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HEAT, HUMIDITY, AND INFANT MORTALITY IN THE DEVELOPING WORLD

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ABSTRACT

We study how extreme temperature exposure impacts infant survival in the developing world. Our analysis overcomes the absence of vital registration systems in many poor countries, which has been a limiting factor in the temperature-mortality literature, by extracting birth histories from household surveys. Studying 53 developing countries that span the globe, we find impacts of hot days on infant mortality that are an order of magnitude larger than estimates from rich country studies, with humidity playing an important role. The size and implied geographic distribution of harms documented here have the potential to significantly alter assessments of optimal climate policy.

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1 Introduction

The Intergovernmental Panel on Climate Change predicts a mean increase in the Earth's surface temperature of 2° to 7°F over the next century, calling it "virtually certain" that there will be more frequent hot temperature extremes experienced over most land areas by 2100 (IPCC, 2014). From the US (Barreca, 2012; Barreca et al., 2016; Deschênes and Moretti, 2009; Deschênes, Greenstone and Guryan, 2009; Deschênes and Greenstone, 2011; Heutel, Miller and Molitor, 2017) and from other middle and high income countries (Gasparrini et al., 2015), there is now evidence on the extent to which extreme temperatures kill. Yet, for developing countries we know little about the temperature-mortality relationship, especially for the least-developed countries, where billions of people live. Extrapolations from the rich word or from middle-income countries with more urbanized economies could be misleading. In particular, very poor populations may be less capable of reducing exposure to extreme heat and humidity, such as via climate-controlled housing and indoor work. Further, the harm conditional on exposure could be greater in the developing world due to baseline health among the poor that is substantially more fragile.

The environmental economics literature has routinely highlighted the need to understand the health impacts of temperature and climate change in developing countries (Greenstone and Jack, 2015). But to date research progress has been limited because the poorest countries lack the kind of vital registration data routinely available in high- and middle-income countries. As a broad coalition of economists recently noted in *Science*, the near exclusive focus in the prior literature on rich countries is "problematic ... because the nature of impacts and context for policy choice could differ greatly relative to developed regions" (Burke et al., 2016). Similarly, Deschênes (2014) explains in a review of this literature: "An important component of future research is to better ascertain the differences in the temperature–mortality response across countries, especially the difference between developed and less developed countries."

This study provides needed evidence on the human mortality effects of extreme heat and humidity in the poorest countries. The prior temperature-mortality literature has generally focused on places where vital statistics data or other complete records of all deaths exist, but many poor countries lack high-quality vital registration systems. We overcome this fundamental data challenge by constructing sample-based measures of mortality using Demographic and Health Surveys. These surveys record information on infant deaths for large, nationally representative samples in many of the poorest countries in the world. We link retrospective fertility histories from surveys of mothers to data on temperature, humidity, and precipitation at fine-grained geographic and temporal resolution. From this, we generate a panel of temperature exposure and child survival from the in utero period into childhood for households in 53 developing countries spanning Africa, Asia, and Latin America.

Because we observe many births within the same villages, and because within a village, observed births occur in the same months of different years, we can flexibly control for locality-specific seasonality. Identifying effects off of only temperature *shocks* addresses any seasonality in the composition of births that could otherwise confound estimates (Barreca, 2017; Barreca, Deschênes and Guldi, 2018; Buckles and Hungerman, 2013).

In addition to extending the temperature-mortality literature to study the poorest populations—these are the least likely to be covered by functioning death registration systems—we innovate by introducing wet bulb temperature (T_{wb}) into the climate economics literature. T_{wb} is an index that combines information on heat and humidity. Sweat evaporation is humans' primary thermoregulatory mechanism in high ambient temperatures, and evaporation depends critically on humidity levels. Wet bulb temperature tracks the physics of evaporative heat exchange better than the familiar ("dry bulb") measurement of temperature. T_{wb} is recognized in textbook treatments of human thermal environments as a more informative signal of both comfort and heat stress (Parsons, 2014). It is also widely employed by climate scientists and biologists interested in describing the envelope of theoretically survivable temperature-humidity combinations (Sherwood and Huber, 2010; Im, Pal and Eltahir, 2017). In practice, we show that this parameterization of temperature best fits the infant mortality patterns we observe.

We find that very hot and humid days generate large infant mortality effects: Experiencing an additional day of mean wet bulb temperature above 85°F (equal to about 100°F at 55% humidity) in the first month of life increases neonatal mortality by 0.7 deaths per thousand births. This infant mortality effect is an order of magnitude larger than most previous econometric estimates of the impacts of hot days, which have primarily been generated from developed country samples. Our parameter estimates are closest to those in Barreca et al. (2016) for the US from 1930 to 1959, prior to the widespread adoption of air conditioning.

We show that the largest and most robust mortality effects are associated with exposure to extreme temperature-humidity combinations experienced during the month of birth, rather than in utero or later in infancy. Further, the largest share of the resulting deaths occur in the birth month, contemporaneously with the timing of temperature exposure. This immediate response suggests a direct biological channel, rather than a channel through eventual agricultural yields and incomes. The findings thus complement work that has highlighted effects of extreme temperatures on agricultural output (Guiteras, 2009), with impacts on economic wellbeing overall (reviewed in Dell, Jones and Olken, 2014) and on health in particular (Burgess et al., 2017). The contrast here suggests that policy responses focused on income smoothing in the face of weather uncertainty, while potentially protective against some harms, may be insufficient to fully counteract the infant mortality effects.

Our paper contributes to the economic analysis of temperature, mortality, and climate change in several important ways. This paper is the first to identify the effect of extreme heat and humidity on early life mortality in a sample that spans very poor countries without vital statistics systems. We thus contribute to a broad economic literature examining the short- and long-term health and human capital consequences of adverse environmental exposures during the in utero period and early childhood (reviewed in Almond, Currie and Duque, 2017). In particular, we build on studies that examine in-utero and infant weather exposure in rich country settings, including Deschênes, Greenstone and Guryan (2009) and Isen, Rossin-Slater and Walker (2017). We likewise complement a very small literature (Burgess et al., 2017; Carleton et al., 2018) that has identified any health impacts of temperature in any developing country context, and a broader literature that considers weather-related natural disasters in developing countries (e.g., Guiteras, Jina and Mobarak, 2015).

Second, the new facts we establish about the role of properly-parameterized humidity have the potential to reshape understanding of the geographic distribution of health damages, an issue of broad current interest (see, e.g., Hsiang, Oliva and Walker, 2017). Figure 1 plots the location of each village or urban block in our global sample, along with temperature and humidity characteristics. Some of the hottest places on Earth are concentrated in sub-Saharan Africa. However, our estimates do not imply the largest incidence of heat-related mortality at these locations, which tend to be dry. Instead, our findings indicate the largest impacts occur in the more humid regions of Asia. In this way, we build on earlier work by Barreca (2012), which showed that absolute humidity is predictive of US adult mortality, but in contrast to our results, found no amplifying effect between heat and humidity.

Third, our findings contribute to the continued evolution of climate damage functions and integrated assessment models used to determine optimal climate policy, including the optimal carbon tax. Though damage functions have historically been crude, the most recent research has attempted to directly incorporate the type of micro-econometric estimates we generate here. In such models for the US, health and mortality impacts comprise the greatest share of total climate damages (Hsiang et al., 2017). Thus, our finding that mortality effects in poor countries are an order of magnitude larger than what has been estimated for the developed world has the potential to significantly alter assessments of optimal policy.

2 Background

We use wet bulb temperature, denoted T_{wb}, to combine information about ambient air temperature and moisture in the air in a functional form that is motivated by the physics of how humans regulate body temperature. T_{wb} is widely used in climate science, biology, and ergonomics as a useful summary statistic for heat stress danger and thermal comfort (Parsons, 2014). As a practical matter, it is also the dominant meteorological variable used for assessing heat exposure danger by the US military, by OSHA, and by (outdoor) sports medicine physicians (Budd, 2008). Mechanically, T_{wb} corresponds to the temperature reading on a standard mercury thermometer whose bulb is wrapped in a continuously dampened cloth. The reading is lower than on a familiar "dry bulb" thermometer because evaporation carries heat energy away from the bulb.

T_{wb} connects naturally to the process of cooling oneself via sweating. As dry bulb ambient air temperatures rise above the skin's surface temperature (typically 96°F), the only biological process that can substantially cool the body is the evaporation of sweat. High humidity exacerbates heat stress by reducing the efficiency of sweating/evaporation: Holding ambient temperature fixed, the rate of heat transfer via evaporation is lower on a humid day (when the sweat clings to the skin rather than quickly evaporates). When sweating functions inefficiently, the cardiovascular system experiences greater stress, dilating blood vessels in the skin and working harder to transport heat away from the body's core towards the skin via blood circulation. This problem can particularly impact neonates, who effectively free-ride on maternal temperature regulation in utero. The baby's own thermoregulation remains poorly controlled for the first days of life (Hey and Katz, 1969).

Because wet bulb temperatures (T_{wb}) are highly non-linear combinations of dry bulb temperature

(T) and relative humidity (H), they do not readily translate into more familiar units. In fact, there is no closed form expression linking T_{wb}, T, and H. A wet bulb temperature of 85°F (a relevant threshold below) corresponds to the following temperature/relative humidity combinations at standard pressure: {120°F, 30%}, {100°F, 55%}, and {90°F, 80%}. If the true model linking human mortality to extreme heat is a function of T_{wb}, then simple linear interactions of temperature and relative humidity may be insufficient to capture the relevant impacts of humidity. We show that this turns out to be empirically true, at least in the cases we study.

3 Data and Empirical Framework

3.1 Data

We link data from two sources: the Demographic and Health Surveys (DHS) and a globally gridded weather dataset. DHS are nationally-representative survey data collected as a joint effort of USAID and the national governments where the surveys are fielded. The main questionnaire modules, which focus on demographic statistics and maternal and child health, are comparable across countries. Women aged 15 to 49 are the primary respondents. Each woman reports her complete birth history (e.g., child #3 was born in March 2006 and survived to the date of interview). Therefore, although we observe each surveyed woman at just one point in time, information on month and year of birth—and, if applicable, date of death—enables us to construct a month-by-month panel of child survival.

Although the DHS are not a complete census of deaths registered by a government agency, the high quality of the DHS mortality data has been established by a literature in economics that uses DHS data to study causes of death other than temperature (but including other weather-related or environmental factors). These include studies of weather-related phenomena, such as the effects of malaria (Kudamatsu, Persson and Strömberg, 2012), rainfall shocks (Burke, Gong and Jones, 2015), dusty wind (Adhvaryu et al., 2016), and coffee prices (Miller and Urdinola, 2010), as well as other factors such as macroeconomic fluctuations (Paxson and Schady, 2005; Bhalotra, 2010), sanitation (Geruso and Spears, 2018), and democracy (Kudamatsu, 2012).

We assemble and harmonize all DHS datasets collected through 2014 for which the latitude and longitude of the primary sampling unit (PSU) was recorded. PSUs correspond to a very fine level of geographic disaggregation: villages in rural areas and city blocks in urban areas. We use *village* as shorthand for PSU below. The universe of DHS surveys with geolocation information includes countries spanning Latin America, Africa, Eastern Europe, South Asia, and Southeast Asia. For many countries we observe several survey rounds (e.g., Bangladesh in 1999/2000, 2004, 2007, and 2011). Even for countries with only a single round, the retrospective nature of birth histories implies that we observe many births within the same village, occurring in different months and years—and in the same months of different years. Our assembled dataset includes 53 countries observed over 111 country $\times$ survey rounds. Figure 1 maps the countries in our assembled data. In Table A1 we list each country and associated survey rounds.

To the DHS data, we match geographically-gridded sub-daily measures of temperature, humidity, and other meteorological variables from the Princeton Meteorological Forcing Dataset (PMFD), generated by Sheffield, Goteti and Wood (2006) and Sheffield, Wood and Roderick (2012). The PMFD combines reanalysis data from NCEP-NCAR with a collection of observation-based data from the Climactic Research Unit and other sources. These weather data have a geographic resolution of 0.25° latitude $\times$ 0.25° longitude and a temporal resolution of 3 hours. The data are described in additional detail in Appendix Section A.1.

To merge the datasets, for each PSU in the DHS we identify the four closest surrounding grid points, and assign weather values averaged across those points, weighted by inverse distance to the PSU. This yields a panel that locates each month of each child's life in time and in latitude $\times$ longitude with linked information on exposure to various weather variables.

Variables of particular interest in our study include daily mean humidity, daily mean dry bulb temperature (T), and daily mean wet bulb temperature (T_{wb}). Daily means are generated by averaging across eight daily temperature readings. Thus, a day described by a mean temperature of 90°F may have daytime highs in excess of 100°F. We follow the recent literature in tabulating the exposure variables semi-parametrically, as counts of days falling in various temperature ranges. In wet bulb degrees Fahrenheit, we count the days per month in each of the following bins: < 30, [30,40), [40,50), [50,60), [60,70), [70,75), [75,80), [80,85), and ≥ 85. Panel D of Figure 1 plots the incidence of daily means across these bins in our sample.

It is important to understand the strengths and limitations of these data, relative to the kinds of vital registration data typically used in temperature-mortality studies. A primary advantage is that DHS data allow us to measure mortality in the poorest countries in the world. As Table A1 summarizes, most of these countries do not have credible national vital registration systems (Mathers et al., 2005). In this way, our approach resembles Young (2012), which uses DHS asset data to measure economic growth in African countries with weak national accounts systems. In addition, even compared to the few, relatively richer developing countries where there is at least partial vital registration coverage (e.g., Brazil, China and India, studied in Carleton et al., 2018 or Brazil, China, and Thailand studied in Guo et al., 2014), the data here allow for finer temporal and geographic resolution in the measurement of births and deaths than is typically possible. This enables us to narrow in on perinatal events and to construct the first econometric estimates of effects of temperature on neonatal mortality in the literature (including in rich country-settings).[1] This advantage proves important in practice, as we show that exposure and death during the birth month accounts for most of the temperature-related mortality in the first year.

A relative weakness of the DHS is that despite our assembled data spanning dozens of countries, the number of lives and deaths represented in each country sample is small relative to the number of lives and deaths represented in birth and death registry data, which are based on complete censuses. Therefore, the analysis here is powered to detect *large* effects, which it finds; we are limited in our ability to detect or rule out mortality effects of the sizes documented in richer populations.

3.2 Empirical Framework

We follow the recent literature to estimate flexible regressions of the form

$$Y_{ijdct} = \sum_B \beta^B \cdot Temp^B_{ijdct} + \sigma_t + \theta_{dm} + \sum_B \zeta^B \cdot \overline{Temp}^{B,\text{ 5-year}}_{ijdct} + \Phi X_{ijdct} + \epsilon_{ijdct}, \tag{1}$$

where j indexes survey PSUs, d indexes about 2,300 administrative divisions ("districts") within countries, and c indexes the 53 countries.[2] Calendar months are indexed by m. We denote month $\times$ year interactions (e.g., July 2009) with t. Observations i are children. The dependent variable Y

[1] To our knowledge, no other study has identified effects of temperature on neonatal mortality in a manner that addresses the potential for endogenous seasonality. The epidemiology literature that examines weather and birth outcomes often explicitly relies on seasonality to identify effects. See Strand, Barnett and Tong (2011) for a review. In both public health (e.g., Guo et al., 2014, Mora et al., 2017) and the econometric literature, studies tend to report annualized deaths in most cases and to estimate a single "age-adjusted" effect that combines infants with adults and the elderly. Even in cases where mortality is measured monthly or infants have been estimated separately, studies have not distinguished between neonatal deaths (month one) and infant deaths (year one).

[2] The units of within-country administrative divisions d vary across countries in the pooled sample, and may refer to districts, divisions, provinces, regions, states, zones, etc., each interacted with urban/rural. We use *districts* for parsimony.

represents a child health outcome, the focal outcomes being an indicator for infant death (first year) or neonatal death (first month). Mortality indicators are multiplied by 1000, so that coefficients correspond to mortality effects per 1000 lives.

The coefficients of interest are β^B, with B indexing temperature range bins. The variables $Temp^B$ count the days in the relevant month for which the child/fetus was exposed to temperatures in some range—e.g., the child experienced 6 days with mean temperatures in the range 75-80°F during her birth month. Coefficients β are interpretable as effects relative to the experiencing a day of mean temperature in the omitted category (60-70°F). Saturated fixed effects for the month $\times$ year, σ_t, accommodate time trends with maximal flexibility. We additionally control for rainfall and household-level characteristics (X) recorded in the DHS.

The identifying assumption in our analysis is that conditional on the controls for typical weather and place-specific seasonality, the actual realization of temperature is random. An important practical consideration is exactly how to control for local seasonality that could otherwise lead temperature to be endogenous to the timing and socioeconomic composition of births. We take several approaches. As written, Equation (1) includes district fixed effects interacted with calendar month, θ_{dm} (e.g., an indicator for rural areas of the Rangpur administrative division of Bangladesh in August), to flexibly control for local seasonal variation in both the weather and patterns of births and deaths. This accommodates seasonality that differs across locales within a country. We investigate sensitivity to coarser controls, including country $\times$ calendar quarter fixed effects, and to finer controls, including village $\times$ month fixed effects. To further account for predictable, seasonal weather at the local level, all regressions also control for the count of days in each bin in the PSU averaged over the preceding 5 years ($\overline{Temp}^{B,\text{ 5-year}}$) for the same calendar month as the main exposure variable ($Temp^B$).

4 Variation in Heat and Humidity

Figure 1 offers several views of the weather variation that identifies mortality effects below. Panel B indicates the locations of the individual survey PSUs in our data, plotted as points. We add special markers to PSUs above the 99th percentile of days in the top dry bulb bin ($T \geq 95°$) in gold. We likewise indicate PSUs above the 99th percentile of days in the top wet bulb bin ($T_{wb} \geq 85°$) in red. Whereas the hottest dry bulb days tend to be located in sub-Saharan Africa, the hottest wet bulb days are more likely to occur in South Asia and Southeast Asia.

Panel C of Figure 1 further illustrates how wet and dry bulb temperatures often diverge. Beginning from observations at the PSU-day level, we calculate the range of wet bulb temperatures that corresponds to various dry bulb temperature bins. The figure shows that for a dry bulb bin that is 10°F wide, variation in humidity can lead to ranges of wet bulb temperatures spanning 20°, 30°, or even 40°F. The variance in T_{wb} conditional on T tends to increase at higher temperatures.

Panel C shows that the hottest wet bulb temperatures are *not* coincident with the highest dry bulb temperatures. The nearly linear relationship between T_{wb} and T breaks around 85°F dry bulb, at which point the sign of the correlation changes. We exploit the non-collinearity of dry and wet bulb temperatures when examining which measure better fits the observed patterns of infant mortality.

5 Results

5.1 Birth Month Exposure and Infant Mortality

Figure 2 displays our main estimates of Equation (1) for both dry and wet bulb temperature. The dependent variable is infant mortality, and weather exposure is measured during the month of birth. We control for interactions of district indicators with month indicators, for rainfall in the exposure month, and for typical weather in the infant's birth month in the infant's village over the five years that precede the birth. The regression thus reveals how, conditional on usual weather and place-specific seasonality of births, the temperature profile experienced during the first month of life impacts infant survival.

The plots show a U-shape that is characteristic of temperature-mortality studies: Mortality decreases moving left to right from colder to warmer temperatures, then bottoms out in the mild temperature range (60-70°F), and finally rises sharply at very high temperatures. Due to the scaling of the dependent variable, effects are per 1,000 births. Therefore, a coefficient of 0.7 for $T_{wb} \geq 85°$ (rightmost point in bottom panel) implies that exposure to one day of mean wet bulb temperature above 85°F in place of a 60-70°F day increases deaths by 0.7 infants per thousand births.

Estimates corresponding to Figure 2, along with additional regression specifications, are reported in Table 1. Although we include as regressors all of the same degree-day bins shown in the figure, in the table we report coefficients for only the coldest and hottest bins. Across the columns, we try various approaches to controlling for local seasonality: In columns 1 and 5, country indicators interacted with calendar quarter indicators; in columns 2 and 6, country indicators interacted with month indicators and additional fixed effects for each district; in columns 3 and 7, these district indicators interacted with month indicators, as in Figure 2.

To examine robustness to very fine geography $\times$ season controls, we add village $\times$ month fixed effects in columns 4 and 8. Here we face a bias-precision tradeoff as this involves identifying about 500,000 village $\times$ month fixed effects. In practice, the addition of these in column 8 increases standard errors but does not impact point estimates relative to column 7, which we treat as the preferred specification. We add household and individual-level covariates in column 9.[3] Consistent with the assumption that conditional on controls for typical local weather, realized weather is as good as random, the inclusion of household controls has essentially no impact on parameter estimates. We show in Appendix A.2 that our estimates are similar when splitting the sample to either focus on or to drop South Asia, where extreme heat and humidity most often occur together.

It is clear from Table 1 that the estimates that are most robust to alternative control sets are the coefficients on $T_{wb} \geq 85°$. The effect of temperatures $< 30°$ are also relatively stable. The stability of the cold temperature effects holds for both the wet and dry bulb measures, which are more strongly correlated at low temperatures than at high temperatures (see Figure 1C). In contrast, the estimated impact of experiencing a day in the $T \geq 95°$ dry bulb bin is imprecisely estimated and varies significantly in magnitude across the columns. Indeed, we show in Appendix A.3 that the wet bulb specifications are much more robust to further reasonable perturbations on the controls for local seasonality and the choice of bin cutoffs.

In columns 10 through 12, we simultaneously include wet and dry bulb variables in the same regressions. Coefficients can be separately estimated because a day with $T \geq 95°$ could correspond to any of several wet bulb bins. In these columns, estimates for $T_{wb} \geq 85°$ remain essentially unchanged while estimates for $T \geq 95°$ move closer to zero.

An alternative approach to parameterizing the impact of humidity would be to interact dry bulb temperatures with measures of absolute or relative humidity. Interestingly, we find that various simple forms of such interactions yield estimates that are small and never statistically significant.[4] Given

[3] Household covariates include the child's sex and whether the mother is literate as well as indicators for birth order, sibship size, household asset wealth quintiles, and household electrification.

[4] See Appendix A.4.

that the broader scientific literature (e.g., Im, Pal and Eltahir, 2017) anticipates non-linear impacts of heat-humidity combinations on human health, this is sensible. The finding is also is consistent with Barreca (2012), which finds null effects for these types of linear interactions in the context of US mortality.

The sum of this evidence suggests that the functional form of T_{wb}—which is intrinsically linked to the physics of evaporation—may better parameterize the underlying process linking heat and humidity to deaths, at least with respect to infant mortality in our developing country sample. This finding fits with the theoretical literature that treats the upper range of survival temperatures as being best described by wet bulb temperature (Sherwood and Huber, 2010), though our paper is the first to our knowledge to provide econometric estimates of the effects of wet bulb temperatures on infant deaths. An open question is whether humidity-indexing is as important for adults and is as important in the less hot, less humid regions of the world (where richer countries are predominately located).

A special feature of our data is that at the person level, we observe household characteristics like wealth and mother's literacy, which are potentially important for child health outcomes (Thomas, Strauss and Henriques, 1991) and may interact with weather exposure to affect mortality. However, in practice we cannot rule in or out economically meaningful heterogeneity by individual or household characteristics.[5] One exception (see Table A2) is that household electrification is correlated with smaller impacts of cold, but not hot, days. The limit to statistical power here is the tradeoff made in using sample survey data to measure effects in populations for which effects would be otherwise unmeasurable. As Setel et al. (2007) explains, "Most people in Africa and Asia are born and die without leaving a trace in any legal record or official statistic."

5.2 Effects in Context

The qualitative pattern in Figure 2 resembles results from the prior literature estimated in US and European data and adult populations, but the scale is importantly different. Many such studies (e.g., Deschênes and Greenstone, 2011; Heutel, Miller and Molitor, 2017) find that exposure to a day in the highest temperature bin increases all-age mortality on the order of 0.01 deaths per 1,000 population. Days with the highest humidity-indexed mean temperatures in our setting cause about 0.7 infant

[5]See Appendix A.2 for results showing these null interactions.

deaths per thousand infants born.

Our study differs from most of the prior econometric literature in its geographic focus (the poorest countries, where mortality rates are highest) and in its age focus (infants, whose mortality rates are higher than adults). Both differences make the larger effects we document plausible. Pregnant mothers and babies in the developing world are more likely than in richer populations to be already physically weakened due to interactions among poor nutrition, infectious disease, and poverty (Foster, 1994). And neonates are especially sensitive to environmental conditions due to their still-developing thermoregulation systems.

For reference, in Table A1 we generate infant mortality rates by country in our sample. In several countries, these rates exceed 100 deaths per 1,000 births. Mean infant mortality in our overall DHS sample is an order of magnitude larger (77 deaths per thousand infants) than all-age mortality in the US and Europe today (8 to 10 deaths per thousand population). Table A1 also shows that these (survey-derived) infant mortality rates tend to be highest in countries with the weakest capacity to generate demographic data (assessed by Mathers et al., 2005). This underscores the possibility that mortality processes may be significantly different between places with and without functioning vital registration systems.

Populations in poor countries are also more exposed to outdoor temperatures: In our sample, which covers births occurring in the 1980s through 2010, a negligible minority of households would have had access to climate-controlled indoor environments, which have been shown to mitigate weather's impacts on fetuses and infants in the US (Isen, Rossin-Slater and Walker, 2017).[6] Our estimates are closest in magnitude to estimates from the historical US, derived from a period prior to the introduction of air conditioning. In a sample spanning 1931 to 1959, Barreca et al. (2016) estimates that the impact of a $> 90^\circ$ day on all-age mortality is about 0.20 deaths per 1,000 population.[7]

5.3 Timing

An important issue in the context of weather-related deaths is "harvesting," or hastening deaths that would have otherwise occurred within a few days or months. Deschênes and Moretti (2009) finds that increases in mortality following days of very high temperatures in the US are primarily driven

[6]Questions regarding AC were not asked by the DHS precisely because they are irrelevant to these populations.

[7]Our dry bulb estimates in Table 1 column 3 for $T \geq 95^\circ$ are similar: 0.24. However, as discussed above these estimates are noisy. We cannot rule in or out effects of dry bulb temperature of the magnitudes that have been documented in studies using vital registries.

by this type of near-term displacement. In contrast, Heutel, Miller and Molitor (2017) does not find evidence of such displacement in its US estimates. Both studies examine displacement up to one month. We examine potential displacement up to two years in Figure 3.

We find that the weather-induced mortality in our setting is not claiming sick babies who would have succumbed in their first two years regardless of having experienced the weather. In Figure 3 we hold the month of exposure fixed at the birth month (month zero), and measure survival through age two in one-month increments. Harvesting here would imply a declining effect size moving right along the horizontal axis, as an initial increase in mortality during the month of exposure would be (partially) offset by a later decrease in mortality, generating a smaller net effect for mortality measured in later months. In contrast to the pattern implied by harvesting, the effects of $T_{wb} \geq 85°$ are stable over the two year period. For $T_{wb} < 30°$, the effect grows as mortality is measured later, indicating that some of the mortality occurs in the future rather than occurring contemporaneously with the month of exposure. The finding that the effects of cold, in particular, are stronger when allowing a longer lag is consistent with Heutel, Miller and Molitor (2017), which studies effects among the US elderly.

So far, we have focused on the impacts of the weather that occurs during each infant's birth month. In Figure 4, we examine impacts of weather that occurs outside of the birth month. Here we regress infant mortality (first 12 months) on the temperature profile experienced during various periods. The exposure period varies along the horizontal axes, organized as trimesters (3-month periods). Towards the left, the exposure variables are calculated as the mother's exposure prior to birth. Toward the right, exposure is calculated as the child's own exposure during various periods post-birth. Each point represents a separate regression. The central point in each panel corresponds to the estimates in Table 1, column 7.

For very cold days (Panel A), the strongest effects correspond to birth month exposure. Exposure in the prenatal and post-neonatal periods is associated with mortality effects that are each positive and on the margin of statistical significance. The only estimate in the panel for which this does not hold is the leftmost point. This point corresponds to the 3-month period that would precede conception for a full-term birth. Cold days thus appear important throughout the prenatal and postnatal periods.

The pattern for very hot and humid days (Panel B) is simpler: The only clear effects occur when the exposure takes place in the month of birth. There is evidence from North America and Europe in the economics (Barreca, 2018) and epidemiology (Kuehn and McCormick, 2017) literatures that hot days cause premature births. A possibility here is that high temperatures cause decreased gestational length, in turn increasing the risk of neonatal death. If this were the case, the total effect of hot and humid days on IMR would be correctly estimated in our regressions, but the mechanism would include causing a change in birth month. (A reliable measure of gestational length is not a part of mothers' self reporting of their birth histories.)

An implication of the apparently contemporaneous timing of hot weather exposure and death in Figure 3B is that it appears most consistent with a direct, biological channel rather than a more complex income feedback mechanism. Exposure and death occurring in the same month would be more difficult to rationalize through, for example, a weather-induced crop failure feeding back into family income at the time of harvest and sale. Although such a channel is known to be important for other outcomes—e.g., adult mortality in Burgess et al. (2017), and economic wellbeing more generally, as reviewed in Dell, Jones and Olken (2014)—the timing here suggests a more direct biological channel for this outcome (Hey and Katz, 1969).

6 Conclusion

We shed important new light on the relationship between temperature and health in the developing world, overcoming the lack of vital registry data by relying on birth history surveys from 53 countries. Our evidence of large effects of heat and humidity on infant mortality highlights several important avenues for future research. First, the apparent importance of humidity-indexing suggests the need for further analysis of the wet bulb parameterization in the economics literature, especially where there is statistical power to identify the best-fit functional form of heat-humidity interactions. Second, our findings cohere with concerns in the climate literature that estimates from rich countries could significantly understate the mortality vulnerability of poor populations. Again, the availability of data is a key constraint. For example, whereas Deschênes, Greenstone and Guryan (2009) shows birth weight effects of extreme weather in the US, no estimates are available from poor populations, where weighing babies at birth is rare (Strauss and Thomas, 1996). Other health and human capital outcomes (e.g., test scores in Zivin et al., 2018) should be explored in developing countries wherever data exists or can be generated by researchers. Finally, assessments of the social costs of climate change should incorporate the high social value of death that occurs in early life, as well as a refined understanding of the geographic distribution of damages across the hot versus the humid regions of the world.

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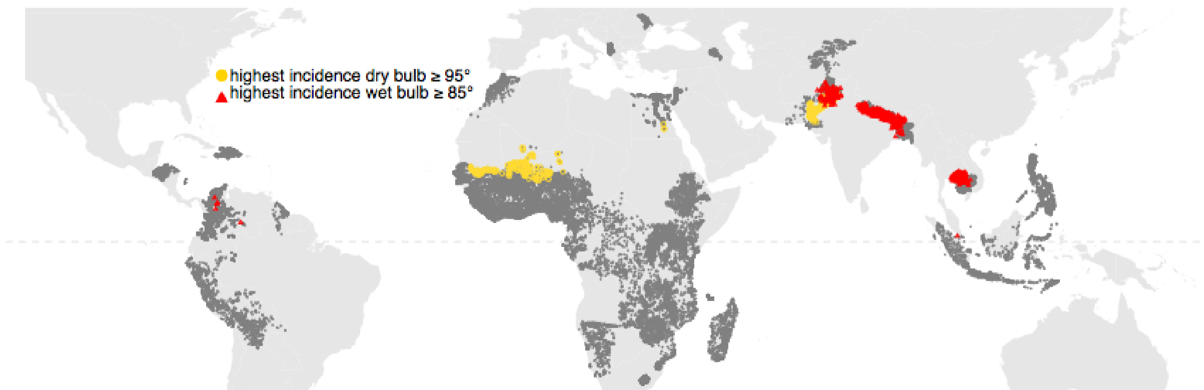
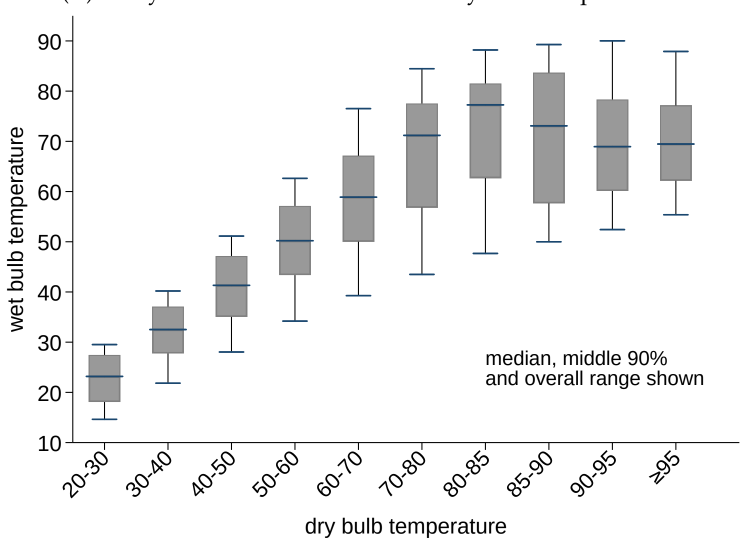
Figure 1: Sample and Summary Statistics

(A) Sample: 53 developing countries

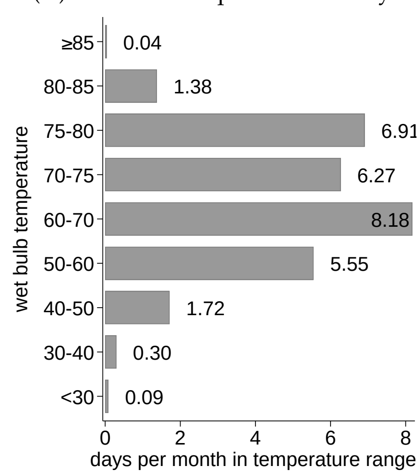
(B) Spatial incidence of hot days and high wet bulb (humidity-indexed temperature) days



(C) Daily means of wet bulb versus dry bulb temperatures



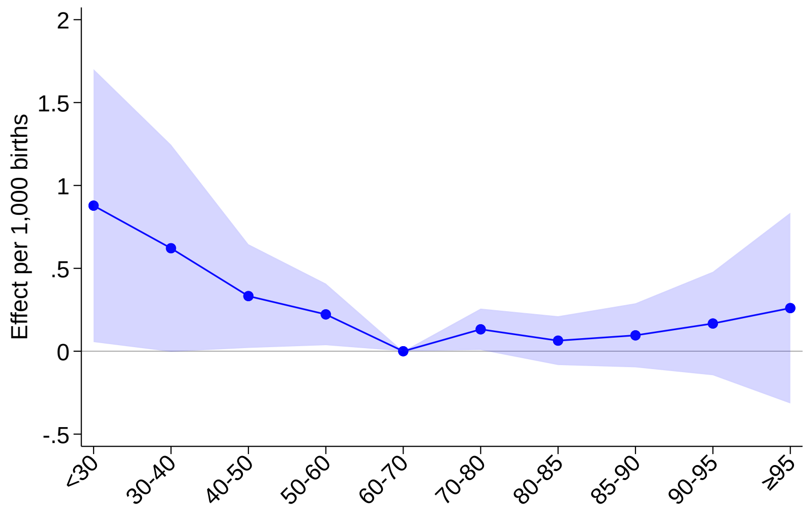
(D) Wet bulb temperature density



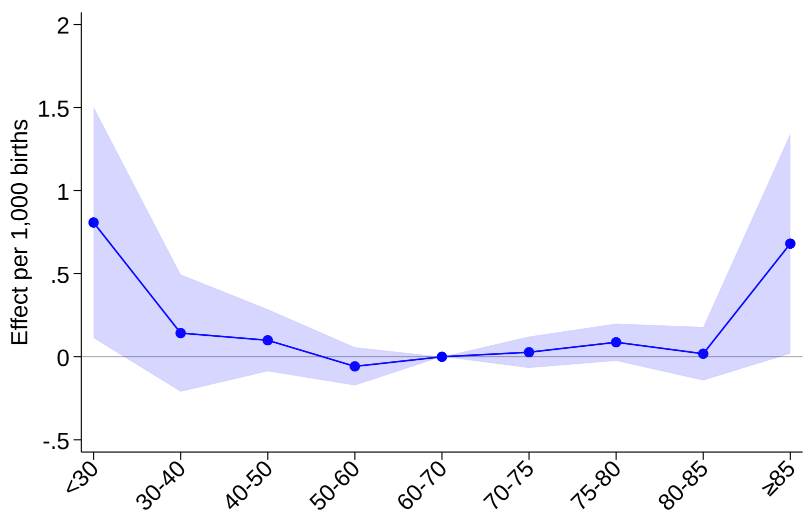
Note: Panel A displays the countries in our sample. Panel B plots the locations of each survey PSU in the sample. PSUs are villages in rural places and blocks in urban places. Gold markers indicate PSUs above the 99th percentile of counts of days with mean dry bulb temperatures above 95°F. Red markers indicate PSUs above the 99th percentile of counts of days of mean wet bulb temperatures above 85°F. Panel C displays the median, middle 90%, and overall range of mean daily wet bulb temperatures associated with various mean daily dry bulb temperatures. Panel D plots the count of days in each wet bulb temperature bin in our sample. In panels B and D, statistics are calculated over the birth months of infants in our sample. In panel C, daily means are taken for each day in the 10 years preceding sample births for each survey PSU in the sample.

Figure 2: Birth Month Exposure and Infant Mortality

(A) IMR and dry bulb temperature



(B) IMR and wet bulb temperature



Note: Figure plots the estimated infant mortality effects of exposure to days in various temperature ranges. The dependent variable is death in the first year of life (infant mortality), scaled by 1,000 so that the vertical axes indicate effects in terms of deaths per thousand births. The regressors of interest measure the counts of days in various temperature ranges in the infant's PSU (village/urban block) during the infant's month of birth. The plotted coefficients express the marginal effect of exchanging a day in the specified temperature range with a day in the excluded range (60-70°F). Panel A displays impacts of dry bulb temperatures. Panel B displays impacts of wet bulb temperatures in a separate regression. Specifications here control for "district" indicators interacted with month indicators. See Table 1 for further description the controls common to all specifications, which include precipitation in the birth month (linear in centimeters), year × month indicators for the birth month (e.g., July 2003), and the typical seasonal weather in the preceding five years in the PSU. Observations are children (live births). Standard errors clustered by PSU. Point estimates and 95% confidence intervals shown.

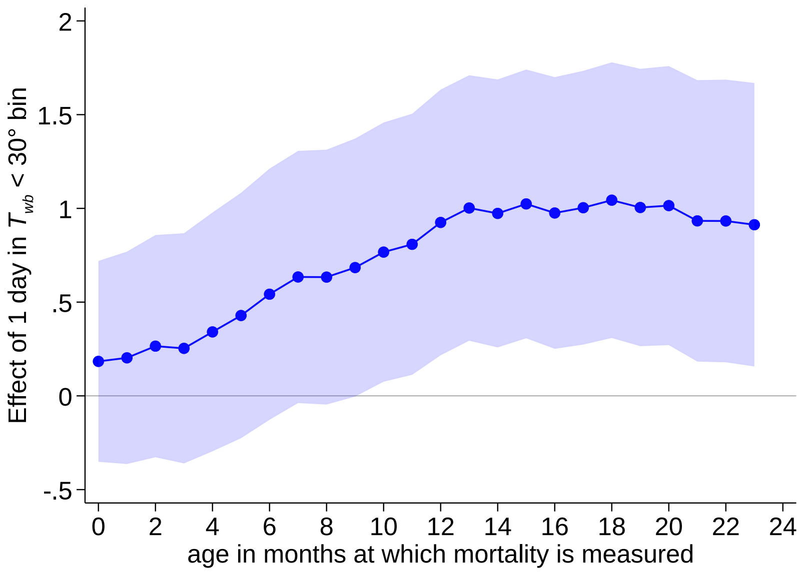
Table 1: Effects of Extreme Wet and Dry Bulb Temperatures on Infant Mortality

	Dry Bulb				Wet Bulb					Wet & Dry Bulb		
Local Seasonlity Controls (Fixed Effects):	Country × Quarter	Country × Month	District × Month	Village × Month	Country × Quarter	Country × Month	District × Month	Village × Month	Village × Month	Country × Month	District × Month	Village × Month
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Dry Bulb												
# Days with T < 30	0.44	0.68+	0.88*	0.62						-0.40	-0.48	0.07
	(0.40)	(0.41)	(0.42)	(0.53)						(1.09)	(1.10)	(1.42)
# Days with T ≥ 95	0.40	0.31	0.26	0.05						0.25	0.19	-0.03
	(0.29)	(0.29)	(0.29)	(0.33)						(0.29)	(0.30)	(0.34)
Wet bulb												
# Days with Twb < 30					0.48	0.66+	0.81*	0.54	0.50	1.02	1.27	0.49
					(0.34)	(0.35)	(0.36)	(0.46)	(0.46)	(0.92)	(0.93)	(1.21)
# Days with Twb ≥ 85					0.67*	0.68*	0.68*	0.71+	0.71+	0.70*	0.67+	0.80*
					(0.33)	(0.33)	(0.34)	(0.39)	(0.38)	(0.35)	(0.35)	(0.40)
Degree-day bins included	All dry bulb bins				All wet bulb bins					All wet and dry bulb bins		
Prior 5 year weather in birth month in village	All dry bulb bins				All wet bulb bins					All wet and dry bulb bins		
Year indicators × month indicators	X	X	X	X	X	X	X	X	X	X	X	X
Local seasonality FEs												
Country × quarter	X				X							
Country × month and district		X				X				X		
District × month			X				X				X	
Village × month				X				X	X			X
Household covariates									X			
Observations (live births)	2,865,898	2,865,898	2,865,898	2,865,898	2,865,898	2,865,898	2,865,898	2,865,898	2,865,898	2,865,898	2,865,898	2,865,898

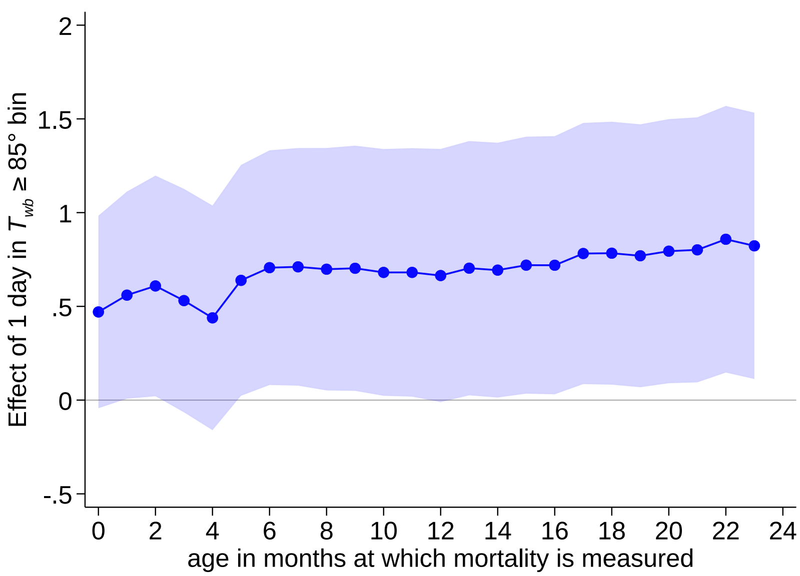
Note: Table reports results from a series of OLS regressions. The dependent variable in all columns is an indicator for death in the first year multiplied by 1,000. The regressors of interest measure the counts of days in various temperature ranges in the infant's PSU (village/urban block) during the infant's month of birth. Coefficients express the marginal effect of exchanging a day in the specified temperature range with a day in the excluded range (60-70°F). All of the same bins shown in Figure 2 are included as regressors here, though the table reports coefficients for only the coldest and hottest bins. All specifications control for precipitation in the birth month (linear in centimeters), for year × month indicators for the birth month (e.g., July 2003), and for the typical seasonal weather in the preceding five years. The latter is constructed as, for each bin, the count of days in the PSU in the same calendar month as the birth month, averaged over the five years preceding the birth. Household covariates include the child's sex and whether the mother is literate as well as birth order (indicators for each order, capped at 6), sibship size (indicators for each size, capped at 6), indicators for asset wealth quintiles, and an indicator for household electrification. Observations are children (live births). To create a consistent sample across specifications, we restrict all regressions to observations that are not dropped by the inclusion of the most granular set of fixed effects. Standard errors clustered by PSU. + $p < 0.1$, * $p < 0.05$.

Figure 3: Mortality Measured at Various Ages for Temperature Exposure Experienced in Birth Month

(A) Exposure month (for $T_{wb} < 30°$) held fixed at month of birth; survival to month x varying



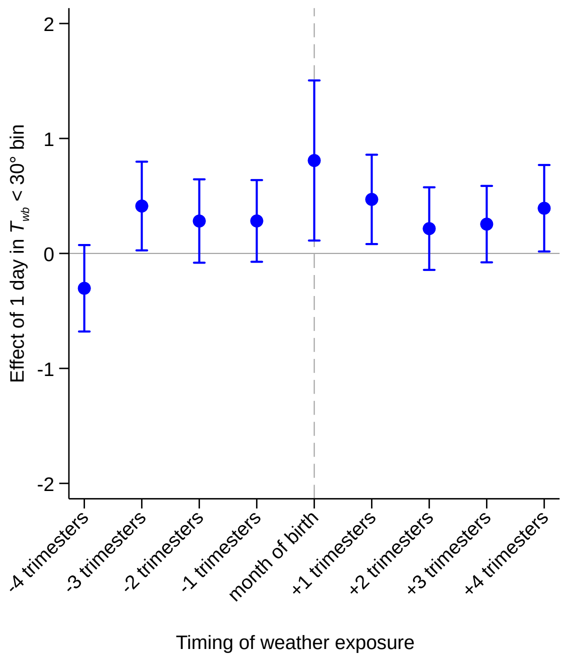
(B) Exposure month (for $T_{wb} \geq 85°$) held fixed at month of birth; survival to month x varying



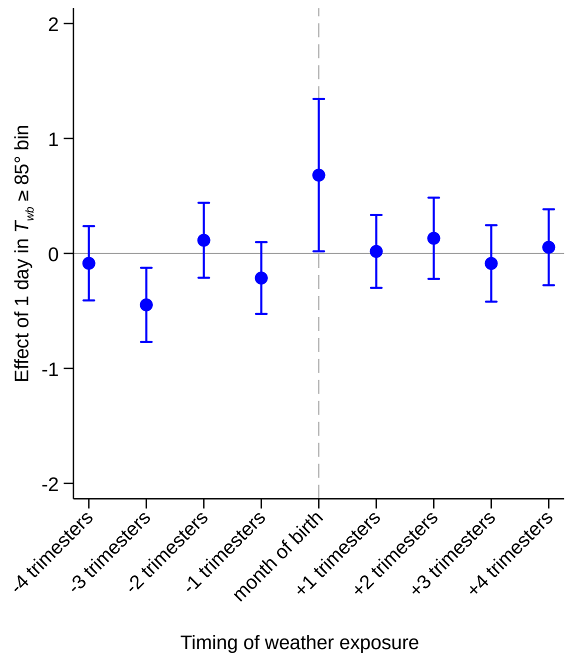
Note: Figure plots the estimated infant mortality effect of exposure to one day of $T_{wb} < 30°$ (Panel A) or one day of $T_{wb} \geq 85°$ (Panel B), relative to the impact of exposure to one day in the excluded bin, [60,70). Each point within each panel is estimated in a separate regression in which the dependent variable is defined as survival up to age x, with x in months indicated along the horizontal axes. The month of weather exposure is held fixed at the birth month (month zero). Survival through month 23 is survival to age 2 years. The control specification matches column 7 in Table 1. Observations are children (live births). Standard errors clustered by PSU. Point estimates and 95% confidence intervals shown.

Figure 4: Effects of in Utero and Postnatal Temperature Exposure

(A) Exposure month (for $T_{wb} < 30°$) varying;
survival measured at 1 year



(B) Exposure month (for $T_{wb} \geq 85°$) varying;
survival measured at 1 year



Note: Figure plots the estimated infant mortality effect of exposure to one day of $T_{wb} < 30°$ (Panel A) or one day of $T_{wb} \geq 85°$ (Panel B), relative to the impact of exposure to one day in the excluded bin, [60,70). The dependent variable is mortality by age one year (end of month 11) scaled per 1,000 births. Each point represents a separate regression in which the weather exposure regressors are varied. Toward the left within each panel, exposure is calculated as the mother's exposure prior to birth. Toward the right, exposure is calculated as the child's own exposure during various periods post-birth. Except for the birth month, exposure periods are grouped into 3-month periods (trimesters). The control specification matches column 7 in Table 1. Observations are children (live births). Standard errors clustered by PSU. Point estimates and 95% confidence intervals shown.

APPENDIX

A.1 Data Appendix: Princeton Meteorological Forcing Dataset

We use the Princeton Meteorological Forcing Dataset for weather variables. The Princeton dataset combines reanalysis data from the National Centers for Environmental Prediction-National Center for Atmospheric Research (NCEP-NCAR) with a collection of observation-based data. The observational data come from the Climactic Research Unit (CRU), which is a gridded historical dataset using weather station observations. Additional observational data come from the Global Precipitation Climatology Project (GPCP), which uses microwave and infrared measurements, outgoing longwave radiation retrievals from multiple satellite instruments, and rain gauge observations.

Reanalysis datasets combine observational data with physics-based models to improve the data in observationally sparse regions. The NCEP-NCAR dataset uses rawisonde (balloon) data from the NCEP-Global Telecommunications System (GTS) data as the main observational data source, along with marine data, aircraft data, and satellite sounder data sources, among others. In the NCEP-NCAR data, upper air temperature and wind are most strongly influenced by the observational data, while humidity and surface temperature rely more strongly on the model. Precipitation is entirely derived from the model. Biases in the reanalysis precipitation and near-surface meteorology are corrected in the Princeton data using observational data on precipitation, temperature, and radiation. We use Princeton data on temperature, specific humidity, pressure and precipitation at a 0.25 degrees latitude x 0.25 degrees longitude, 3-hourly resolution, which are available from 1948-2010. To produce our final weather variables, we make the following calculations:

1. From 3-hourly temperature, specific humidity, and pressure, we calculate relative humidity using the following equation[1]

$$rh = 0.263 \times p \times sh \times \left[exp\left(\frac{17.67(t-273.16)}{t-29.65} \right) \right]^{-1} \tag{2}$$

where rh is relative humidity (%), p is pressure (Pa), sh is specific humidity, and t is temperature in Kelvin.

2. From 3-hourly temperature and relative humidity, we calculate wet bulb temperature using the Stull Calculation, which is standard for sea level pressure:

$$wb = t \times \left(atan[(0.151977 \times (rh + 8.313658)^{\frac{1}{2}}] \right) + atan(t+rh) - atan(rh - 1.676331) + 0.00391838(rh)^{\frac{3}{2}} \times atan(0.023101rh) - 4.686035 \tag{3}$$

Here, temperature is in degrees Celsius and rh is again relative humidity.

3. We create daily means of each weather variable across the 8 observations. For the precipitation data, we create a daily total.

[1] This equation can be derived as follows: relative humidity is defined by the World Meteorological Organization as the ratio of the mixing ratio to the saturation mixing ratio ($\frac{w}{w_s}$), where $w_s = 0.622\frac{e_s}{p-e_s}$, where p is pressure and e_s is the saturation vapor pressure. This can be closely approximated by $0.622\frac{e_s}{p}$. Specific humidity can be used as an approximation for w (http://glossary.ametsoc.org/wiki/Mixing_ratio). Substituting a commonly-used approximation for the Clausius-Clapeyron equation for e_s (http://glossary.ametsoc.org/wiki/Clausius-clapeyron_equation) results in the calculation we use.

4. From the daily means, we collapse to the monthly level, generating counts of days in various temperature range bins, as well as monthly precipitation, monthly mean relative humidity, and other variables.

5. For each DHS PSU/month, we create a weighted average of each weather variable for the four surrounding 0.25-degree grid points. The average is weighted by inverse distance from the PSU.

To merge weather data with the DHS data, we divide the world into regions and generate weather variables beginning 10 years prior to the earliest country survey in each region. The resulting coverage of survey years and birth years linked to weather data for each country is listed in Table A1. To account for predictable, seasonal weather at the local level, our regressions control for the count of days in each bin in the PSU averaged over the preceding 5 years ($\overline{Temp}^{B,\text{ 5-year}}$) for the same calendar month as the main exposure variable ($Temp^B$), which is often calculated for the birth month. For 12% of observations, the weather data do not extend far enough backward to generate a full five-year average. 5.5% of observations rely on a lookback of one or two years to generate this variable.

A.2 Heterogeneity in Effects

In Table A2 we examine heterogeneity in effects across different world regions and heterogeneity in effects by household-level characteristics within regions. Column 1 repeats our main estimate for reference (Table 1 column 7). In columns 2 through 5, the regression is estimated over subsamples defined by world regions. Because the combination of high heat with high humidity is most common in our sample in South Asia (in our data Bangladesh, Nepal and Pakistan), we show results separately for South Asia alone and for the world other than South Asia. We repeat the exercise for Southeast Asia, another region where high heat and high humidity most often combine. At face value the point estimates suggest the impacts of hot, humid days are larger in South Asia and Southeast Asia, where these days are more common. However, the various splits do not yield statistically significant differences, consistent with our treatment of the effects as homogeneous.

In columns 6 through 9, we examine whether individual- and household-level characteristics (and the unobserved endowments and behaviors of which these are correlates) appear to protect against the effects of extreme weather. The variables of interest are indicators for: mother being literate, household asset wealth in the highest quintile, electricity present in the household, and whether the household is in a rural area. To preserve sample size, missing covariate data are coded as zero for the high assets indicator and as zero for the electricity present in the household indicator. These variables are interacted with each temperature bin, though only the interaction coefficients for the highest and lowest temperature bins are reported. Each of the main effects shows an economically large and statistically significant effect on infant mortality in the expected direction, indicating that these variables are informative of endowments and behaviors that materially affect infant survival.[8] In contrast, in the interaction terms, there is no clear pattern in which greater endowments are associated with smaller effect sizes than the main effects presented in Table 1, though the confidence intervals are wide and could accommodate economically meaningful heterogeneity. One exception is that household electrification appears protective against cold but not hot days. The limited sample size of our survey data cannot in practice be used to rule in or out economically meaningful heterogeneity by potentially relevant individual or household characteristics.

[8] The main effect of rural is subsumed in the "district" fixed effects.

Our paper relies on high-dimensional fixed effects to control for local seasonality in our pooled global sample. Although high-dimensional fixed effects are a core tool in the applied microeconometric literature that identifies environmental effects off of variation in the weather (Dell, Jones and Olken, 2014), a potential concern with computing a pooled global estimate is that, if the effects of weather are in fact heterogeneous across places, then the regression would be misspecified for estimating the developing world population-weighted average. This is because regression, in the case of parameter heterogeneity, does not recover the simple average of the observation-specific potential treatment effects in the population or the sample. Instead, as Angrist and Pischke (2009) explain, "regression puts the most weight on covariate cells where the conditional variance of treatment status is large." In other words, regression implicitly up-weights observations where the independent variable of interest has a large variance conditional on the other independent variables (Angrist and Krueger, 1999). A more recent literature has focused on the implications of this general fact about regression for the special case of fixed effects (Wooldridge, 2005). As Gibbons, Serrato and Urbancic (2018) prove, "in the presence of heterogeneous treatment effects, the [fixed effects coefficient] gives a weighted average of these effects. The weights depend not only on the frequency of the groups, but also upon sample variances within the groups."

With that in mind, we directly investigate the conditional variance in the regressors of interest, net of the fixed effects. Table A3 shows the weights implicit in our fixed effects regressions by global region. Columns 3 and 4 of the table are computed by first regressing count of days in the $T_{wb} < 30^{\circ}$ bin (column 3) or $T_{wb} \geq 85^{\circ}$ bin (column 4) on all other regressors from the main infant mortality regression. Residuals from these regressions are then calculated and squared. The table shows that the conditional variance of high wet bulb days is much greater in Asia, especially South Asia, than in Africa. This is precisely because high wet bulb days are less common in Africa (see Figure 1.)

This fact offers another motivation for Table A2, which estimates parameters separately for only South Asia, for the sample excluding South Asia, for only Southeast Asia, and for the sample excluding Southeast Asia. Although the precision of the estimates is reduced in these split-sample regressions, the point estimates reflect comparably large effect sizes within each subsample for which effects are estimable. Of course, there is no method that could identify the effects of high wet bulb days other than than by doing so for the places where such temperatures have been observed, but it is nonetheless useful to understand the geographic pattern of the underlying variation and to see that results are similar when disaggregating.

A.3 Robustness

In this section, we report additional specifications to allow the reader to assess the robustness of various estimates. Table A4 presents wet and dry bulb estimates for a wider combination of fixed effects, controls for temperatures in the 5-year window preceding the birth, and household-level covariates. Columns 1 to 4 do not control for the count of days in each bin in the PSU averaged over the preceding 5 years ($\overline{Temp}^{B,\text{ 5-year}}$). Columns 5 to 8 add these controls. Columns 9 to 12 additionally control for the household covariates described in Table 1. The most stable coefficient estimates are for the effect of day with wet bulb temperatures in excess of 85° (Panel B). Point estimates for $T \geq 95$ (Panel A) are more sensitive to the control set and never statistically significant at $p < .05$. The estimates for the coldest bin ($< 30^{\circ}$, both panels) are less sensitive in columns 4 through 12 and similar in the wet and dry bulb specifications, though often not statistically significant.

In Table A5 we show that the lack of statistical significance for hot dry bulb days is not due to the choice of drawing the cutoff temperature for the highest bin at $T \geq 95^{\circ}$. For the births in our estimation sample, the average count of days during the birth month with dry bulb temperatures exceeding 90°, 95°, and 97.5° are 0.85, 0.13, and 0.03, respectively. By comparison the average count of days in the birth month with with wet bulb temperatures exceeding 85° is 0.04. Across the columns in Table A5, the cutoffs for the highest bin are set at $T \geq 90°$, $T \geq 95°$, and $T \geq 97.5°$. In the alternative binning, none of the high dry bulb bins yield statistically significant coefficients, though confidence intervals remain large. We conclude that this analysis is not powered to detect moderately-sized effects of hot dry bulb days.

A.4 Alternative Heat-Humidity Interactions

Wet bulb temperature is a humidity-indexed measure of heat with a functional form that tracks the thermodynamics of evaporation. We find that simpler forms of interactions between dry bulb temperature bins and humidity are small and never statistically significant. In Table A6 we explore alternative parameterization of the heat-humidity interaction. Across the columns, the functional form of the heat-humidity interaction is varied: In columns 1 and 2, days falling in the highest bin range ($T \geq 95°$) are split according to whether each day's relative humidity was above the median for days above 95°. In columns 3 and 4, the count of days for which $T \geq 95°$ is interacted with the mean relative humidity in the month. In columns 5 and 6, the count of days for which $T \geq 95°$ is interacted with the mean specific humidity in the month. In the table, the main effects of humidity are statistically significant and negative, which is consistent with the Barreca (2012) finding of greater mortality on very low humidity (but possibly very cold) days. Interactions between dry bulb temperature bins and humidity are small and never statistically significant, suggesting that wet bulb may better parameterize humidity information in the temperature-mortality relationship.

Note that in general, high humidity cools the air, which is one reason why days that are both very hot and very humid are rare. In our sample the average count of days in the birth month with wet bulb temperatures exceeding 85° is 0.04. By comparison, the average count of days during the birth month with dry bulb temperatures exceeding 90°, 95°, and 97.5° are 0.85, 0.13, and 0.03, respectively.

In columns 7 to 10, we add controls for specific and relative humidity to the main wet bulb specifications. The addition of these controls increases point estimates and statistical significance of the coefficients on $T_{wb} \geq 85°$. However, the interpretation becomes more complex, as the marginal effect of a day at, say, 100°F and 60% relative humidity in place of a day in the excluded category (60-70°F wet bulb) would include both a humidity component and a T_{wb} component. For example, taking the estimates from column 8: $(60\%) \times -0.15 + (1) \times 0.81 = 0.72$. The corresponding estimate without humidity controls from Table 1 (column 7) was 0.68.

Table A1: Sample: Nationally Representative Surveys Merged to Gridded Weather Data

(1) Country	(2) DHS Survey Rounds (Years of Interviews)	(3) Birth Years Matched to Weather Data	(4) DHS-Derived IMR in Sample (per 1,000 births)	(5) Quality of *non-DHS* Mortality Registration[a]
Albania	2008, 2009	1996-2008	29	Low
Armenia	2010	1996-2009	23	Low
Bangladesh	1999, 2000, 2004, 2007, 2011, 2014	1990-2010	69	(Incomplete)
Benin	1996, 2001, 2011, 2012	1981-2010	69	(Incomplete)
Bolivia	2008	1991-2007	66	(Incomplete)
Burkina Faso	1992, 1993, 1998, 1999, 2003, 2010	1981-2009	94	(Incomplete)
Burundi	2010, 2011	1981-2010	88	(Incomplete)
Cambodia	2000, 2005, 2006, 2010, 2011, 2014	1991-2010	81	(Incomplete)
Cameroon	1991, 2004, 2011	1981-2010	76	(Incomplete)
Central African Republic	1994, 1995	1981-1994	102	(Incomplete)
Colombia	2009, 2010	1991-2009	24	Medium
Comoros	2012	1981-2010	39	(Incomplete)
Congo, Democratic Republic	2007, 2013, 2014	1981-2010	85	(Incomplete)
Cote d'Ivoire	1994, 1998, 1999, 2011, 2012	1981-2010	92	(Incomplete)
Dominican Republic	2007, 2013	1991-2010	34	(Incomplete)
Egypt	1992, 1993, 1995, 1996, 2000, 2005, 2008	1983-2007	63	Low
Ethiopia	2000, 2005, 2010, 2011	1981-2010	99	(Incomplete)
Gabon	2012	1981-2010	44	(Incomplete)
Ghana	1993, 1994, 1998, 1999, 2003, 2008, 2014	1981-2010	68	(Incomplete)
Guinea	1999, 2005, 2012	1981-2010	106	(Incomplete)
Guyana	2009	1991-2008	36	Medium
Haiti	2000, 2005, 2006, 2012	1991-2010	74	(Incomplete)
Honduras	2011, 2012	1991-2010	29	(Incomplete)
Indonesia	2002, 2003	1991-2002	49	(Incomplete)
Jordan	2002, 2007, 2012	1983-2010	26	(Incomplete)
Kenya	2003, 2008, 2009, 2014	1981-2010	55	(Incomplete)
Kyrgyz Republic	2012	1996-2010	32	Medium
Lesotho	2004, 2005, 2009, 2010, 2014	1981-2010	74	(Incomplete)
Liberia	2006, 2007, 2013	1981-2010	113	(Incomplete)
Madagascar	1997, 2008, 2009	1981-2008	73	(Incomplete)
Malawi	2000, 2004, 2005, 2010	1981-2009	98	(Incomplete)
Mali	1995, 1996, 2001, 2006, 2012, 2013	1981-2010	117	(Incomplete)
Moldova	2005	1996-2004	24	(Incomplete)
Morocco	2003, 2004	1983-2003	60	(Incomplete)
Mozambique	2011	1981-2010	88	(Incomplete)
Namibia	2000, 2006, 2007, 2013	1981-2010	45	(Incomplete)
Nepal	2001, 2006, 2011	1990-2010	74	(Incomplete)
Niger	1992, 1998	1981-1997	129	(Incomplete)
Nigeria	1990, 2003, 2008, 2013	1981-2010	93	(Incomplete)
Pakistan	2006, 2007	1990-2006	76	(Incomplete)
Peru	2000	1991-1999	49	Low
Phillipines	2003, 2008	1991-2007	31	Medium
Rwanda	2005	1981-2004	100	(Incomplete)
Senegal	1992, 1993, 1997, 2005, 2010, 2011	1981-2010	72	(Incomplete)
Sierra Leone	2008, 2013	1981-2010	127	(Incomplete)
Swaziland	2006, 2007	1981-2006	58	(Incomplete)
Tajikistan	2012	1996-2010	42	Low
Tanzania	1999, 2009, 2010	1981-2009	82	(Incomplete)
Timor-Leste	2009, 2010	1991-2009	71	(Incomplete)
Togo	1998, 2013, 2014	1981-2010	74	(Incomplete)
Uganda	2000, 2001, 2006, 2011	1981-2010	86	(Incomplete)
Zambia	2007, 2013, 2014	1981-2010	73	(Incomplete)
Zimbabwe	1999, 2005, 2006, 2010, 2011	1981-2010	47	(Incomplete)
Pooled Sample IMR			77	
US Crude Death Rate (all ages; per 1,000 lives), 2016			8	
EU Crude Death Rate (all ages; per 1,000 lives), 2016			10	

Note: Table lists DHS surveys used in construction of the sample. Column 1 lists countries in the sample. Column 2 lists the DHS survey round years. Column 3 indicates the birth years included in our sample matched in time and place to weather variables. These years extend backwards from the survey date, as mothers are reporting on their birth histories. Column 4 reports our DHS-based calculation of mean IMR in the sample, by country. Column 5 describes the completeness and quality of national mortality registration data (from Mathers et al., 2005) as a point of contrast. Data on the US and EU crude mortality rates come from the World Bank: https://data.worldbank.org/indicator/SP.DYN.CDRT.IN.
[a] Source for column 5 data is Mathers et al. (2005). The label "incomplete" was applied by Mathers et al. (2005) if the country did not supply registration data on cause-of-death with at least 50% completeness or coverage as estimated by WHO.

Table A2: Heterogeneity by World Region and Household Characteristics

	By World Region					Interactions with HH Characteristics			
	World, Main Estimate	South Asia	World Minus South Asia	Southeast Asia	World Minus Southeast Asia	Mother Literate	HH Asset Wealth	HH Electricty	Rural
Mean days of 85 ≤ Twb in birth month:	0.04	0.45	0.01	0.13	0.04	0.04	0.04	0.04	0.04
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
# Days with Twb < 30	0.81*	0.45	0.70+	--	0.80*	0.96*	0.77*	1.82**	0.47
	(0.36)	(1.01)	(0.38)		(0.36)	(0.40)	(0.37)	(0.57)	(0.58)
# Days with Twb ≥ 85	0.68*	1.11*	1.03	1.12	0.54	0.70+	0.72*	0.43	0.19
	(0.34)	(0.56)	(0.64)	(0.80)	(0.39)	(0.42)	(0.36)	(0.42)	(0.56)
Mother Literate						-15.54**			
						(1.02)			
Mother Literate × # Days with Twb < 30						-0.53			
						(0.55)			
Mother Literate × # Days with Twb ≥ 85						-0.09			
						(0.51)			
High Asset Wealth							-19.92**		
							(1.33)		
High Asset Wealth × # Days with Twb < 30							0.24		
							(0.41)		
High Asset Wealth × # Days with Twb ≥ 85							-0.25		
							(0.59)		
Electricity in HH								-17.69**	
								(1.16)	
Electricity in HH × # Days with Twb < 30								-1.28*	
								(0.53)	
Electricity in HH × # Days with Twb ≥ 85								0.56	
								(0.52)	
Rural × # Days with Twb < 30									0.50
									(0.69)
Rural × # Days with Twb ≥ 85									0.66
									(0.65)
Degree-day bins included			All wet bulb bins				All wet bulb bins		
Prior 5 year weather in birth month in village			All wet bulb bins				All wet bulb bins		
Year indicators × month indicators	X	X	X	X	X	X	X	X	X
Local seasonality FEs									
Country × quarter									
Country × month and district									
District × month	X	X	X	X	X	X	X	X	X
Village × month									
Observations (live births)	2,865,898	196,782	2,669,116	183,378	2,682,520	2,865,898	2,865,898	2,865,898	2,865,898

Note: Table reports results from a series of OLS regressions. The dependent variable in all columns is an indicator for death in the first year multiplied by 1,000. In columns 2 through 5, the regression is estimated over subsamples defined by world regions. In columns 6 through 9, the indicated household-level covariates are interacted with each temperature bin, though only the coefficients for the highest and lowest bins are reported. These interaction variables are indicators for: mother being literate, household asset wealth in the highest quintile, electricity present in the household, and rural. The control set for all regressions matches the specification in column 7 of Table 1. See Table 1 notes for additional information on control variables. Observations are children (live births). Standard errors clustered by PSU. + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$.

Table A3: Residual Variance that Identifies High-Dimensional FE Estimates

	Observations	Fraction of Observations	Fraction of Squared Residuals for Twb<30	Fraction of Squared Residuals for Twb≥85
	(1)	(2)	(3)	(4)
sub-Saharan Africa	1,946,595	0.68	0.13	0.07
Southeast Asia	183,378	0.06	0.00	0.33
Europe and Central Asia	27,754	0.01	0.53	0.00
Latin America and Caribbean	228,189	0.08	0.06	0.01
Middle East and North Africa	283,200	0.10	0.06	0.00
South Asia	196,782	0.07	0.22	0.58
Total	2,865,898	1.00	1.00	1.00

Note: Table tabulates how various regions contribute to the count of observations and how observations across regions are implicitly weighted in the fixed effects regressions in Table 1. See Appendix Section A.2 for a full discussion of the issue of implicit weights. To create column 3, residuals are calculated by regressing count of days in the $T_{wb} < 30^{\circ}$ bin on all regressors (other than # Days with $T_{wb} < 30^{\circ}$, which here is the dependent variable) from the specification in column 7 of Table 1. Residuals from these regressions are calculated and squared. Column 3 tallies the sum of squared residuals for the $T_{wb} < 30^{\circ}$ regression that arise from each region and divides by the total sum of squared residuals. An analogous calculation for $T_{wb} \geq 85^{\circ}$ is made for column 4. South Asia in our sample includes Bangladesh, Nepal, and Pakistan. Southeast Asia includes Indonesia, Cambodia, Philippines, and Timor-Leste. North Africa includes Egypt, Jordan, and Morocco.

Table A4: Robustness to Alternative Controls for Local Seasonality and Household Covariates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel A: Dry Bulb												
# Days with T < 30	0.95**	1.46**	1.93**	0.57	0.44	0.68+	0.88*	0.62	0.41	0.54	0.71+	0.62
	(0.26)	(0.36)	(0.42)	(0.52)	(0.40)	(0.41)	(0.42)	(0.53)	(0.40)	(0.41)	(0.42)	(0.52)
# Days with T ≥ 95	0.38+	0.08	-0.04	0.06	0.4	0.31	0.26	0.05	0.36	0.28	0.22	0.08
	(0.19)	(0.20)	(0.25)	(0.33)	(0.29)	(0.29)	(0.29)	(0.33)	(0.29)	(0.29)	(0.29)	(0.33)
Panel B: Wet bulb												
# Days with Twb < 30	1.12**	1.27**	1.63**	0.52	0.48	0.66+	0.81*	0.54	0.46	0.54	0.67+	0.5
	(0.22)	(0.29)	(0.32)	(0.45)	(0.34)	(0.35)	(0.36)	(0.46)	(0.34)	(0.35)	(0.35)	(0.46)
# Days with Twb ≥ 85	0.35	0.59*	0.55+	0.66+	0.67*	0.68*	0.68*	0.71+	0.67*	0.66*	0.65+	0.71+
	(0.28)	(0.28)	(0.31)	(0.39)	(0.33)	(0.33)	(0.34)	(0.39)	(0.33)	(0.33)	(0.33)	(0.38)
Degree-day bins included	All dry bulb (Panel A) or wet bulb (Panel B) bins											
Prior 5 year weather in birth month in village					X	X	X	X	X	X	X	X
Year indicators × month indicators	X	X	X	X	X	X	X	X	X	X	X	X
Local seasonality FEs												
Country × quarter	X				X				X			
Country × month and district		X				X				X		
District × month			X				X				X	
Village × month				X				X				X
Household covariates									X	X	X	X
Observations (live births)	2,865,898	2,865,898	2,865,898	2,865,898	2,865,898	2,865,898	2,865,898	2,865,898	2,865,898	2,865,898	2865898	2,865,898

Note: Table reports results from a series of OLS regressions. The dependent variable in all columns is an indicator for death in the first year multiplied by 1,000. Within each column, Panels A and B report results from separate regressions with parallel control sets. See Table 1 notes for additional information on control variables. Observations are children (live births). Standard errors clustered by PSU. + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$.

Table A5: Alternative Dry Bulb Temperature Binning

	(1)	(2)	(3)	(4)	(5)	(6)
# Days with T < 30	0.68+	0.88*	0.68+	0.88*	0.68+	0.88*
	(0.41)	(0.42)	(0.41)	(0.42)	(0.41)	(0.42)
# Days with T ≥ 95	0.31	0.26				
	(0.29)	(0.29)				
# Days with T ≥ 90			0.22	0.18		
			(0.15)	(0.16)		
# Days with 95 ≤ T < 97.5					0.43	0.28
					(0.37)	(0.38)
# Days with T ≥ 97.5					0.08	0.22
					(0.55)	(0.59)
Year indicators × month indicators	X	X	X	X	X	X
Local seasonality FEs						
Country × quarter						
Country × month and district	X		X		X	
District × month		X		X		X
Village × month						
Observations (live births)	2,865,898	2,865,898	2,865,898	2,865,898	2,865,898	2,865,898

Note: Table reports results from a series of OLS regressions. The dependent variable in all columns is an indicator for death in the first year multiplied by 1,000. Across the columns, the binning of dry bulb temperatures for the hottest days is varied. Columns 1 and 2 repeat columns 2 and 3 from Table 1: $<$ 30, [30,40), [40,50), [50,60), [60,70), [70, 80), [80,85), [85,90), [90,95), and $\geq$ 95. Columns 3 and 4 use the dry bulb bins: $<$ 30, [30,40), [40,50), [50,60), [60,70), [70, 80), [80,85), [85,90), and $\geq$ 90. Columns 5 and 6 use the dry bulb bins: $<$ 30, [30,40), [40,50), [50,60), [60,70), [70, 80), [80,85), [85,90), [90,95), [95,97.5), and $\geq$ 97.5. In all cases, the controls for typical weather match the Table 1 specification. See Table 1 notes for additional information on control variables. Observations are children (live births). Standard errors clustered by PSU. + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$.

Table A6: Alternative Heat-Humidity Interactions

	Dry Bulb × Humidity Interactions						Wet Bulb Effects with Humidity Controls			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
# Days with T ≥ 95	0.32	0.22	0.23	-0.14	0.17	-0.13				
	(0.37)	(0.41)	(0.56)	(0.64)	(0.59)	(0.68)				
# Days with Twb ≥ 85							0.77*	0.81*	1.01**	1.13**
							(0.34)	(0.34)	(0.35)	(0.37)
# Days with T ≥ 95 × high rel. humidity on day	0.00	0.08								
	(0.48)	(0.55)								
Relative humidity in month			-0.07*	-0.13**			-0.11**	-0.15**		
			(0.03)	(0.04)			(0.03)	(0.04)		
Rel. humidity in month × # Days with T ≥ 95			0.00	0.01						
			(0.02)	(0.02)						
Specific humidity in month					-0.17	-0.37*			-0.66**	-0.92**
					(0.12)	(0.16)			(0.24)	(0.29)
Spec. humidity in month × # Days with T ≥ 95					0.02	0.05				
					(0.06)	(0.07)				
Degree-day bins included	All dry bulb bins						All wet bulb bins			
Prior 5 year weather in birth month in village	All dry bulb bins						All wet bulb bins			
Year indicators × month indicators	X	X	X	X	X	X	X	X	X	X
Local seasonality FEs										
Country × quarter										
Country × month and district	X		X		X		X		X	
District × month		X		X		X		X		X
Village × month										
Observations (live births)	2,865,898	2,865,898	2,865,898	2,865,898	2,865,898	2,865,898	2,865,898	2,865,898	2,865,898	2,865,898

Note: Table reports results from a series of OLS regressions. The dependent variable in all columns is an indicator for death in the first year multiplied by 1,000. Across the columns, the functional form of the heat-humidity interaction is varied. In columns 1 and 2, days falling in the highest bin range ($T \geq 95°$) are split according to whether each day's relative humidity was above the median for days above 95°. In columns 3 and 4, the count of days for which $T \geq 95°$ is interacted with the mean relative humidity (%) in the month. In columns 5 and 6, the count of days for which $T \geq 95°$ is interacted with the mean specific humidity (grams water per grams air) in the month. In columns 7 to 10, controls for specific and relative humidity are added to the main wet bulb specifications. See Table 1 notes for additional information on control variables. Observations are children (live births). Standard errors clustered by PSU. + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$.