate change goes beyond what is indicated by the statistical relationship between temperature and mortality when individuals invest resources in adaptation or self-protection. Indeed, the model shows that the correct measurement of the willingness to pay to avoid climate change requires knowledge of how temperature affects mortality and how it affects self-protection investments that reduce mortality risks.[4] Monetizing such direct and indirect impacts on mortality and all relevant defensive investments comes with tremendous data requirements. Indeed, most empirical studies ignore the economic value of defensive investments altogether while a few studies consider a handful of defensive investments such as residential energy consumption and air-conditioning (Deschenes and Greenstone 2011, Barreca et al. 2016). As panel data on self-protection investments are not consistently available for the sample countries, this sort of analysis is beyond the scope of this paper. Accordingly, the analysis presented here is limited in that it is only informative about the effects of climate change on mortality rates and not directly informative on the economic and social costs of the mortality-related component of climate change.

III. Data Sources, Sample Construction, and Summary Statistics

A. Data Sources

In order to quantify the effect of temperature and rainfall shocks on mortality rates in 16 SESA countries, I have assembled a country-level data set for the

[4]More generally, the correct measure of willingness to pay should consider all the monetized health impacts, and all health-improving defensive investments, not just the components related to mortality.

1960–2015 period. The key inputs to that data set are daily gridded weather variables obtained from the National Centers for Environmental Prediction and National Center for Atmospheric Research (NCEP/NCAR) Reanalysis Project combined with annual mortality rate data from the WDI. The following paragraphs describe these data sources in more detail and present summary statistics.

Sample construction. The empirical analysis focuses on 16 SESA countries for which the relevant outcomes, controls, and weather variables are consistently available: Bangladesh, Bhutan, Cambodia, India, Indonesia, Japan, Malaysia, Mongolia, Nepal, Pakistan, the People's Republic of China (PRC), the Philippines, the Republic of Korea, Sri Lanka, Thailand, and Viet Nam. In 2015, these countries had a combined population of 3.8 billion, which was over half the world's total population.

Weather data. The recent literature has emphasized the importance of nonlinearities in the relationship between temperature and health that make the use of annual or monthly temperature averages inappropriate (Deschenes 2014). Thus, daily data are required. Daily temperature records based on weather station measurements are available for nearly all countries through the Global Historical Climatology Network. Unfortunately, the geographical and temporal consistency of these data is limited in most Asian countries. In particular, many stations have sporadically missing data across days, making the construction of daily temperature bins impossible since those require a consistent set of 365 daily observations for each station.

Instead, I make use of the daily gridded weather variables obtained from the NCEP/NCAR Reanalysis Project (Kalnay et al. 1996).[5] The reanalysis data are available at the daily and subdaily level for a grid of 2.5° (longitude) by 2.5° (latitude).[6] I then assign each grid cell in the NCEP/NCAR data to a subcountry population cell from the Gridded Population of the World.[7] To proceed, I use an inverse distance weighted average of all NCEP/NCAR grid cell variables within 300 kilometers of each population grid cell centroid. Finally, I construct the country-year weather variables (including nonlinear transformation of daily average temperature such as cooling degree days and temperature bins) using a weighted average of all population grid cells within a country, where the weights correspond to the population within each cell. This produces a balanced panel of country-year observations on the relevant weather variables for the period 1960–2015 that is

[5]These data are available from National Oceanic and Atmospheric Administration. Earth System Research Laboratory. http://www.esrl.noaa.gov/psd/ (accessed July 31, 2017).

[6]This includes grid points located above land and oceans due to the many island and coastal countries in the sample. NCEP/NCAR grid points must be located within 300 kilometers of the population centroid grid points to be included in the assigned weather data.

[7]Center for International Earth Science Information Network, Socioeconomic Data and Applications Center. Gridded Population of the World, Version 3. http://sedac.ciesin.columbia.edu/data/collection/gpw-v3 (accessed April 14, 2017).

representative of the within-country population distribution as measured in the Gridded Population of the World file.

World Development Indicators. The data for the main outcome and control variables used in this study are taken from the World Bank's WDI database. These data are compiled by the World Bank from officially recognized international sources and represent the most current and accurate global measures of the key variables in this study. Specifically, I use the WDI data to construct a country-year level panel of annual mortality rates for the 16 countries in the sample over the period 1960–2015. Importantly, the WDI reports mortality rates (per 1,000 population) for three separate age groups: (i) all-age or crude mortality rate, (ii) infant mortality rate (ages 0–1), and (iii) adult mortality rate (ages 15–60).[8]

In addition to the mortality rate data, I also rely on the WDI for control variables and for variables used to construct interaction effects. These include total population (a count of all residents of a country regardless of legal status or citizenship), GDP per capita (expressed in current US dollars), electrification rate (fraction of population with access to electricity), access to an improved water source (fraction of population with access), number of hospital beds (per 1,000 population), access to improved sanitation facilities (fraction of population with access), and urbanization rate (fraction of population living in urban areas as defined by national statistical offices). Finally, I use the prevalence of undernourishment in the population and the prevalence of stunting in children aged 0–4 years to explore the mechanisms connecting temperature and mortality.

Climate change prediction data from Global Circulation Models. Data on "predicted" temperature and precipitation distributions are required to estimate, ceteris paribus, the impact of future climate change on mortality rates. To this end, I rely on model output from the NCAR's CCSM3, which is a coupled atmospheric-ocean general circulation model used in the Intergovernmental Panel on Climate Change's 4th Assessment Report (IPCC 2007). Predictions of future realizations of climatic variables are available for several emission scenarios, which are drivers of the simulations, corresponding to "storylines" describing the way the world (e.g., populations and economies) may develop over the next 100 years. I focus on the A2 scenario, which is a business-as-usual scenario that predicts a substantial rise in global average temperatures similar to the temperature change projections for Asia reported in ADB (2014).

The data are processed in the same manner as in Deschenes and Greenstone (2011), so I omit most details here. Data on daily average temperature and total precipitation for the period 2000–2099 are assigned to each sample country using the same procedure applied to the daily NCEP/NCAR Reanalysis Project data. Specifically, I assign each grid cell in the CCSM3 file to a subcountry population

[8]The crude mortality rate is defined by the WDI as "the number of deaths occurring during the year per 1,000 population estimated at midyear."

cell from the Gridded Population of World file using an inverse distance-weighted average with a radius of 300 kilometers from each population grid cell centroid. The country-year variables are constructed using a weighted sum of all population grid cells within a country, where the weights correspond to the population in each population cell. This produces a balanced panel of country-year observations on the relevant CCSM3 variables for the period 2000–2099. In order to account for any systematic model error, I define the future climatic variables (daily average temperature, realized annual temperature bins, annual cooling degree days, and total annual precipitation) as follows. The model error is calculated for each of the 365 days in a year separately for each country as the average difference between the country-by-day-of-year specific variable from the NCEP/NCAR data and the CCSM3 data during the 2000–2015 period.[9] This country-by-day-of-year specific error is then added back to the CCSM3 data over the 2020–2099 period to obtain an error-corrected climate change prediction.

B. Summary Statistics

Table 1 reports summary statistics on the resident population and average mortality rates across the 16 countries in the sample over the 1960–2015 period. Large differences in country size are evident. For example, average population during 1960–2015 ranges from 0.5 million (Bhutan) to 1.1 billion (PRC). Population growth rates between 1960 and 2015 also vary significantly across countries. These important differences in country size motivate the inclusion of controls for population in the regression models below. The next panel shows average annual crude mortality rates (all ages) ranging from 5.3 deaths per year per 1,000 population in Malaysia to 15.8 deaths per year per 1,000 population in Cambodia. The remarkable improvements in well-being and health are clearly showed by comparing the mortality rates in 1960 and 2015. Across the 16 countries, all-age mortality rates have declined by factors of 2–3 (e.g., the PRC's mortality rate declined from 25.4 to 7.1 during the review period). Similar cross-sectional differences can also be seen in infant mortality rates in the last panel (defined as deaths under the age of 1 divided by number of births). One issue with the infant mortality rate is that data are not available for every country, especially in the first decades of the sample period. As a result, the primary outcome studied in the paper is the all-age mortality rate, which is available for all time periods for all countries. The large cross-sectional differences in the all-age and infant mortality rates may reflect fundamental differences in health determinants across countries, as well as differences in public health infrastructure, economic growth, and the underlying climate. These permanent differences across countries will be addressed by country fixed effects included in all empirical specifications.

[9]This is the only period in which the NCEP/NCAR and CCSM3 data series overlap.

Table 1. **Summary Statistics on Population and Mortality Rates**

Country	Population (million)				All-Age Mortality Rate per 1,000				Infant Mortality Rate per 1,000			
	1960–2015	N	1960	2015	1960–2015	N	1960	2015	1960–2012	N	1960	2015
Bangladesh	102.0	56	48.2	161.0	10.2	56	20.3	5.4	88.1	56	176.3	30.7
Bhutan	0.5	56	0.2	0.8	13.5	56	31.3	6.2	80.3	47	n.a.	27.2
Cambodia	9.6	56	5.7	15.6	15.8	56	21.8	6.0	72.8	41	n.a.	24.6
India	845.3	56	449.7	1,311.1	11.2	56	22.4	7.3	85.7	56	165.1	37.9
Indonesia	171.7	56	87.8	257.6	9.0	56	18.0	7.2	62.0	56	148.4	22.8
Japan	117.5	56	92.5	127.0	7.4	56	7.6	10.2	7.5	56	30.4	2.0
Malaysia	18.0	56	8.2	30.3	5.3	56	10.6	5.0	17.7	56	67.4	6.0
Mongolia	2.0	56	1.0	3.0	10.0	56	19.9	6.1	56.7	38	n.a.	19.0
Nepal	18.5	56	10.1	28.5	12.8	56	27.6	6.3	93.8	56	219.6	29.4
Pakistan	105.1	56	44.9	188.9	10.4	56	20.7	7.3	100.2	56	192.0	65.8
People’s Republic of China	1,066.4	56	667.1	1,371.2	7.3	56	25.4	7.1	36.1	47	n.a.	9.2
Philippines	60.2	56	26.3	100.7	7.1	56	11.2	6.8	38.0	56	67.9	22.2
Republic of Korea	40.5	56	25.0	50.6	6.5	56	14.3	5.4	15.7	56	80.2	2.9
Sri Lanka	16.0	56	9.9	21.0	7.1	56	12.3	6.8	26.9	56	72.7	8.4
Thailand	51.7	56	27.4	68.0	7.6	56	13.2	8.0	35.1	56	102.2	10.5
Viet Nam	62.7	56	34.7	91.7	7.1	56	12.0	5.8	34.1	52	n.a.	17.3

n.a. = not available.
Note: The summary statistics are calculated from a sample of 896 country-year observations.
Source: Author’s calculations from World Development Indicators data.

The empirical analysis uses daily weather data taken from the NCEP/NCAR Reanalysis Project to develop the relevant country-year level measures for temperature and precipitation variables. Table 2 reports summary statistics on some of the country-year level measures of observed weather during 1960–2015. These are calculated across all country-by-year observations available (896). The first panel of the table reports average daily temperatures in Fahrenheit (°F). The well known climatic differences across the SESA countries are seen by contrasting the averages, which range from 29°F (Mongolia) to 81°F (Cambodia). There is also sizable within-country variation across years, as shown by the minimum and maximum values. (These correspond to the lowest and highest annual average temperatures for each country between 1960 and 2015.) For each country, the range is about ±2°F from the average of daily temperatures across years. This variation will be exploited to identify the country fixed effect regression models reported below.

As noted earlier, the relevant temperature variables to predict mortality rates are measures of exposure to the extremes of the temperature distribution. Figure 1 explores this distribution in more detail. The eight light bars in Figure 1 show the distribution of daily average temperatures across eight temperature categories ("bins") for the 16 sample countries during the 1960–2015 period.[10] The bins correspond to daily average temperatures of less than 30°F, greater than 90°F, and the six 10°F-wide bins in between. The height of the bar reports the mean number of days per year in each bin; this is calculated as the average across country-by-year realizations. The modal bin is 70°F–79°F, with 150 days per year, which is to be expected because many countries in the sample are located in tropical areas along or just north of the equator. As emphasized in the literature review above, recent studies of the effects of temperature on health have highlighted the importance of nonlinear effects, represented by a difference in marginal effects of temperature increases across the temperature distribution. For example, an extra degree of daily average temperature at 90°F may have a much larger impact on mortality than an extra degree of daily average temperature at 70°F. To this end, the number of days in the highest two bins (80°F–89°F and >90°F) are especially important. On average, there are 64 days per year in the 80°F–89°F range and 6 days per year in the >90°F range. The eight bins displayed in Figure 1 form the basis for the flexible modeling of temperature effects on mortality rates as is now commonly used in the literature (Deschenes 2014).

Figure 1 also shows how the full distributions of daily mean temperatures are expected to change. The dark bars report the predicted number of days in each temperature category across the 16 sample countries for the period 2080–2099 under the business-as-usual scenario. The most important changes in the

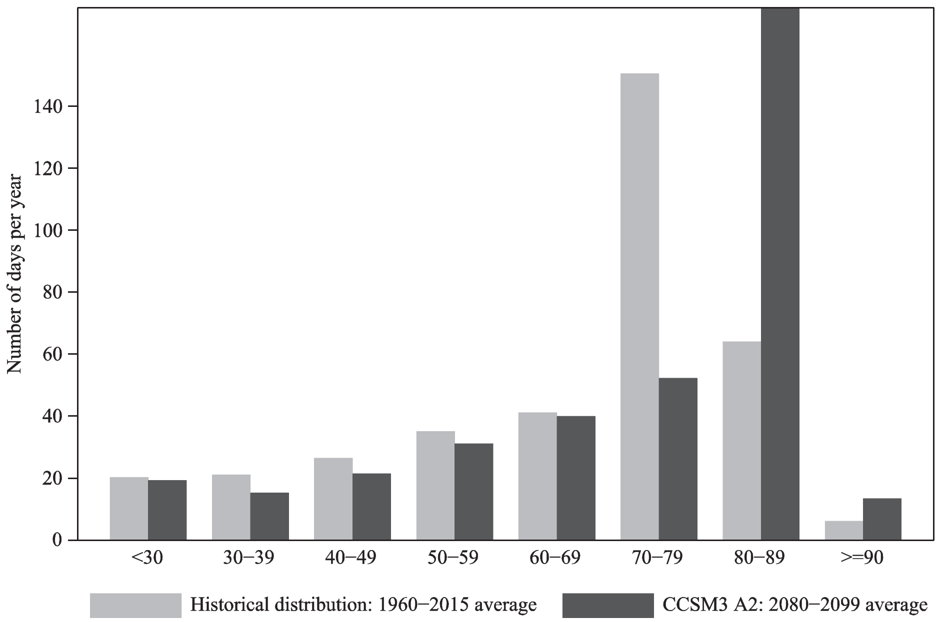
[10] Daily average temperatures are the simple average of the daily minimum and maximum. Therefore, a daily average temperature of 90°F may correspond, for example, to a day with a high of 100°F and a low of 80°F.

Table 2. **Summary Statistics on Temperature and Precipitation Variables**

	Daily Temperature (°F)			Annual Days >80°F			Annual Days >90°F			Annual Precipitation (inches)		
Country	**Average**	**Min**	**Max**	**Average**	**Min**	**Max**	**Average**	**Min**	**Max**	**Average**	**Min**	**Max**
Bangladesh	78.4	76.9	79.6	124.2	84.6	149.2	5.7	0.4	28.7	62.4	44.4	91.7
Bhutan	49.0	47.5	51.0	0.2	0.1	0.4	0.0	0.0	0.1	70.6	33.5	106.6
Cambodia	81.0	79.3	82.6	83.9	29.8	158.4	0.3	0.0	2.7	105.3	72.4	123.5
India	78.0	76.3	79.4	137.5	104.3	157.4	33.5	22.8	42.3	41.2	30.5	51.2
Indonesia	79.2	78.2	80.3	76.0	29.3	144.3	0.0	0.0	0.0	112.1	73.4	161.4
Japan	57.6	56.1	59.5	8.2	1.1	21.8	0.0	0.0	0.0	60.2	36.5	84.4
Malaysia	79.4	78.1	80.7	35.2	9.1	76.4	0.0	0.0	0.0	141.0	102.6	180.0
Mongolia	29.0	25.8	32.7	2.0	0.2	5.9	0.0	0.0	0.7	15.1	11.0	27.0
Nepal	68.4	66.4	70.2	9.1	6.2	13.1	2.0	1.2	3.5	64.7	46.5	84.1
Pakistan	74.3	72.0	76.0	138.2	117.7	156.9	57.4	35.2	77.5	17.3	10.3	31.6
People's Republic of China	57.4	55.8	59.2	15.0	2.8	28.2	0.1	0.0	0.4	51.2	39.6	70.8
Philippines	80.2	78.8	81.8	147.6	23.9	216.0	0.0	0.0	0.0	72.1	44.9	91.8
Republic of Korea	53.2	50.9	55.4	1.4	0.0	10.0	0.0	0.0	0.0	31.8	18.1	47.3
Sri Lanka	79.8	78.7	81.2	188.0	43.2	265.2	0.1	0.0	0.3	80.0	43.2	109.8
Thailand	79.9	78.3	81.7	83.1	33.7	143.5	0.8	0.0	4.4	102.5	85.1	126.2
Viet Nam	76.6	75.3	78.0	115.9	27.9	153.9	0.0	0.0	0.2	91.2	75.2	106.8

Note: The summary statistics are calculated from a sample of 896 country-year observations.
Source: Author's calculations from NCEP/NCAR Reanalysis Project data.

Figure 1. **Distribution of Daily Average Temperatures (°F), 1960–2015 and Predicted Distribution of Daily Average Temperatures (°F), 2080–2099**



CCSM3 = Community Climate System Model 3.
Notes: This figure shows the historical average distribution of daily mean temperatures and predicted future distribution of daily mean temperatures across eight temperature bins for the 16 South, East, and Southeast Asian countries in the sample. Light bars represent the average number of days per year in each temperature bin during the period 1960–2015. Darker bars show the corresponding predicted distribution derived using daily data from error-corrected CCSM3 A2 model data for the period 2080–2099.
Sources: Author's calculations from NCEP/NCAR Reanalysis Project data and NCAR CCSM3 data.

distribution are in the last three bins. The CCSM3 A2 model predictions indicate that exposure to daily average temperatures in the 70°F–79°F range will be greatly reduced, dropping from 150 days per year on average to 52 days. It is evident that all of this change is offset by an equally large increase in the number of days per year where the mean daily temperature is between 80°F and 89°F—such exposure is predicted to increase from 64 days to 174 days per year. Finally, another change is the increase in the frequency of days with a mean temperature in excess of 90°F, which is predicted to rise from roughly 6 days to 14 days per year.

Returning to Table 2, the middle two panels report statistics on the number of days per year in each country when the daily average temperature exceeds 80°F and 90°F. Once again, both cross-country and within-country variation is clearly evident. The range in the number of >80°F days per year is between 0.2 (Bhutan) and 188 (Sri Lanka) on average. Within countries, we observe a large degree of interannual variation that is almost as wide as the cross-country variation. For example, in Indonesia the range of the number of annual days with an average daily temperature >80°F is between 29 and 144. This within-country variation will drive the identification of the country fixed effects regression models. Similar patterns emerge when examining the cross- and within-country variation in days with temperature >90°F. However, it is evident that many countries do not experience such days with high frequency. Only Bangladesh, India, and Pakistan are exposed to more than 5 days per year with mean temperature >90°F on average. As such, most of the empirical identification of the >90°F impacts will be disproportionally driven by these three countries. As a result, the empirical analysis will consider a few alternative specifications to model the effects of high temperatures on mortality.

IV. Econometric Approach

This section describes the econometric models used in the paper. Specifically, the estimates are obtained from fitting the following equation:

$$Y_{ct} = \sum_{j} \theta_j TMEAN_{ctj} + \sum_{k} \gamma_k PREC_{ctk} + X'_{ct}\delta + \alpha_c + \beta_t + \varepsilon_{ct} \qquad (1)$$

where Y_{ct} is the mortality rate in country c in year t. As mentioned before, we focus on the all-age mortality rate, the infant mortality rate, and the adult mortality rate. The last term in equation (1) is the stochastic error term, ε_{ct}.

The independent variables of interest are the measures of temperature and precipitation, which are constructed to capture the full distribution of annual fluctuations in weather. The variables $TMEAN_{ctj}$ denote the number of days in country c in year t when the daily average temperature is in the j^{th} of the eight temperature bins reported in Figure 1. This functional form imposes the relatively weak assumption that the impact of the daily mean temperature on the annual mortality rate is constant within 10°F-degree intervals. The empirical analysis will also consider a few alternative specifications of the temperature effects. The variables $PREC_{ctk}$ are simple indicator variables based on total annual precipitation in country c in year t that represent the following intervals: less than 30 inches, 30–59 inches, 60–89 inches, 90–119 inches, and more than 120 inches.

The regression model includes a full set of country fixed effects (α_c), which absorb all unobserved country-specific time-invariant determinants of health and mortality rates. For example, the notable differences in climate across countries documented in Table 2 will be controlled for by these fixed effects. Further, any permanent differences in health care provision or infrastructure across countries will not confound the effect of weather on health. The equation also includes year fixed effects (β_t), which will be allowed to vary across subgroups of countries in some specifications. These fixed effects will control for unobserved time-varying factors in the dependent variable that are common across all countries or subgroups of countries.

The validity of the predicted climate change impacts reported in this paper depends crucially on the assumption that the estimation of equation (1) will produce unbiased estimates of the temperature–mortality relationship coefficients (θ_j). Since the estimating equation includes country and year fixed effects (or region-year fixed effects), these coefficients are identified from country-specific deviations in temperature from long-term averages after controlling for shocks common to all countries in a given year. Since year-to-year weather fluctuations in a given location are exogenous (as they are driven by natural variability in the climate system), it seems reasonable to assume that these fluctuations are orthogonal to unobserved determinants of mortality rates.

V. Results

This section is divided in two subsections. The first provides estimates of the relationship between daily temperatures and mortality rates. The second subsection uses these estimated relationships to predict the impacts of climate change on annual mortality in the SESA countries.

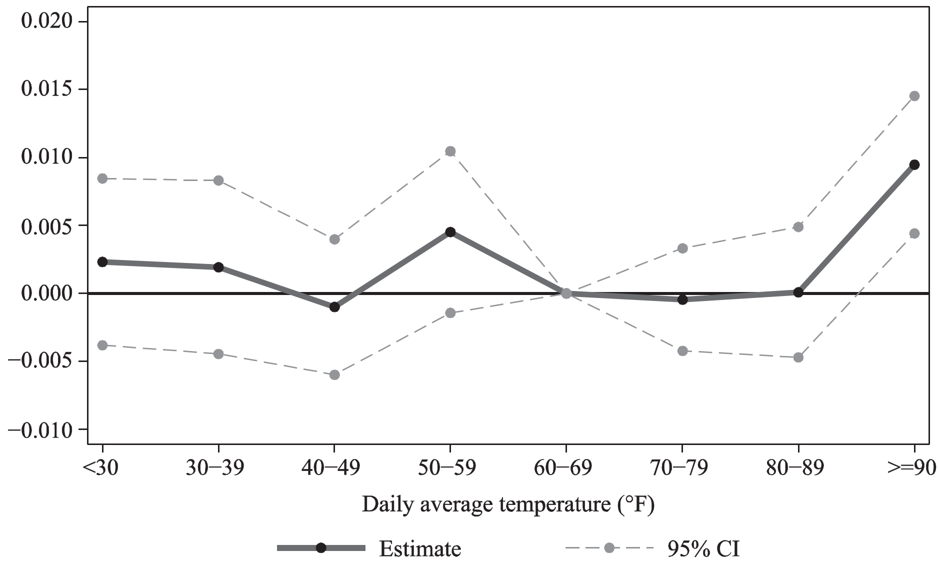
A. Baseline Estimates of the Impact of Temperature on Mortality

Figure 2 presents the estimate of the temperature–mortality relationship obtained from fitting equation (1). The figure reports the estimated regression coefficients associated with the daily temperature bins (i.e., the θ_j's) where the 60°F–69°F bin is the reference (omitted) category. That is, each coefficient measures the estimated impact of 1 additional day in temperature bin j on the log annual mortality rate, relative to the impact of 1 day in the 60°F–69°F range. The dashed lines correspond to the 95% confidence intervals when standard errors are clustered at the country level.[11]

The figure reveals a mostly null relationship, with the exception of high mortality risks at extreme temperatures (i.e., for daily average temperatures above 90°F). The point estimates underlying the response function indicate that exchanging 1 day in the 60°F–69°F range for 1 day above 90°F would increase the mortality rate by approximately 1% (i.e., 0.0095 log mortality points). This point estimate is statistically significant with a standard error of 0.0024. However, all other point estimates are close to zero and statistically insignificant at the 5% level. This result is somewhat in contrast with the "U-shaped" relationship found in many studies of the US (see Deschenes 2014 and Portier et al. 2010 for

[11] Since there are only 16 clusters, I also computed standard errors using the wild cluster bootstrap method proposed by Cameron, Gelbach, and Miller (2008). Based on those calculations, it appears that the simple cluster-robust standard errors are understated by about 30%. This does not change the conclusion of the tests of statistical significance for most of the key coefficient estimates presented in the paper.

Figure 2. **Estimated Temperature–Mortality Relationship for 16 SESA Countries, 1960–2015**



CI = confidence interval; SESA = South, East, and Southeast Asia.
Notes: The plotted lines report seven coefficient estimates (circle markers) representing the effect of a single day in each of the corresponding seven temperature bins, relative to the effect of a day in the 60°F–69°F reference bin, on the annual log all-age mortality rate. Dashed lines represent the 95% confidence interval for the estimates. Standard errors clustered by country.
Sources: Author's calculations from World Development Indicators and NCEP/NCAR Reanalysis Project data.

reviews of the literature), although these are the first comprehensive estimates of the temperature–mortality relationship over the entire 20th century.

Table 3 reports the point estimates associated with the key temperature variables underlying Figure 2 in order to better characterize the results and evaluate their robustness across alternative samples and subpopulations. While the underlying regression models include all seven temperature bin variables, the table only reports the coefficient estimates associated with the number of days below 30°F, the number of days between 30°F–39°F, the number of days between 80°F–89°F, and the number of days above 90°F.

Panel A reports the coefficient estimates separately by age group for the baseline specification that includes temperature and precipitation variables, country fixed effects, and year fixed effects. Standard errors clustered at the country level are reported in parentheses. There are several important observations to be made from Panel A. First, the effect of extreme high temperatures on mortality documented in the overall population (all age groups) is also detectable for infants. In particular, the effect of >90°F temperature days is similar (0.0083 versus 0.0095 log mortality rate points). Further, colder temperatures significantly predict increases in infant

Table 3. **Estimates of the Impact of High and Low Temperatures on Log Annual Mortality Rates by Age Group**

	Number of Days Per Year with Mean Temperature				
	<30°F	**30°F−39°F**	**80°F−89°F**	**>90°F**	**N**
A. Baseline Specification Estimates					
1. All-age mortality rate	0.0023	0.0019	0.0001	0.0095**	896
	(0.0029)	(0.0030)	(0.0023)	(0.0024)	
2. Infant mortality rate (0–1)	0.0046	0.0052*	0.0031	0.0083*	841
	(0.0028)	(0.0023)	(0.0021)	(0.0040)	
3. Adult mortality rate (15–60)	−0.0036	−0.0009	−0.0008	−0.0001	878
	(0.0060)	(0.0034)	(0.0025)	(0.0023)	
B. Alternative Specifications, All-Age Mortality					
1. Adding region-year fixed effects	0.0017	0.0002	−0.0006	0.0108**	896
	(0.0027)	(0.0030)	(0.0033)	(0.0031)	
2. Adding additional controls	0.0022	−0.0001	−0.0014	0.0098**	859
	(0.0033)	(0.0031)	(0.0029)	(0.0032)	
3. Adding controls for relative humidity	0.0002	−0.0012	0.0003	0.0115**	859
	(0.0029)	(0.0027)	(0.0023)	(0.0037)	

Notes: The coefficient estimates correspond to the effect of single days with daily temperatures in the <30°F, 30°F–39°F, 80°F–89°F, and >90°F ranges on log annual all-age mortality rate, relative to days with daily temperatures in the 60°F–69°F range. The number of days in the 40°F–49°F, 50°F–59°F, and 70°F–79°F bins are also included in the regressions. Each row corresponds to a single regression. Standard errors are clustered by country. Asterisks denote p-values of <0.05 (*), <0.01 (**), and <0.001 (***).
Sources: Author's calculations from World Development Indicators and NCEP/NCAR Reanalysis Project data.

mortality rates, a pattern not detected for the other age groups. Finally, for adults (defined by the WDI as ages 15–60), the relationship between temperature and mortality is essentially null: none of the point estimates are statistically significant and all are of very small magnitude. Taken together, these results are consistent with the previous literature, which has repeatedly found that younger and older individuals are more vulnerable to extreme temperatures, in part due to their weaker thermoregulatory functions. An important implication of this difference in effects across age groups is that it indicates that climate change will have unequal effects across different demographic groups within the same country, an issue I will investigate below.

Panel B reports on the robustness of the baseline all-age mortality estimates reported in Row 1 of Panel A. In Row 1 of Panel B, the year fixed effects are replaced by region-year fixed effects, where the three regions are defined as follows: Bangladesh, Bhutan, India, Nepal, Pakistan, and Sri Lanka (roughly corresponding to South Asia); the PRC, Japan, the Republic of Korea, and Mongolia (East Asia); Cambodia, Indonesia, Malaysia, the Philippines, Thailand, and Viet Nam (Southeast Asia). The advantage of this specification over "pooled" year fixed effects is that the region-year fixed effects controls for unobserved shocks to health, economic activity, weather, and any other unobserved factor that predicts health and varies regionally over time.

Row 2 of Panel B adds the following country-level control variables to the specification of Row 1: log GDP per capita, the fraction of the population residing in urban areas, and a variable corresponding to the number of hospital beds per 1,000 population as a crude control for the level of health care infrastructure in each country.[12] Finally, Row 3 of Panel B adds controls for relative humidity to the specification of Row 2 by including variables representing the number of days per year of low relative humidity (defined as days below the 25th percentile of the observed relative humidity distribution) and high relative humidity (defined similarly as days above the 75th percentile). This addition is motivated by prior research for the US that shows that the temperature–mortality relationship may be different when humidity is included as a predictor in addition to temperature (Barreca 2012).

It is evident from examining the results in Panel B that none of these alterations to the baseline specification lead to meaningful changes in the estimates of the effect of extreme temperatures on mortality. Some of them modestly change point estimates, but in comparison to the standard errors, none of the alternative estimates appear different than the corresponding baseline estimates. Nevertheless, in order to minimize concerns about omitted variables bias, I will maintain the "preferred specification" that controls for relative humidity and region-year fixed effects (in addition to the controls included in the baseline specification) for the remainder of this paper.

B. Alternative Specification and Heterogeneity of the Temperature Effects

One limitation of the estimates based on the full temperature bins approach is that the >90°F bin is primarily identified by a handful of countries that are exposed to such days with a high enough frequency (i.e., Bangladesh, India, and Pakistan as shown in Table 2). As an alternative, Table 4 considers a specification with a single measure of heat exposure: cooling degree days with a base of 80°F (CDD80).[13] This variable is computed as the annual sum of the deviation between the daily average temperature and the base 80°F. Negative values (temperatures below 80°F) do not contribute to CDD80. For example, a day where the daily average temperature is 81°F contributes one CDD80 and a day where the daily average temperature is 93°F contributes 13 CDD80. These daily deviations are then summed over the entire calendar year by country to form the measure of CDD80 used in the empirical models. The average CDD80 over the entire sample is 246.4. A key advantage of the CDD80 specification over the temperature bin specification, which is very unevenly distributed across countries in the high temperature ranges, is that every

[12]The results including per capita income should be interpreted with caution since studies have shown that temperature fluctuations affect per capita income (Burke, Hsiang, and Miguel 2015; Dell, Jones, and Olken 2012).

[13]Heating and cooling degree days are often used in energy demand analysis.

Table 4. **Estimates of the Impact of Cooling Degree Days on Log Annual Mortality Rates by Age Group and Country**

	Annual Cooling Degree Days with Base 80°F (÷10)	
	Coefficient	**Standard Error**
A. Estimates by Age Group		
1. All-age mortality rate	0.0075***	(0.0017)
2. Infant mortality rate (0–1)	0.0054	(0.0030)
3. Adult mortality rate (15–60)	0.0054*	(0.0022)
B. Estimates by Climate Zones, All-Age Mortality Rate		
Countries below median CDD80 (27.2)	0.0171	(0.0135)
Countries above median CDD80 (465.6)	0.0077***	(0.0017)
C. Country-Specific Estimates, All-Age Mortality Rate		
Bangladesh (430.1)	0.0051***	(0.0011)
Bhutan (0.5)	n.a.	n.a.
Cambodia (191.3)	−0.0049	(0.0044)
India (862.8)	0.0061*	(0.0024)
Indonesia (76.1)	0.0024	(0.0141)
Japan (12.4)	0.0811*	(0.0360)
Malaysia (39.8)	0.0203	(0.0162)
Mongolia (5.6)	n.a.	n.a.
Nepal (53.0)	0.0585**	(0.0156)
Pakistan (1225.2)	0.0108**	(0.0027)
People's Republic of China (29.0)	0.0585	(0.0457)
Philippines (209.3)	0.0205*	(0.0086)
Republic of Korea (1.3)	n.a.	n.a.
Sri Lanka (391.7)	0.0068	(0.0041)
Thailand (201.0)	0.0096	(0.0059)
Viet Nam (213.0)	0.0083	(0.0085)

CDD80 = cooling degree days with a base of 80°F, n.a. = not available.

Notes: The coefficient estimates correspond to the effects of annual cooling degree days with base 80°F (divided by 10) on log annual mortality rates. The rows in Panel A are from separate regressions. The rows in Panels B and C are from pooled regressions across climate zones (Panel B) and countries (Panel C). Each regression includes country fixed effects; region-year fixed effects; and controls for precipitation, relative humidity, log population, and other country-specific controls. Standard errors are clustered by country. Asterisks denote p-values of <0.05 (*), <0.01 (**), and <0.001 (***).

Sources: Author's calculations from World Development Indicators and NCEP/NCAR Reanalysis Project data.

country in the sample is exposed to positive amounts of CDD80 every year. While the across-country sample average is 246.4, the country-specific averages ranges from 0.5 (Bhutan) to 1,225 (Pakistan). Given that the empirical support for CDD80 is stronger, the remainder of the paper will focus on the CDD80 specification to model the effects of high temperatures on the various outcomes.

Panel A of Table 4 reports the coefficients and standard errors associated with the CDD80 from models for the three mortality rates variable. For presentation purposes, the CDD80 variable is divided by 10 in the regression and so the estimates correspond to a 10-unit change in the CDD80 variable (about a 5%

change compared to the 246.4 mean). The coefficient in Row 1 of Panel A indicates that a 10-unit increase in CDD80 increases the annual mortality rate by 0.75%.[14] As expected, the estimates from the CDD80 specification are more precise since there is greater population exposure to CDD80 than to days with a daily average temperature above 90 °F. In the case of all-age mortality, the cluster-robust t-statistic is larger than 4. The coefficient estimates for infant and adult mortality rates are both 0.0054, indicating that a 10-unit increase in CDD80 increases the infant and adult mortality rates by about 0.5%. Both of these estimates have larger standard errors and only the one for adult mortality is statistically significant at the 5% level.[15]

Panels B and C explore the extent to which the effects of high temperatures (as captured by the variable CDD80) vary across country-specific exposure to CDD80 (Panel B) and across country (Panel C). The motivation for these additional analyses is that there are important cross-country differences in average CDD80 per year (as shown by the number in parenthesis in Panel C). As a result, different countries or subregions may have undertaken investments that mitigate the impact of extreme temperatures on mortality, or its population may have physiologically acclimatized to different climates. Additional differences across countries in the estimated effects of high temperatures may reflect differences in public health investments, infrastructure, primary types of economic activity, and other factors.

Panel B reports the coefficient estimates of the effect of CDD80 separately for the countries below the sample median exposure to CDD80 (133.7), estimated from a pooled regression with the same set of fixed effects and controls as for the estimates reported in Panel A. The numbers in parenthesis in Panel B are the average CDD80 for the countries below (27.2) and above (465.6) median CDD80. Consistent with the differential adaptation hypothesis listed above, the coefficient estimates are twice as large for countries below the median exposure compared to countries above the median. Notably, the estimated effect for countries below the median exposure is very imprecise with a standard error of 0.0135. As a result, Panel B only provides weak evidence of adaptation to high temperatures based on the underlying climate.

Panel C reports country-specific estimates of the effect of CDD80 on the all-age mortality rate, also estimated from a pooled regression with country and region-year fixed effects.[16] Countries that have fewer than 10 CDD80 per year are omitted from this analysis (i.e., Bhutan, the Republic of Korea, and Mongolia). There is important heterogeneity in the estimated effects of CDD80 on mortality, with coefficient estimates ranging from –0.0049 to 0.0811. The precise

[14]The corresponding estimate for cooling degree days with a base of 90°F is 0.0133 with a standard error of 0.0058.

[15]Adding interactions between the relative humidity variables and the CDD80 variable increases the estimated coefficient on CDD80 and reduces the marginal effect of CDD80 on the log annual all-age mortality rate.

[16]The country-specific estimates of the CDD80 effects are identified primarily through time series variation.

interpretation of the highest coefficient, for example, is that a 10-unit increase in CDD80 increases annual mortality rates by about 8% in Japan. The estimated impact is positive for 12 out of 13 countries and statistically significant in 6 of 13 cases. Notable estimates include 0.5% for Bangladesh, 0.6% for India, about 1% for Pakistan, and about 2% for the Philippines.

The most straightforward explanation for the differences in the measured effect of high temperatures on mortality across countries is that populations in hotter areas may be better adapted either through technology or physiology to respond to high temperatures than populations in colder areas. For example, in the US, Barreca et al. (2015) find that the impact of extreme heat (defined as days with an average temperature above 90°F) on mortality is notably larger in states that infrequently experience extreme heat. In particular, they find that the measured effect of high temperatures on mortality is more than 10 times larger for states in the lowest decile of the long-term distribution of high-temperature days than it is for states in the highest decile (where such high temperatures are relatively frequent).

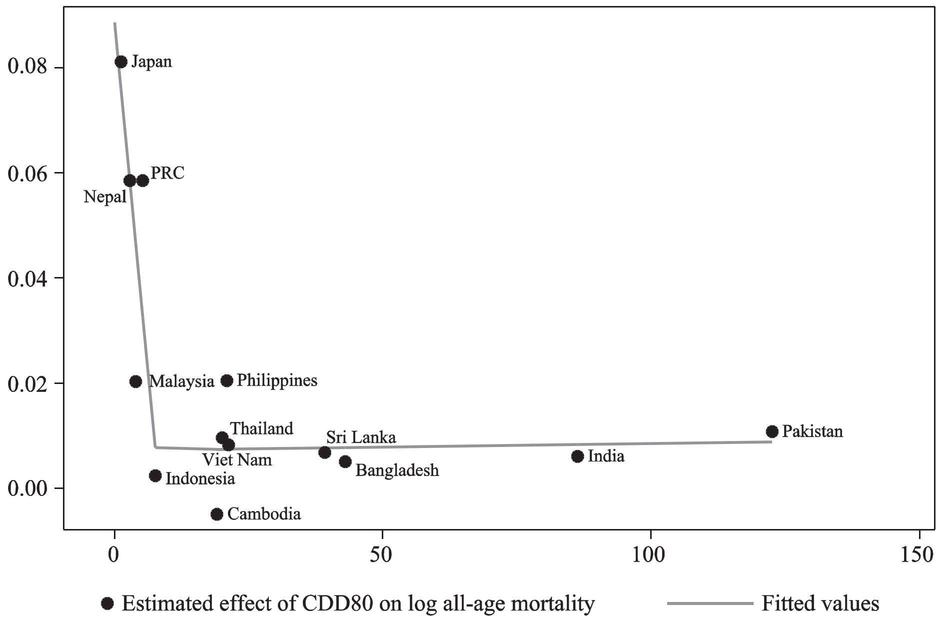
Figure 3 investigates this hypothesis by plotting the country-specific estimated impacts of CDD80 from Panel C in Table 4 against the historical average CDD80 for each country. As before, CDD80 are normalized by 10, so that 100 on the figure represents 1,000 CDD80. The negative relationship between the measured effect of CDD80 on mortality and average CDD80 is evident at first glance. The countries with low average CDD80—Japan, Malaysia, Nepal, and the PRC—are the four countries with the largest estimated mortality effects.

Further investigation of the patterns in Figure 3 reveals a "two-segment" relationship, where we observe a first segment with massive reductions in the measured effect of CDD80 up to about 10 CDD80 (100 in untransformed units): the estimated coefficient for log mortality rates drops from 0.08 (Japan) to about 0.01 (Thailand). This is followed by a second segment where increases in average CDD80 are no longer associated with marked reductions in its effect on mortality. To highlight this pattern, Figure 3 superimposes the fitted line from a piecewise linear regression with a knot at 7.5 CDD80 (75 in untransformed units).[17] The fit of the regression (with 13 observations) is striking: the simple piecewise linear representation explains 75% of the variance in the estimated CDD80 coefficient on log mortality. The first estimated slope segment is –0.011 (with a standard error of 0.0019), while the second estimated slope segment is a statistically insignificant 0.00001. Thus, it appears from this simple exercise that there are limits to mortality-reducing adaptations: the data suggest no further dampening of the temperature–mortality relationship beyond an average exposure of 75–100 CDD80.[18]

[17] The knot point was estimated using a nonlinear regression routine.

[18] This exercise is identified by cross-sectional variation and so the usual caveat to this interpretation applies.

Figure 3. **Country-Specific Estimates of the Effect of High Temperatures on Log Annual Mortality Rates**



CDD80 = cooling degree days with a base of 80°F, PRC = People's Republic of China.
Notes: This figure plots the country-specific estimated impacts of CDD80 from Panel C in Table 4 against the historical average CDD80 for each country, where base 80°F cooling degree days are divided by 10. The country-specific estimated impacts of CDD80 are from the pooled regression across 13 countries. (Bhutan, the Republic of Korea, and Mongolia are excluded due to their low exposure to CDD80.) The regression includes country fixed effects; region-year fixed effects; and controls for precipitation, relative humidity, log population, and other country-specific variables.
Sources: Author's calculations from World Development Indicators and NCEP/NCAR Reanalysis Project data.

C. Explorations into Possible Mechanisms

As highlighted earlier, the mechanisms connecting extreme temperatures and human health are especially complex in developing economies, where large shares of the population are employed in weather-dependent economic activities. With this in mind, a simple framework to understand the effect of high temperatures on mortality should consider two broad channels: (i) a direct channel connecting high temperatures and mortality through human physiology or disease; and (ii) an indirect economic channel through which high temperatures depress real incomes leading to higher incidences of undernutrition, lower levels of investment in health-producing goods, and other income- and nutrition-related health hazards.

The challenge in separating between these two channels is that both contribute to observed mortality, especially given that cause-specific mortality rates are not available in the WDI data. Put another way, the information in the mortality

Table 5. **Estimates of the Impact of Cooling Degree Days on Log Fraction of Population Undernourished and Log Fraction of Stunting in Children Under 5**

	Annual Cooling Degree Days with Base 80°F (÷10)	
	Coefficient	**Standard Error**
Log fraction of population undernourished	0.0088*	(0.0033)
Log fraction of stunting in children age 5 or younger	0.0018	(0.0088)

Notes: The coefficient estimates correspond to the effects of annual cooling degree days with base 80°F (divided by 10) on the log fraction of the population undernourished and the log fraction of stunting in children under the age of 5. Each regression includes country fixed effects; region-year fixed effects; and controls for precipitation, relative humidity, log population, and other country-specific controls. Standard errors are clustered by country. Asterisks denote p-values of <0.05 (*), <0.01 (**), and <0.001 (***).

Sources: Author's calculations from World Development Indicators and NCEP/NCAR Reanalysis Project data.

records used to construct the WDI data does not identify deaths as being due to, for example, a heat stroke (a direct, or physiological, channel) versus deaths due to, for example, chronic malnutrition (an indirect channel). In order to shed light on the mechanisms underlying the relationships documented in Figures 2−3 and Tables 3–4, I make use of information on the prevalence of undernourishment (percent of population) and prevalence of stunting (percent of children under the age of 5) that is available at the country-year level from the WDI. It should be noted that these data are sparser than the mortality rates and are missing in specific countries and years.

Table 5 reports estimates of the effect of high temperatures on the prevalence of undernourishment and stunting based on the same specification as the model in Table 4 (i.e., the base 80°F cooling degree days specification). Panel A of Table 5 reports the coefficients and standard errors associated with the CDD80 variable from panel regression models for the undernutrition indicators. Like in Table 4, the CDD80 variable is divided by 10 in the regression, so the estimates correspond to a 10-unit change in the CDD80 variable (about a 5% change compared to the mean).

The estimates suggest that a 10-unit increase in CDD80 increases the undernourished share of the population by almost 1%. The estimate is statistically significant at the 5% level. In the case of stunting, the point estimate is also positive but not significant. Overall, the estimates in Table 5 are consistent with the notion that the observed temperature–mortality relationship is driven in part by an indirect channel due to undernutrition, as opposed to being entirely driven by a purely physiological relationship. More broadly, this finding has implications for climate change adaptation policy: interventions that increase the availability of nutritional intake (or income) in years of extreme heat, especially among poorer populations, may substantially mitigate the negative health consequences of climate change.

Table 6. **Estimates of the Impact of Climate Change on Log Annual Mortality Rates, Based on Error-Corrected CCSM3 A2 Model**

	Predicted Impact on Log Mortality Rate:		
	Due to ΔCDD80	**Due to ΔPrecipitation**	**Overall Impact**
A. Estimates for 2080–2099			
All-age mortality rate	0.4519**	0.0060	0.4579**
	(0.1326)	(0.0049)	(0.1337)
Infant mortality rate (0–1)	0.2000	−0.0061	0.1939
	(0.2735)	(0.0052)	(0.2741)
Adult mortality rate (15–60)	0.3860*	0.0063*	0.3923*
	(0.1817)	(0.0030)	(0.1809)
B. Estimates by Time Period, All-Age Mortality			
2020–2039	0.0475**	−0.0087	0.0388*
	(0.0139)	(0.0072)	(0.0142)
2050–2069	0.2163**	−0.0016	0.2146**
	(0.0635)	(0.0013)	(0.0632)
2080–2099	0.4519**	0.0060	0.4579**
	(0.1326)	(0.0049)	(0.1337)
C. Estimates by Subregion, All-Age Mortality, 2080–2099			
East Asia	0.2428	0.0047	0.2475
	(0.2049)	(0.0412)	(0.1793)
Southeast Asia	0.2704	−0.0462	0.2242
	(0.5311)	(0.0526)	(0.5751)
South Asia	0.3358**	−0.0032	0.3326**
	(0.1042)	(0.0033)	(0.1015)

CCSM3 = Community Climate System Model 3, CDD80 = cooling degree days with a base of 80°F.
Notes: The entries in this table report calculations for the predicted impact of climate change on log annual mortality rates based on the error-corrected CCSM3 A2 model. Underlying regressions include country fixed effects, region-year fixed effects, and controls for precipitation, relative humidity, log population, and other country-specific controls. Standard errors are clustered at the country level. Asterisks denote p-values of <0.05 (*), <0.01 (**), and <0.001 (***). See the text for more details.
Sources: Author's calculations from World Development Indicators, NCEP/NCAR Reanalysis Project data, and NCAR CCMS3 data.

D. Predicted Impacts of Climate Change on Asian Mortality Rates

The relationship between annual temperature fluctuations and mortality rates documented in the previous tables and figures can be combined with scientific predictions about future climate change to develop estimates of the impacts of climate change on mortality rates. This exercise—essentially a ceteris paribus projection—is not without limitations, which are discussed at length in the next section.

Table 6 reports the results of such a calculation, obtained by combining the empirical estimates of the temperature–mortality relationship as shown in Table 4 with the CCSM3 A2 projections for the 16 sample countries over the 2020–2099 period. The estimates are calculations of the predicted change in the annual mortality rate (in percentage terms) due to the predicted change in high temperatures (annual CDD80) and annual precipitation recovered from the

CCSM3 A2 model. The impacts reported are based on country-level predictions calculated as the average of

$$\hat{\theta}_{CDD80}\Delta CDD80_{cj} + \sum_{k}(\hat{\delta}_k \Delta PREC_{ck}) \tag{2}$$

That is, the predicted change in the annual CDD80 in a country ($\Delta CDD80_{cj}$) is multiplied by the corresponding estimated coefficient of its effect on the log mortality rate ($\hat{\theta}_{CDD80}$). A similar calculation is done for the number of days in each precipitation bin. The final estimate corresponds to the weighted average of equation (2) across all countries in the sample. The standard errors of the predictions are calculated accordingly.

The columns in Table 6 break down each component of the calculation: the predicted impact due to the change in CDD80; the predicted impact due to the change in precipitation; and the overall impact, which is the sum of the previous two. Finally, the three panels correspond to predicted climate change impacts across age groups, horizon time periods, and regional subgroups.

The end of century results (i.e., over the 2080–2099 horizon) in Panel A indicate that all-age mortality rates are predicted to increase by 45%. By comparison, Deschenes and Greenstone (2011) find a corresponding effect of 3% for the US; thus, it is clear that climate change poses a much larger risk for human health in Asia than in the US. The rest of panel A decomposes the all-age estimates into a component for infants (Row 2) and a component for the prime-aged population (ages 15–60, Row 3). For both age groups, the estimate is positive and large: 20% for infants and 39% for ages 15–60, though only the latter is statistically significant. This evidence suggest that the burden of climate change on human health in Asia will be distributed more or less the same across all age groups.

Panel B reports predicted impacts on all-age mortality across different time horizons: 2020–2039, 2050–2069, and 2080–2099. These results show that impacts grow over the time horizon in a linear fashion, reflecting the fact that CCSM3 predicts a rising trend in global average temperatures as well as in measures of high temperatures such as CDD80. The fact that the projected impacts grow linearly with the time horizon emphasizes the need for implementing strategies in the near future to avoid large impacts on human health due to climate change.

Finally, Panel C reports estimates for the three subregions of Asia (East, South, and Southeast). The impact estimates are derived from subregion-specific estimates of the temperature–mortality relationship and subregion-specific climate change predictions regarding future levels of CDD80 and precipitation. The predictions are for all-age mortality rates for the 2080–2099 period. Overall, the predicted impacts are similar across subregions, ranging from 24% in Southeast Asia to 34% in East Asia. Only the latter estimate is statistically significant. Thus, it appears each region will be similarly impacted by climate change; therefore, concerns about climate change reinforcing inequality of well-being and economic status across countries are not warranted here in the case of human health impacts.

VI. External Validity of the Projected Mortality Impacts of Climate Change

Are studies based on historical variations in temperature and mortality, such as this one, externally valid to assess the impacts of climate change on mortality? A central issue is that empirical studies are necessarily identified by observed historical variation in weather rather than a permanent future shift in the climate. Absent the random assignment of climates across otherwise identical populations, there is no research design that can fully address this point. At the very least, standard economic theory suggests that this approach leads to an overstatement of the projected human health costs of climate change. This is because the set of health-preserving adaptations that are available to respond to a temperature shock that occurs in the short term is smaller than the set of health-preserving adaptations that are likely to be available in the long term. Indeed, some recent studies attempt at addressing this problem by exploiting exogenous variation in long-term average temperatures, such as the one caused by the "Little Ice Age" (Waldinger 2017).

Therefore, in the case of this analysis with country-year data, it is important to recognize the limitations inherent in using year-to-year variation in weather. Such variation is informative about the health effects related to the "transition" between the current and future climate distribution. However, it is not informative about the complete long-term effects of climate change on health, since the full set of defensive investments an individual can engage in is restrained to a period of 1 year rather than a longer time frame.

The end-of-century predicted mortality impact estimates indicate that climate change will increase mortality rates by about 45%. To put this estimate in some context, the all-age mortality rate declined from 21.6 to 7.2 per 1,000 between 1960 and 2015 (see Table 1), which is a decline of about 0.25 percentage points, or about 1%, per year (relative to 1960 mortality rates). If the point estimates are taken literally, the predicted increase in mortality due to climate change is roughly equivalent to losing half a century's worth of improvement in longevity, which is a remarkably large effect. This finding highlights the urgency to slow down and reverse the strong trend in rising average temperatures documented in Asia and worldwide. Failure to do so threatens to negate multidecade improvements in living standards and economic development in Asia. Furthermore, it underscores the critical role that private and public climate change adaptation will need to assume if these dire predictions are to be avoided.

There are a number of caveats to these calculations, and to the analysis more generally, that must be emphasized. First, the effort to project outcomes at the end of the century requires a number of strong assumptions, including that (i) the climate change predictions are correct, (ii) relative prices (e.g., for all health-improving inputs) will remain constant, (iii) the same health technologies will prevail, and (iv) the geographical distribution of populations in the 16 Asian countries in the sample will remain unchanged. These assumptions are not realistic, but the alternative approach involves making further assumptions about future population growth, mobility patterns, relative prices, technological innovations, and economic growth. Incorporating such additional assumptions in climate change impact predictions is beyond the scope of this paper.

Second, there is still considerable uncertainty about the reliability of the future climate predictions derived from Global Circulation Models. Climate models can produce inconsistent predictions that differ in terms of the magnitude and sign of future changes in key climate variables. As a result, climate change impact estimates based on a projection of the future climate from a single climate model can be unreliable (Burke et al. 2015). One approach proposed by the Burke et al. (2015) study is to compute climate change impact predictions from the 15 or so climate models from which future predictions are available. The range of predicted impacts across the ensemble of all climate models accounts for some (although not all) of the uncertainty inherent in Global Circulation Models. However, this approach is computationally very demanding when daily climate data outputs are required. As a result, this approach is beyond the scope of this paper.

Third, as emphasized before, it is likely that these estimates overstate the increase in mortality due to climate change because the identification strategy relies on interannual fluctuations in weather rather than a permanent change in the weather distribution (climate). As a result, there are a number of mortality-reducing adaptations that cannot be undertaken in response to a single year's weather realization. For example, permanent climate change and continued economic growth in Asia is likely to lead to institutional adaptations (e.g., improvements in public health services and hospitals' ability to treat heat-related illnesses, higher penetration rates of air-conditioning). Another natural response to permanent climate change's impact on heat-related mortality is migration to cooler regions. The empirical approach in this paper fails to account for these adaptations.

Finally, these predicted climate change impacts on mortality do not capture the full impacts of climate change on health. In particular, there may be increases in the incidence of morbidities due to the temperature increases. Additionally, there are a series of indirect channels through which climate change could affect human health, including greater incidence of vector-borne infectious diseases (e.g., malaria and dengue fever). At the same time, many other climatic variables whose distributions are expected to change due to climate change have effects on mortality rates and other health outcomes. For example, changes in the patterns of the monsoon, increased drought incidence, or stronger hurricanes will have their own health impacts. However, this study is not equipped to shed light on these issues.

VII. Conclusion

This paper presents the first empirical analysis devised to understand the complex relationship between extreme temperatures and mortality in 16 Asian countries representing more than 50% of the world's population. Using a country-year panel on mortality rates and various measures of high temperatures for 1960–2015, the paper produces two primary findings. First, high temperatures are strong predictors of increases in mortality rates. Second, this effect is larger in countries where high temperatures are infrequent.

Applying predictions on future temperature and rainfall distributions from a Global Circulation Model to the estimated temperature–mortality relationships provides an opportunity to learn about the possible impacts of climate change on health in Asia. The ceteris paribus predictions reported in the paper indicate that in the short term (i.e., over the 2020–2039 horizon), climate change, through its effects on temperature and rainfall alone, will have modest impacts on mortality rates in Asia, with a predicted increase of 4%. In the long term (i.e., over the 2080–2099), the corresponding predictions are dramatically larger, with a predicted increase of 45%. Such an increase roughly corresponds to the remarkable decline in mortality rates in Asia during the 1960–2015 period. This finding therefore underscores the importance of climate change adaptation to mitigate some of the expected negative effects on human health. Without adaptation, climate change may reverse the public health achievements and economic progress of Asia over the last half-century.

This paper only represents a first attempt at empirically analyzing the temperature–mortality relationship in Asia and providing climate change impact projections that can inform policymaking. Many key implications for future research emerge from this analysis. Future studies should attempt to use panel data with within-country variation in both the outcomes and the climatic variables, as in Burgess et al. (2014). Such within-country analysis will allow the specification of more robust econometric models that control for local unobserved shocks. Additionally, within-country panel analysis can inform climate change adaptation strategies by studying specific policies or technology deployments that can mitigate the effect of temperature extremes on health, as in Barreca et al. (2016).

Finally, as emphasized earlier, climate change will bring changes to a host of climatic variables in addition to temperature, many of which can have significant impacts on health. All of these considerations should be priorities for future research in this area.

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