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Doctor of Philosophy
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by

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June 2020

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by

Juliana Helo Sarmiento

To my parents, Luis Helo Kattah and Clara Sarmiento de Helo,

who always support me in every endeavor.

And in loving memory of my grandfather, Guillermo Sarmiento Angulo, who always inspired and encouraged critical thinking.

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Working Papers

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Presentations and Workshops

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Teaching Experience

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Abstract

Temperature and health outcomes in the developing world

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This dissertation explores the responses of different dimensions of health to temperature changes in tropical developing countries in three separate essays. The first studies the relationship between temperature and mortality in Colombia. I show that even at narrow temperature ranges, which are characteristic of the tropics, anomalously hot or cold days increase mortality. Unlike temperate locations, I find that deaths attributed to infectious diseases and respiratory illnesses drive this relationship in the hot part of the distribution, affecting children aged 0-5 primarily. These findings uncover new factors and populations at risk after the occurrence of hot temperature shocks. I calculate that the average person who dies after a hot temperature shock loses approximately 30 years of life. The second essay focuses on the relationship between temperature and health services usage in Colombia. I find that hospitalization rates monotonically increase with temperature. Infectious diseases and maternal-related care mainly explain these results, suggesting that children, fetus *in-utero*, and women could be significantly affected by changes in temperature. Assuming temperatures will continue to rise as they did in sample and no further adaptation measures are undertaken, my estimates imply 1,161.3 additional hospitalizations per 100,000 inhabitants per year (33.6% of the average annual rate of 3458.87). These findings suggest that changes in temperature could impose a burden on the health system, but alternatively it could be an important mediating factor between climate change and mortality. In the last essay, my collaborators and I ask if temperature shocks differentially affect children's health by gender in sub-Saharan

Africa. We find that hot temperature shocks decrease anthropometric measures for children under five, with girls seeming to bear much of the effect after exposure to extreme hot days.

Contents

Chapter 1

Introduction

The changing climate has spurred an interest in quantifying the economic damages of this environmental risk.[1] Damages intend to include, but are not limited to, changes in agricultural productivity, property damages from floods, ecosystem services and human health [3]. The costs associated to human health have been of particular interest given that health is not only valuable in itself because its an indicator that people are living better lives, but because health has a productive side. Better health implies that people can work harder and longer, eventually translating into higher incomes.

Of the measures associated to health, mortality has received most of the attention partly because of data availability. In fact, a vast literature aims at quantifying the costs of climate change in terms of mortality risk based on empirically founded estimates of the relationship between temperature and mortality. Several papers have documented that instances of extreme heat and cold increases human mortality, resulting in a 'U'-shape relationship between the two over a wide range of temperature with close to zero effect at mild temperatures ([4], [5], [6], [7], [8], [9]). Morbidity, or outcomes that not necessarily result in death, have received less attention, partly because of data limitations.

[1] see [1] and [2] for a review.

A small literature has found that emergency room visits and hospitalizations increase after exposure to extreme heat and cold temperatures ([10], [11]). Fetal exposure to extreme heat in the gestational period also affects health outcomes at birth ([12], [13]).

However, most of this knowledge comes from developed countries located in temperate latitudes,[2] such as the U.S or Europe. Understanding how mortality and other health oucomes react to temperature shocks in tropical developing countries is important for several reasons, but one of them is that almost 40% of the world's surface is located in these latitudes. This region hosts 40% of the world's population and 55% of children under 5 years old, both shares expected to increase to approximately 50% and 60% respectively by 2050 [14]. Moreover, there are important differences in terms of environmental, economic and demographic conditions from their counterparts in temperate regions that might trigger differential responses in health from variations in temperature.

This dissertation contains three chapters documenting the effect of temperature changes on different dimensions of health in tropical developing countries. Each chapter explores a different health outcome and focuses on countries where temperatures remain almost constant throughout the year, a common feature across tropical countries given their closeness to the Equator. I provide new insights on the relationship between temperature and health that we would have missed entirely if we were to extent the estimates from the temperate region.

The second chapter studies the relationship between temperature and mortality in Colombia. Using data from over 1000 municipalities, I show that even at narrow temperature ranges, characteristic of the tropics, anomalously hot or cold days increase mortality. An additional day with mean temperature above 27°C (80.6°F) increases mortality rates by approximately 0.24 deaths per 100,000, equivalent to almost 0.7% of monthly death rates. Unlike temperate locations, I find that deaths attributed to infectious diseases and

[2]Those between latitude 35° and the polar circles.

respiratory illnesses drive this relationship in the hot part of the distribution, affecting children aged 0-5 primarily. These findings uncover new factors and populations at risk after the occurrence of hot temperature shocks. These findings imply that the average person who dies after a hot temperature shock loses approximately 30 years of life.

Chapter three documents the relationship between temperature and health services usage. Using detailed information on four morbidity outcomes for over 1000 Colombian municipalities, I find that hospitalization rates monotonically increase with temperature. Exchanging a day in the reference bin 23-25°C for a single day above 27°C increases hospitalization cases by 29.6 per 100,000, equivalent to 0.86% of the average annual hospitalization rate, whereas an additional day below 17°C leads to a decrease of 21.7 hospitalizations per 100,000 (0.63%). Infectious diseases and pregnancy-related and maternal care mainly explain these results. Assuming that temperature will continue to rise as it has been doing historically in Colombia, and no other adaptation measures are undertaken, these findings imply 1161.3 additional hospitalizations per 100,000 inhabitants per year (33.6% of the average annual rate of 3458.87).

Chapter four departs from South America, and in joint work with Tamma Carleton, Olivier Deschenes and Kelsey Jack we explore the effect of temperature shocks on children's health in sub-Saharan Africa. We further ask if temperature variations will differentially affect children's health by gender. We assemble a rich dataset of individual health records from the Demographic and Health Surveys (DHS) and pair these with high-resolution weather outcomes at the subnational level for 21 sub-Saharan African countries. Exploiting temperature variation within administrative units in each country, we find that hot temperature shocks decrease both weight-for-height and height-for-age for children under five. Having established that children's biophysical measures react to temperature, we show that for extreme hot temperature shocks girls seem to bear a stronger effect.

1.1 Permissions and Attributions

1. The content of chapter 3 and appendix C is the result of a collaboration with Professors Tamma Carleton, Olivier Deschenes and Kelsey Jack, using public available data from IPUMS-Demographic and Health Surveys: Version 7 compiled by Elizabeth Heger Boyle, Miriam King and Matthew Sobek from Minnesota Population Center and ICF International.

Chapter 2

Into the Tropics: Temperature and Mortality in Colombia

2.1 Introduction

The changing climate has spurred a large literature examining the effects of short-term variations in temperature on a number of economic and health outcomes, including morbidity and mortality.[1] Several papers have documented that instances of extreme heat and cold increases human mortality, resulting in a 'U'-shape relationship between the two over a wide range of temperature with close to zero effect at mild temperatures ([4], [5], [6], [7], [8], [9]). However, most of this knowledge comes from countries located in temperate latitudes,[2] such as the U.S. These countries have strong seasonality in temperature, with extreme temperatures observed during the winters and summers. The exposure of populations over a wide range of temperature throughout the year, along with particular economic, institutional, and demographic characteristics in these countries,

[1] see [1] and [2] for a review.
[2] Those between latitude 35° and the polar circles.

have shaped the relationship between temperature and mortality, and the strategies and technologies adopted to adapt to variations in weather (e.g. adoption of heating or air conditioning technologies).

This paper estimates the relationship between temperature and mortality in a tropical country and provides evidence on the underlying mechanisms. Understanding how mortality reacts to temperature shocks in such a setting is important for several reasons, but one of them is that almost 40% of the world's surface is located in tropical latitudes. This region hosts 40% of the world's population and 55% of children under 5 years old, both shares expected to increase to approximately 50% and 60% respectively by 2050 [14]. However, the lack of comprehensive datasets in tropical countries has limited our knowledge on how mortality reacts to variations in temperature in these settings, and the potential drivers of this relationship.

Moreover, there are important differences in terms of environmental, economic and demographic conditions from their counterparts in temperate regions that might trigger differential responses in mortality from variations in temperature. On the one hand, populations in tropical latitudes are subject to narrow ranges of temperature throughout the year due to the lack of seasonal variation in temperature. Extending the estimates from the temperate region, would suggest close to zero effect in mortality from weather shocks occurring along the temperatures observed in many tropical places. However, there is evidence of harmful 'de-adaptation' to infrequent experienced temperatures in the U.S. [8], suggesting that higher mortality risks could arise even at the mild end points of a narrow temperature distribution if those temperatures are not experienced very often.

On the other hand, differences in the underlying causes of death that give rise to the temperature-mortality response function might differ between latitudes. For example, tropical environments are more hospitable to human diseases, given the absence of winter temperatures [15]. These, include among others, those related to respiratory illness and infectious diseases that involve viruses and bacteria. Evidence from the epidemiology literature suggests that higher than average temperature shocks aid in the replication of microbes causing human diseases, and subsequently increases viral transmission. For example, [16] show that dengue incidence increased succeeding higher temperatures in Singapore. Unlike temperate areas, these factors in tropical climates might pose additional risk to human health after temperature shocks. If this is the case, policies and technologies that could be appropriate for temperate countries to adapt to temperature shocks might not necessarily be cost-effective for tropical areas.

Several other explanations can result in differences in the temperature-mortality response function. For example, the literature has highlighted the importance of income in shaping this relationship ([7]). Since tropical countries tend to host developing countries, this explanation could be relevant. This paper provides suggestive evidence regarding the role of income, but the analysis focuses primarily on the role of i) temperature distributions populations are exposed to; and ii) differences in relevant causes of death that are correlated to temperature shocks.

To study the relationship between temperature and mortality, I use a unique data set that combines monthly Vital Statistics from 1,033 Colombian municipalities over the period 1993-2016 with daily weather data from reanalysis models to produce a balanced panel with close to 300,000 observations. An advantage of using Colombian data is that the country's proximity to the Equator and its rugged geography implies that different populations are observed over different temperature ranges that resemble several climates in other tropical countries. For example, temperature ranges in the capital city, Bogota, located at high altitude, are also observed in large urban centers of Ecuador, Peru, and Ethiopia. Climate in coastal cities like Barranquilla or Cartagena are comparable to populous places in Venezuela, Congo, Vietnam, the Caribbean, Nigeria, among others.

These differences in exposure to temperature allows for the estimation of separate response functions for different temperature distributions.

Using monthly data at the municipality level and panel regressions, the main specification includes municipality-by-year and month-by-year fixed effects to account for most sources of unobserved heterogeneity. The empirical analysis is divided into three parts. I first document that mortality risk is highest at the end points of the narrow temperature distribution considered, suggesting that even small variations in mild temperatures can affect human mortality. Specifically, I find that an additional day with mean temperature below 17°C or above 27°C increases monthly mortality rates by approximately 0.24 and 0.16 deaths per 100,000 respectively, equivalent to 0.62% and 0.43% of monthly death rates. Put another way, a day below 17°C in my setting has a higher effect than what [5] find for an additional day below 4°C for the U.S. during the period 1931-1959 (0.53%). At 17°C estimates for the U.S. are very close to zero. On the hot part of the temperature distribution, a day above 27°C in my setting has an effect similar to a day between 27-32°C in the U.S. (0.37%).

These estimates correspond to cumulative dynamic effects of temperature shocks after an exposure window of five months, while [5] account for an exposure window of two months. Including lagged temperature variables in the main empirical strategy, allows for the possibility of inter-temporal mortality displacement (e.g. harvesting or delayed effects). Including additional lags beyond five months, I find that mortality effects peak after an exposure window of five months for unusually 'cold' days and after seven months for hot days. An additional day above 27°C increases mortality by 0.27 deaths per 100,000 after seven months, corresponding to a percentage effect of 0.72%. After accounting for the possibility of further delayed effects of hot temperature shocks, mortality increases much more than the estimates for the U.S. during the period 1931-1959.

This finding contributes to the literature that studies how temperature shocks propagate over time. Evidence regarding near-term mortality displacement, also referred to as 'harvesting', and understood as the idea that deaths caused by a contemporaneous weather shock could be compensated by a subsequent fall in mortality over the following days or weeks, is mixed. [17] show that in the U.S. harvesting is substantial after heat shocks meaning that effects are close to zero after an exposure window of 30 days. In contrast, [9] find that heat effects in Mexico are still significant after 30 days, and [5] find that U.S. estimates remain virtually unchanged after two months. I find that hotter than average days have a longer window of delayed effects than what the literature has documented thus far, with no evidence of a 'harvesting' effect after hot temperature shocks.

Having established that mortality reacts to changes in temperature, the second part investigates whether differences in relevant causes of death and populations at risk explain the effects described in part one. I find that mortality effects are unequally distributed across causes of death and age groups. Heat-related mortality is mainly attributed to respiratory and infectious diseases, with an additional day above 27°C increasing specific-cause mortality rates by 2.7% and 2.0% respectively. As for age-groups, children aged zero to nine are at higher risk after the occurrence of hot temperature shocks.

This is a novel finding because it uncovers new populations and risk factors associated to heat-related mortality. Most studies have identified infants (0-1) as a risk group [10]. I find a broad effect on children, with deaths associated to respiratory and infectious diseases playing a significant role. Respiratory and infectious related deaths, include among others, deaths associated to diseases such as whooping cough, flu, malaria, dengue, zika, tuberculosis, etc. Temperature and extreme climate events have been associated to the proliferation of such viruses and bacteria (e.g. vector, water-borne, etc.), and especially, to tropical diseases that thrive in hot and humid conditions [18].

In contrast, the economics literature has identified cardiovascular diseases as the leading cause of heat-related mortality ([17], [9], [2]). This is likely due to the fact that viruses and bacteria are less of an issue in the temperate region [15]. Deaths associated to infectious diseases, for example, are close to zero in the U.S. [17]. These insights are consistent with the finding that hot-temperature shocks have delayed effects and take up to an exposure window of seven months to fully translate into mortality effects. Higher-than average temperature shocks aid in the replication of microbes causing human diseases, and subsequently increase viral transmission [19]. But these processes don't occur immediately and take a while to develop.

Finally, the third part investigates the role of income in explaining the effects on mortality. I perform two different analyses. The first splits the sample into rich and poor municipalities, and by urban and rural classification. I find that rich and urban municipalities drive the effects of heat-related mortality, consistent with the epidemiological finding that proliferation and contagion of infectious and respiratory diseases are influenced by population density. The second, investigates whether the response function evolved over time to shed some light on possible adaptation behaviors. Overall, I find a 55% decline in cold-related mortality over the period 1993-2016, while heat-related mortality remained stable throughout the period or even increased. This is a novel finding since studies in the U.S. have found a decline in heat-related mortality over the course of the 20th century, mainly attributed to the diffusion of residential air conditioning. Access to such technology reduces stress in people's thermoregulatory systems and thus deaths associated to cardiovascular diseases [5].

These findings provide suggestive evidence that differences in heat-related mortality with the temperate region are not solely due to lower income in tropical countries. Colombia is a middle-income country with GDP per capita doubling over the past 25 years, with improvements in health coverage and services, infrastructure, electrification, poverty, etc.. While cold-related mortality did decline over the sample period, likely due to better health services or improved infrastructure, heat-related mortality did not observe the same behavior. Additionally, separate analysis by urban and rural areas within the country point to no statistical differences in the temperature-mortality function between them.

The paper proceeds as follows. Section 2.2 describes the data sources, the main characteristics of temperature and mortality in Colombia and summary statistics that inform the empirical strategy. Section 2.3 outlines the econometric models used to estimate the temperature-mortality response function. Section 2.4 discusses the main results from fitting the regressions, heterogeneous findings and the evolution of the relationship throughout the years in the sample. Section 2.5 concludes and discusses policy implications of the findings.

2.2 Data and Descriptive Trends

This section describes the data used in the analysis and uses it to characterize the temperature distribution and the mortality profile in Colombia over the period 1993-2016. Any key differences with countries in the temperate region will also be described in this section. Four main points arise from the descriptive analysis. First, average temperature remains almost constant throughout the year with very small variations between months. Second, variation in temperature results from geographical differences in elevation. Temperature is inversely related to elevation. Third, mortality profiles in Colombia differ from the U.S. Lastly, mortality trends differ substantially from municipality to municipality within Colombia.

Weather Data: Temperature and rainfall data are drawn from the European Centre for Medium-Range Weather Forecasts (ECMWF), which periodically uses forecast models and data assimilation systems to produce climate reanalysis data in the ERA-Interim product.[3] ERA-Interim data is available on a $0.125° \times 0.125°$ quadrilateral grid daily since January 1979.[4] The key variables for the analysis are daily average temperature and daily total precipitation. Daily average temperature corresponds to the average of four readings per day reported at different times during the day.[5] The daily grid-level data is aggregated at the municipality level by taking an area-weighted average of the weather variable of interest in each municipality.[6] The weights are defined by the area of each grid that belongs to a particular municipality.[7] I use daily weather data to construct a balanced panel consisting of 301,656 municipality-monthly observations for the period 1993-2016.

Figure 2.1 depicts a discrete version of the annual temperature distributions in Colombia and the U.S. Daily average temperatures over the year are classified over ten temperature categories or bins in increments of 5.5°C. The lowest temperature category includes everything less than -12°C and the highest everything above 32°C. The height of the bars correspond to the average number of days in the year in each temperature bin that the average person in each country experiences. To that end, observations are weighted by population.The figure reveals the main difference between temperate and tropical countries in terms of temperature. Populations in Colombia are exposed to a much narrower temperature range over the year, as the distribution is mainly concentrated in four out of the ten categories (13°C-32°C). This difference arises because of the lack of seasonality in temperature, which is explained by Colombia's closeness to the Equator.

Given the narrower temperature range in Colombia, the empirical analysis considers

[3]The data can be downloaded from http://apps.ecmwf.int/datasets/data/interim-full-daily/levtype=sfc/

[4]This corresponds to grids of approximately $16km \times 16km$

[5]Daily total precipitation is the sum of all the readings per day.

[6]Municipalities are the smallest administrative area, grouped in Departments, where the latter can be though of as States in the United States. There are currently 1,222 municipalities, each one led by an elected mayor and administered by a municipal council.

[7]Shape files for Colombian municipalities are superposed over the grid weather data file extracted from ERA-Interim that contains Colombia, to aggregate at the municipality level

finer temperature categories to guarantee enough variation within municipality to identify effects on mortality (i.e. 2°C temperature categories). Panel (a) in figure 2.2 shows the monthly distribution of daily mean temperature grouped across seven temperature categories or bins.[8] These bins represent daily temperatures of less than 17°C, higher than 27°C and five 2°C wide bins in between. The average number of days in a month in the modal bin 17-19°C is 9.1. Most of the distribution is concentrated around this bin, and only a few days are observed in the extreme bins: 1.8 per month in the less than 17°C and 2 in the greater than 27°C bin. This discrete version of the monthly distribution of temperature will be used as the main explanatory variables in the empirical analysis. This strategy preserves the daily variation in temperature to capture non-linearities in the temperature-mortality relationship *a la* [4].

The key feature in tropical countries is that the monthly distribution is very similar across the twelve months in the year. Panel (b) in figure 2.2 plots monthly distributions in different months of the year, and indicates that there are no differences between them. For the entire country average temperature in all twelve months ranges from only 20.7°C to 21.1°C.

Figure 2.3 presents another key feature common to tropical countries: the temperature distribution depends on elevation. As countries get closer to the Equator, differences in temperature across municipalities are determined by their elevation relative to sea-level, with average temperature declining as altitude increases. To highlight the elevation-temperature gradient, I group municipalities in two elevation groups: mountain and sea-level. The former corresponds to those located more than 1000 meters above sea-level and the latter, to those below this threshold.[9] In municipalities closer to sea level, average daily temperature below 21°C are not observed, whereas average temperatures

[8]This is a discretized version of the continuous distributions of temperature

[9]This is a typical classification of mountainous areas

above 25°C are rare in mountainous areas (Panels (a) and (b) in figure 2.3). Panels (c) and (d) in figure 2.3 plot the distribution for the two groups by different months of the year, supporting the fact that temperature exhibits no strong seasonality and variations between months are small. It is worth highlighting that approximately 75% of the Colombian municipalities and population are located in the mountainous region.

Finally, figure 2.4 plots the annual temperature distribution over two time periods: 1993-2005 and 2006-2016, separately for mountainous and sea-level municipalities[10]. Exposure to hotter days increased in both regions, with the number of days in temperature bin > 27°C almost doubling between the two time periods in lower elevation municipalities. The number of days in the coldest temperature bin, <17°C, declined by a factor higher than two in mountainous areas.

Mortality Data: Mortality data are taken from Vital Statistics produced by the National Statistics Department of Colombia (DANE). Individual death records, including age, gender, cause of death, municipality of occurrence and type of insurance, are available for the period 1993-2016. I aggregate death records at the monthly-municipality level and combine this information with population data drawn from DANE, to construct age-adjusted monthly mortality rates per 100,000 inhabitants.[11] Age-adjusted mortality rates refer to a weighted average of crude death rates. Weights are determined by the 2005 population distribution in Colombia. Following the literature, I use this adjusted rates to allow for comparisons across municipalities and time. I also construct specific-cause death rates using the causes of death reported by DANE, following the guidelines of the International Statistical Classification of Diseases and Related Health Problems by the World Health Organization (ICD-10 WHO).

Table 2.1 summarizes all-cause and cause specific annual mortality rates by age group,

[10]These time periods are chosen to have an approximate equal number of years in the two subsamples
[11]Population data in each municipality comes from the series produced by DANE based on census records and projections.

as well as the contribution of each cause of death to total mortality. The average annual mortality rate for the period 1993-2016 is 457.3 deaths for every 100,000 inhabitants, with the highest rates for children under 5 and the elderly.[12] As has been documented in different contexts (e.g., [17]), cardiovascular disease is the leading cause of death, especially in people over 40. Infectious and respiratory diseases explain almost 25% and 14% of deaths in children aged 0 to 4 and 5 to 9 respectively.

External causes of death also explain most deaths, specially for younger people. In fact, accidents are the leading cause of death for children aged 5 to 9 with a share of 33.8%, and an approximate of 20% for teenagers and young adults. A key and unique feature of Colombian mortality data arises in Table 2.1: political conflict. Homicides explain most of deaths in age groups 10 to 40. Annual mortality rates for these groups are higher than what have been reported elsewhere.[13]

Comparing these shares with data from [17] for the U.S., reveals important differences in the mortality profiles for both countries. Even though cardiovascular diseases are the leading cause of death in Colombia, the share for the entire population is much smaller than that in the U.S. Figure 2.5 plots the share of total deaths attributed to five causes of death for Colombia and the U.S. While the total share in Colombia is 28.4%, in the U.S. it accounts for almost 50%. Causes of death that have previously been linked to small changes in temperature, such as infectious diseases that include vector borne like dengue, malaria, zika, or yellow fever, appear to have an important role in explaining deaths in Colombia. Almost 3.5% of deaths in Colombia are attributed to infectious diseases, while they only account for 1% in the U.S. The differences for age group 0-9 are more dramatic, with a share of 10.2% and 6.23% for children 0 to 4 and 5-9 respectively in Colombia,

[12] For comparison purposes this is a monthly mortality rate of 38.21 and approximately daily mortality of 1.26 deaths per 100,000. This number appears consistent with Mexican data, which [9] document as 1.3 for the period 1998-2010

[13] An annual mortality rate of 116.8 in age group 10-19 implies a daily rate of approximately 0.31 deaths per 100,000. [9] report a daily rate of 0.15 for this same group in Mexico.

and 2.6% and 3.8% for age 0 and 1-9 in the U.S. Finally, the other category that contains external causes of death, including accidents and homicides that have also been shown to react to temperature, almost doubles the share in the U.S [20]. These differences in the mortality profile could explain any differences in the temperature-mortality relationship that could arise with the temperate region.

Overall, all-cause death rates declined over the period 1993-2016, but trends differ substantially from region to region, or even between municipalities. Panel (a) in figure 2.6 shows the evolution of annual mortality rates per 100,000 throughout this period separately by mountainous and sea-level municipalities. A clear declining trend was observed for high-elevation municipalities, whereas death rates remained almost stable at lower elevations. But even within regions mortality rates followed a different annual pattern, as panel (b) in figure 2.6 shows. Bogota and Medellin are both classified as mountainous municipalities, but the rate at which they declined differs. Barranquilla on the other hand is a coastal city, and it's trend is substantially different from the other two. The declining trend of deaths related to cardiovascular diseases and homicides seem to drive the fall in overall mortality, especially in high-altitude municipalities, since the rest of the causes of death remain quite stable during the period (panels (c) and (d) in figure 2.6). These trends and their differences across municipalities inform my empirical strategy which I turn to next.

2.3 Empirical Strategy

This section presents the models used to estimate the temperature-mortality response function. Exploiting the granularity of the data, I estimate contemporaneous and cumulative dynamic effects of temperature shocks. The facts and trends previously described inform the preferred specification.

2.3.1 Contemporaneous Effect

To quantify the contemporaneous effect of weather on all and specific-cause mortality in any given month and location, I estimate fixed-effects linear regressions. Specifically, I fit variants of the following specification:

$$DR_{imy} = \sum_{j=1}^{T} \beta_j BinTemp_{jimy} + \gamma_1 LOWP_{imy} + \gamma_2 HIGHP_{imy} + \eta_{iy} + \nu_{my} + \varepsilon_{imy} \quad (2.1)$$

where DR_{imy} is the age-adjusted death rate in municipality i, month m and year y. Temperature variables are constructed using a discrete version of the monthly distribution, which allows to capture a flexible non-linear relationship with mortality following [4]. As such, the variables $BinTemp_{imy}$ denote the number of days in municipality i in month m in year y in which the average daily temperature is in the j^{th} bin of the seven 2°C bin described in Figure 2.2. Since the number of days in a month is constant and the temperature variables add up to this constant, temperature bin 23-25°C (73.4-77°F) is excluded from estimation and used as a reference bin. This means that the coefficient of interest β_j on the variable temperature bin j is interpreted as the effect on mortality from exchanging a day in the reference bin to a day in temperature bin j.

All of the specifications control for precipitation. The variables $LOWP_{imy}$ and $HIGHP_{imy}$, capture unusually low or high amounts of rainfall in a municipality i in month-year my. Specifically, $LOWP_{imy}$ is an indicator variable that measures whether realized precipitation in municipality i in month-year my is below the $25th$ percentile of historical monthly distribution of that municipality. In contrast, $HIGHP_{imy}$ measures if the realization is above the $75th$ percentile.[14]

[14]This specification assumes that temperature and precipitation are independent. I am considering specifications with interactions between the two. Also I plan to obtain data for humidity.

The last term of equation (2.1), ε_{imy} is a stochastic error term. η_{iy} denotes a full set of municipality-by-year fixed-effects, and ν_{my} month-by-year fixed effects. Municipality-by-year fixed-effects absorb all unobserved municipality-specific determinants of mortality. This municipal specific flexible time trend captures factors like health conditions that are specific to the municipality in the give year, or availability and quality of health services in each municipality. The descriptive analysis in the previous section suggests significant differences in mortality trends in each municipality, justifying the inclusion of the flexible heterogeneous year trends per municipality. The month-by-year fixed effects account for time-varying differences in mortality rates that are common across all municipalities, as well as the seasonal patterns in death rates described in the previous section.

By conditioning on this structure of fixed-effects, identification of the parameters of interest, β_j,comes from municipality-specific deviations in weather from municipality averages after controlling for precipitation, time-trends specific for each municipality and seasonality common to the whole country that can vary over time. The empirical validity of this specification relies on the identifying assumption that conditional on the fixed effects structure, weather variables are not correlated with the idiosyncratic error term. This implies that:

$$E(BinTemp_{jimy}\varepsilon_{imy}|BinTemp_{-jimy}, LOWP_{imy}, HIGHP_{imy}, \eta_i, \psi_{iy}, \nu_{my}) = 0$$

Due to the randomness of weather variations, the assumption is reasonable and widely made in the literature. Variations in weather are likely orthogonal to unobserved determinants of mortality. Standard errors are clustered at the municipality level to account for correlation within municipality over time. Weather is highly localized given Colombia's rugged geography and heterogeneity in causes of death, provide additional reasons to cluster standard errors at the municipality level.

The lack of seasonality and spatial distribution of temperature within this context implies that the effect of exposure to 'colder' temperatures on mortality is identified by municipalities in higher elevations, while the effect of hotter temperatures is driven by those closer to sea-level. To explore the existence of heterogeneous responses at narrower ranges of temperature, I also estimate equation 2.1 separately for two elevation groups; those above 1000 meters referred to as mountain and those below 1000 meters referred to as sea level. To that end, the temperature bins for the mountainous area range from below 17°C to 25°C. The 'hottest' two bins are grouped in one given that temperatures above 27°C are rarely observed at higher elevations. For municipalities located closer to sea-level, temperature bins are defined between below 23°C and 27°C. In both cases, temperature bin 23-25°C (73.4-77°F) is excluded from estimation for comparison purposes.

2.3.2 Dynamic Effect

The relationship between temperature shocks and mortality is likely to be dynamic, as weather shocks could either have lasting effects or anticipate deaths that would have occurred a few days or months later had the event not occurred [17]. The latter is usually referred to as mortality displacement or harvesting. To investigate this possibility, I fit the following specification:

$$DR_{imy} = \sum_{j=1}^{T}\sum_{l=0}^{L}\beta_{jl} BinTemp_{ji(my-l)} + \sum_{l=0}^{L}\gamma_l f(Prec_{ki(my-l)}) + \eta_{iy} + \nu_{my} + \varepsilon_{imy} \quad (2.2)$$

This model allows the effect of weather variables up to L months in the past to affect mortality rates in the current month. To that end, the contemporaneous effect of temperature bin j is β_{j0}, while the dynamic causal effect comes from summing all of the coefficients on temperature bin j: $\sum_{l=0}^{L} \beta_{jl}$. If temperature or weather shocks lead to mortality displacement, an immediate increase in mortality (i.e. $\beta_{j0} > 0$) should be followed by a compensatory fall in subsequent months. On the contrary, weather shocks might have delayed effects on mortality if estimates accumulate over time. For example, β_{j0} could be positive or zero, and subsequently followed by positive coefficients on the lagged variables, such that $\sum_{l=0}^{L} \beta_{jl} > \beta_{j0}$.

2.4 Findings

2.4.1 All-Cause Mortality and Temperature

Table 2.2 presents estimates of the temperature mortality-relationship from fitting equations 2.1 and 2.2 using different exposure windows up to nine months (i.e. using 0, 1 lag up to 8 lags). Only results for contemporaneous and exposure windows of five, seven and nine months are presented. All the coefficients associated to temperature bins measure the estimated impact of exchanging one day in temperature bin j with respect to the reference bin 23-25°C. The results reveal that mortality risks are highest at the endpoints of the narrow temperature distribution observed in Colombia. Exchanging a day in the reference bin 23-25°C for a single day below 17°C leads to a contemporaneous increase of 0.17 deaths per 100,000. This impact correspond to 0.4% as compared to the mean monthly mortality rate of 37.58 per 100,000 reported in table 2.2. The effect becomes smaller for temperatures closer to the reference bin, but still important and significant at conventional levels. Contemporaneously, the effect of an additional day above 27°C is smaller than the effect of additional days in the 'colder' temperatures, with an estimated effect of 0.06 deaths per 100,000 (0.16%).

Estimated effects at all temperature bins become larger, when considering dynamic effects. The second column in table 2.2 presents estimates for equation 2.2 using four lags, which correspond to an exposure window of five months. The effect of an additional day below 17°C accumulates up to 0.24 deaths per 100,000 (0.64%) (i.e. $\sum_{l=0}^{4} \beta_{jl} > \beta_{j0}$), while an additional day above 27°C increases in magnitude when adding up the contemporaneous and lagged effects to 0.16 (0.43%). Figure 2.7 present estimates of the temperature-mortality relationship from fitting equation 2.2, using an exposure window of five months, indicating that mortality reacts to temperature shocks even at the narrower range of temperature observed in Colombia.

Columns 3 and 4 in table 2.2 present results for longer exposure windows: seven and nine months respectively. The effect of an additional day above 27°C continues to accumulate after five months, up to 0.25 deaths per 100,000 (0.62%) after seven months, and persists at this level even after nine months of exposure. This indicates that hot temperature shocks take time to fully translate into mortality effects. In contrast, the effects of colder temperature shocks vanish almost completely after an exposure window of seven months returning to zero. The analysis by cause of death sheds light on why this is the case, and I will return to this in that section.

For reference, these estimates are close in magnitude or even higher than what the literature has found for extreme temperatures in settings with wider ranges of temperature and more variability. Figure 2.8 places the cumulative dynamic effect for five months in the context of findings in the literature. The most comparable in terms of methods and socio-economic characteristics are [5] and [9]. The former estimates the mortality response function for the U.S. for two time periods, 1960-2004 and 1931-1960 using an exposure window of two months. The latter correspond to Mexico 1998-2010 after an exposure window of one month, more comparable in terms of development. The figure reveals that the effects of additional days above 27°C accumulate to a higher level than what is reported in U.S. and Mexico (0.67% v.s. 0%, 0.12% and 0.37%).

Panels (a) and (b) in figure 2.9 report estimates separately for mountainous and lower elevation areas respectively. Both in high and low elevation municipalities, mortality risk is highest at the extremes of their corresponding temperature distributions. However, the effect of additional days below 21°C for sea-level municipalities (i.e. 'cold' days for municipalities that are hot on average) is imprecisely estimated, due to the low frequency of these events at lower level municipalities and the fact that only 25% of the sample resides in these areas. Estimating the temperature-mortality response function separately for elevation groups reveals that populations at higher elevations are more vulnerable to additional days with average temperature above 25°C than those in lower elevation municipalities (0.82% vs. 0.14% not significant). The difference is statistically significant with a p-value of 0.053 for the F-test. Pooling data for the entire country misses this point. Days above 25°C imply high mortality risk for mountainous populations, while for sea-level municipalities it is highest at 27°C (0.84% after an exposure window of nine months). This suggests that populations are harmfully 'de-adapted' to infrequent experienced temperatures even if they are considered 'mild' temperatures, supporting what [8] find for the U.S (detailed results available in Appendix A).

2.4.2 Specific-Cause Mortality and Temperature

To explore the potential mechanisms that give rise to the temperature-mortality relationship in Colombia, this section estimates equations 2.1 and 2.2 for seven specific causes of death that explain almost 80% of total mortality. Results reveal that respiratory and infectious diseases are associated to heat-related mortality, and this can explain the differences in the dynamics of hot-weather shocks in a temperate setting vs. a tropical one.

I perform the analysis using the entire sample, but results hold if estimated separately by mountainous and sea-level municipalities. Heat-mortality risks are highest for mountainous populations at 25°C, while the risk is highest at 27°C for sea-level municipalities. Heterogeneous estimates for elevation and cause of death are presented in Appendix A.

Figures 2.10 and 2.11 reveal that heat-related mortality is largely explained by increases in deaths due to infectious and respiratory diseases. Panel (a) in figure 2.10 indicates that deaths attributed to infectious diseases don't react immediately to temperature shocks, with a flat relationship between temperature and mortality at the contemporaneous level. However, as the exposure window broadens mortality due to infectious diseases increase monotonically in temperature. An additional day in temperature bin >27°C increases mortality by 0.025 death per 100,000, which correspond to a 2.0% effect of average monthly mortality rates due to infectious diseases (panel (b)). This finding coincides with the idea that hot temperature shocks contribute to the proliferation and breeding of vector, water and air-borne diseases with subsequent contagion to populations. In contrast, 'colder' temperature shocks reduce the incidence of deaths due to infectious diseases. Figure 2.11 also shows that mortality rates attributed to respiratory illness after hot temperature shocks, react only after an exposure window of more than five months. An additional day in temperature bin >27°C increases mortality by 0.1 deaths per 100,000 after nine months (2.7%). As with infectious diseases, the relationship between temperature and mortality becomes monotonically increasing.

The leading causes of cold-related mortality are cardiovascular and respiratory illnesses. Figures 2.12 and 2.11 present estimates for these two causes respectively. Both contemporaneous effects accumulate after an exposure window of five months to 0.14 and 0.05 deaths per 100,000 respectively for an additional day below 17°C. These impacts correspond to a 1.2% and 1.3% effects respectively. These two causes of deaths have been linked to weather shocks in the medical literature and also documented by [17], however, the effects in this setting take longer to fully translate into mortality effects. The 'cold' temperature at which cardiovascular and respiratory related deaths react in Colombia are much higher than those in the U.S. (e.g. 17°C). This supports the idea and recent evidence from Mexico that even mild days, either hot or cold, can impact human health [9].

These results suggest that attenuation of the effects after 'cold' temperature shocks over an exposure window of seven months that were documented previously, are likely related to how shocks propagate in each cause of death. Contemporaneously and after five months, deaths due to cardiovascular and respiratory illness increase mortality. But after five months, these effects are counteracted by the fall in deaths associated to infectious diseases. Rather than evidence on harvesting after cold temperature shocks, they suggest that the potential mechanisms affecting mortality varies by the time of occurrence of the shock and likely affecting different age groups.

Figures 2.14 and 2.15 present estimates for external causes of death: homicides and accidents. Figurel 2.14 indicates that homicides increase monotonically with temperature as has been documented in other contexts by [20]. An additional day below 17°C decreases contemporaneous mortality by 0.025 (-0.6%), whereas an additional day above 27°C increases it by 0.02 deaths per 100,000 (0.3% effect). Unlike estimates from health-related mortality, homicides only react contemporaneously.

Figure 2.15 shows that deaths caused by accidents respond to higher temperatures but only contemporaneously. This is reasurring in the sense that there is no reason to suspect that a temperature shock should affect accidents beyond thier day of ocurrence. Particularly, an additional day in temperature bin >27°C increases mortality rates by 0.01 per 100,000, which correspond to an effect of 0.4% compared to average death rate for accidents-related deaths. These results suggest that warmer conditions might encourage individuals to engage in outdoor activities such as swimming and driving, increasing the likelihood of accidents. [17], for example, find that cold days reduce male teenagers mortality through a fall in motor-vehicle accidents in the U.S.). Finally, out of the seven causes of death analyzed, two do not react to temperature shocks: deaths attributed to suicide and those caused by neoplasms (figure 2.13).

In conclusion, the evidence presented suggests that cold related mortality is to a very large extent driven by cardiovascular and respiratory illness in municipalities located at higher elevations. Heat-related mortality, however, is similar in all municipalities through the incidence of respiratory and infectious diseases. In terms of external causes of death, accidents and homicides respond contemporaneously and increase with hotter days. The fact that infectious and respiratory diseases, together with homicides and accidents react to hot temperature shocks, which play a significant role in Colombia's mortality profile, might explain why differences with the temperate region estimates arise.

2.4.3 All-Cause by Age Group Mortality and Temperature

The results reported so far describe the relationship between temperature and mortality for the population as a whole, but these effects are likely to be unequally distributed across age groups. Table 2.3 examines heterogeneous effects by age-groups to identify populations at risk after the occurrence of temperature shocks. In the interest of making the estimates accessible, the table only reports percentage effects for the corresponding extremes of the temperature distribution. For comparison purposes of the effects across age groups, I report these percentage effects since mortality rates increase with age. Table 2.3 reports the contemporaneous and dynamic cumulative effects obtained from fitting equations 2.1 and 2.2 with four lags, divided by mean monthly mortality rates for each age group. The full regression results are available in Appendix A.

Examination of the age-specific estimates reveal differences in populations at risk based on weather they are exposed to cold or hot temperature shocks. Children aged 0-9 are at risk at all elevations after hot-temperature shocks, whether it is days above 25°C or 27°C in higher and lower altitude municipalities respectively. Deaths attributed to infectious and respiratory diseases, which primarly affect children, mainly explain this result. Consistent with what [17] and [9] find for the U.S and Mexico, excess mortality caused by 'cold' temperature shocks increases with age. Remarkably, these same patterns are documented at much milder temperatures than observed in these two other countries. Senior people (>60) are more vulnerable to colder days and estimates are not necessarily attributable to mortality displacement. In fact, effects are highest four months after the occurrence of the weather shock.

Taken as a whole, age-specific by cause of death estimates reveal two significant findings. First, children are at risk at all elevations after the occurrence of hot temperature shocks, with respiratory and infectious diseases largely explaining deaths. Second, cold-related deaths in mountainous areas increase with age and seniors (60 and older) are more vulnerable, through incidence of respiratory, cardiovascular and infectious diseases. These findings suggest that hot-temperature shocks having a bigger impact on children, have higher effects on life expectancy.

2.4.4 The Potential Role of Income

To investigate the role of income in shaping the temperature-mortality relationship documented so far, and whether differences with the temperate region estimates could arise through this channel, I perform two different analyses. The first splits the sample into rich and poor municipalities, and by urban and rural classification. I find that rich and urban municipalities drive the effects of heat-related mortality. The second, investigates whether the response function evolved over time to shed light on possible adaptation behaviors. Overall, I find a 55% decline in cold-related mortality over the period 1993-2016, while heat-related mortality remained stable throughout the period or even increased.

Rich and Poor Municipalities

I classify municipalities by three income subgroups based on the multidimensional poverty index (MPI) constructed by the Colombian Government using census data from 2005. The sample is divided into three groups: 25% poorest municipalities, 25% richest municipalitoes and the remaining 50% of municipalities whose MPI falls in between the twenty-fifth and seventy-fifth percentile of the distribution. I estimate equations 2.1 and 2.2 fully interacted with income groups, including all the set of fixed effects, equivalent to estimating regressions separately by income group. Contemporaneously, equality on coefficients for each temperature bin for the three groups (e.g. $\beta^{Rich}_{\leq 17} = \beta^{Middle}_{\leq 17} = \beta^{Poor}_{\leq 17}$) cannot be rejected at any conventional level. However, figure 2.16 shows that rich municipalities drive results in the hot part of the distribution when allowing for a broader exposure window with four lags (panel (a)). In fact, the null hypothesis for equality in the coefficient for temperature bin ≥ 27 across the three groups is rejected at the 3% level.

Similar findings emerge when classifying the sample by urban, sub-urban and rural. The Colombian Government defines these categories based on municipality size, population density and access to public services. The first category, urban, includes the largest cities in Colombia like Bogota, Medellin and Barranquilla. The semi-urban category are municipalities with populations between 25,000 and 100,000 inhabitants. Panel (a) in figure 2.17 shows that effects in the hot part of the distribution are driven by urban municipalities, with the hypothesis of equality being rejected at the 2% level. These findings are consistent with infectious and respiratory diseases driving mortality after hot temperature shocks, which in turn corroborates results from the epidemiological literature that link proliferation and contagion of these diseases to population density.

These findings suggest that development levels might not necessarily explain the differences with estimates from the temperate region, especially in the hot part of the distribution. Higher effects on mortality after hot temperature shocks in urban areas, which coincide with better access to health services and utilities for example, suggests this. On the colder part of the distribution, income and access to services might play a role because though not statistical different effects seem to be higher in poorer and rural areas.

Temperature-Mortality Relationship over Time

To investigate the role of income through a different dimension, this section explores whether the mortality-temperature response function documented so far has evolved over time. Colombia experienced significant growth over the years in the sample, for example, GDP per capita increased from \$ 4,000 to \$7,700 (Constant 2010 US\$) between 1993-2016. Living conditions have also improved. According to the 2018 household livings standards survey (Encuesta de Calidad de Vida, 2018), 97.7% has access to electricity, 93.5% has access to health services. Air conditioning penetration is 4.7% in the entire country, and close to 15% in one of the regions located at sea-level. Access to a fan is much higher, with 37.7% for the entire country and 89.5% for municipalities close to sea-level. Finally, close to 86% of households cook with natural and propane gas.

Panels (a) and (b) in figure 2.18 plot estimated coefficients on temperature variables from fitting equations 2.1 and 2.2) for two different time periods: 1993-2005 and 2006-2016 respectively. P-values for F-tests on the differences between each temperature coefficient between the two time periods are reported at the bottom of each graph. Panel (a) reports contemporaneous effects, whereas (b) plots cumulative dynamic effects after five months of exposure. Two interesting findings emerge from panels (a) and (b) in figure 2.18 that correspond to estimates for the entire sample of municipalities. First, cold-related mortality significantly declined between these two time periods. P-values at the bottom panel (a) suggests that the difference in the effect at bin temperature 17°C and 17-19°C between the two time periods are statistically significant at the 5% and 7.9% level respectively. Panel (b) shows the same pattern for dynamic cumulative effects after four months. These estimates imply a 55% and 60% decline in mortality, for the two 'coldest' bin temperatures respectively. Second, heat-related mortality remained stable throughout the period or even increased. Specifically, the effect of an additional day between 25-27°C increased from 0.012 deaths per 100,000 inhabitants during the period 1993-2005 to 0.121 per 100,000 in the more recent years, corresponding to a remarkable increase of 908%. For higher temperatures, the difference was not statistically significant.

Comparing these results with [5], I document a similar decline in the mortality impact of a day with average temperature below 4.4°C in the US. Improvements in access to services or growth experienced in Colombia during the time period studied, might have played a role in explaining this decline. Understanding the reason why this has been the case is out of the scope of this paper, but is an open question I'm working on. However, unlike the results for the U.S. where they find a sharp decline in heat-related mortality after 1960, I find that estimates remained stable or even increased. This result contributes to the hypothesis that differences with estimates from the temperate region might solely be due to levels of development.

2.5 Discussion

This paper advances our understanding of heat-related mortality by focusing on populations that face inherently different environmental, economic and demographic conditions than their counterparts in temperate areas. I document that short-term variations in temperature, even at narrower temperature ranges, have significant effects on mortality rates. Using a unique data set from a tropical developing country, I find that hot temperature shocks not only increases mortality rates contemporaneously, but take up to seven months to fully translate into higher mortality effects unlike findings in the temperate climates.

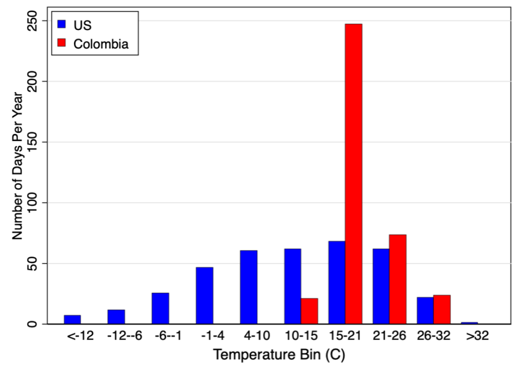
In exploring the potential reasons why differences with the temperate region could arise, this paper identifies new risk factors after the occurrence of hot temperature shocks. I show causes of death in tropical areas that react to even small changes in temperature drive the relationship between temperature and mortality. Respiratory and infectious diseases mainly explain the underlying temperature-mortality response function in the hot part of the distribution, affecting primarily children aged zero to nine. This contrasts the finding in temperate areas where cardiovascular diseases affecting the elderly drive heat-related mortality.

These findings suggest that appropriate technologies to mitigate the effects of hot temperature shocks might differ from what has been sucesfull in temperate areas. Results in this paper raise the question as to whether the appropriate technologies in the temperate region necessarily translate into tropical areas. For example, adoption of air conditioning have been highly effective in the U.S. to mitigate the effects of hot temperature shocks [5]. When cardiovascular diseases are the primary cause of death, this technology is appropriate because it serves as a means to stabilize body temperature and reduce stress in people's thermoregulatory systems. As to policies regarding adaptation to heat-related mortality, the analysis so far indicates that in the verge of increasing temperatures any solution should account for the fact that respiratory, infectious diseases and external causes of death are fundamental in explaining the results.

Finally, though mechanisms underlying the differences in the temperature-mortality response function between tropical and temperate regions cannot be fully disentangled, I provide suggestive evidence that they are not solely attributed to income or development. This is especially true in the hot part of the distribution, where the effects are driven by urban and rich municipalities. Also, effects after hot temperature shocks remained unchanged over the sample period, despite improved economic conditions in Colombia from 1993 to 2016.

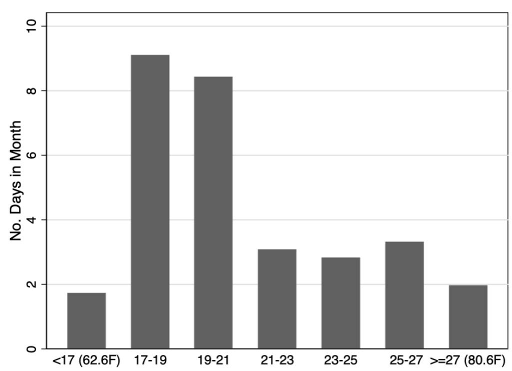
Income and development, however, might have played a role in reducing the effects on the colder part of the distribution. Though it is out of the scope of this paper, the question as to why cold-related mortality declined over the years in the sample remains open. The findings so far regarding cold-related mortality, particularly, the association to the elderly affected primarily through cardiovascular and respiratory diseases, suggest that health policies or improved infrastructure in housing could be possible explanations. Adoption of heating technology is not likely, given that temperatures are fairly mild.

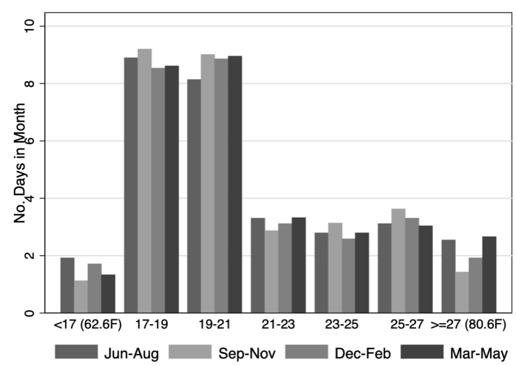
Figure 2.1: Comparison between U.S. and Colombia Annual Temperature Distribution



Notes: Historical (1993-2016) annual temperature distribution in Colombia as compared to the U.S. distribution for the period 1900-2004 ([5]), across ten temperature bins measured in Celcius. Observations are weighted by total population in the municipality in the respective year, so that the bars represent the number of days per year/month in each bin that an average person experiences.

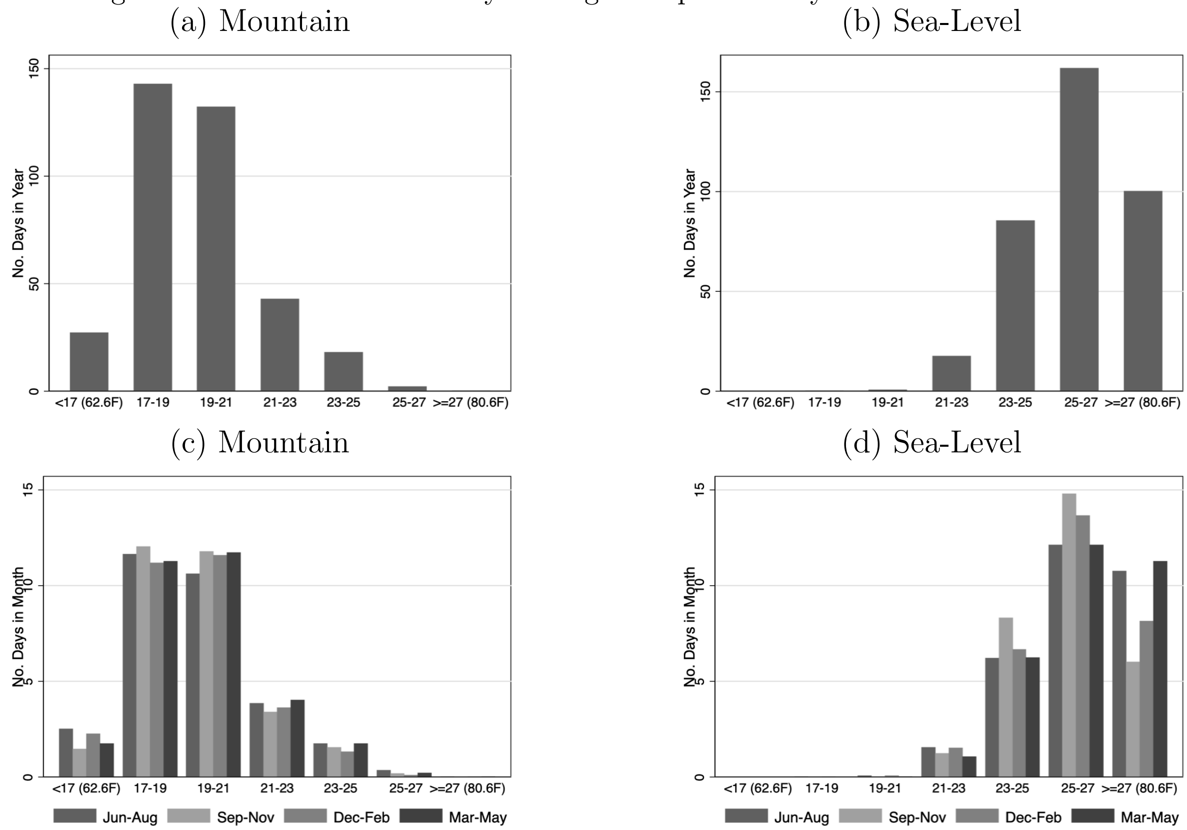
Figure 2.2: Distribution of Daily Average Temperature by Bins





Notes: Panel (a) shows the monthly temperature distribution. Panel (b) shows Colombian daily mean temperature distribution separately for different months across seven 2°C temperature bins. Observations are weighted by total population in the municipality in the respective year, so that the bars represent the number of days per year/month in each bin that an average person experiences.

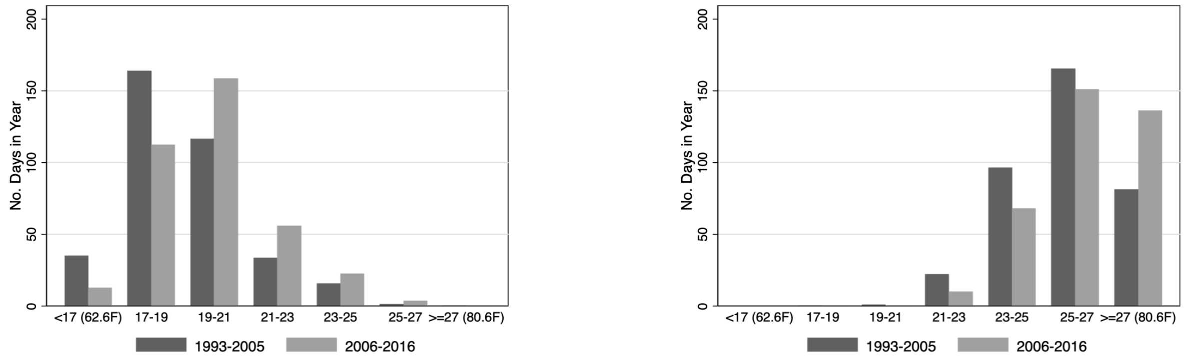
Figure 2.3: Distribution of Daily Average Temperature by Elevation and Season



Notes: The figure plots monthly temperature distribution of average daily temperture separately by elevation group and by season. Panel (a) and (b) depict the average monthly distribution using the entire year, while panels (c) and (d) separate the average by season.

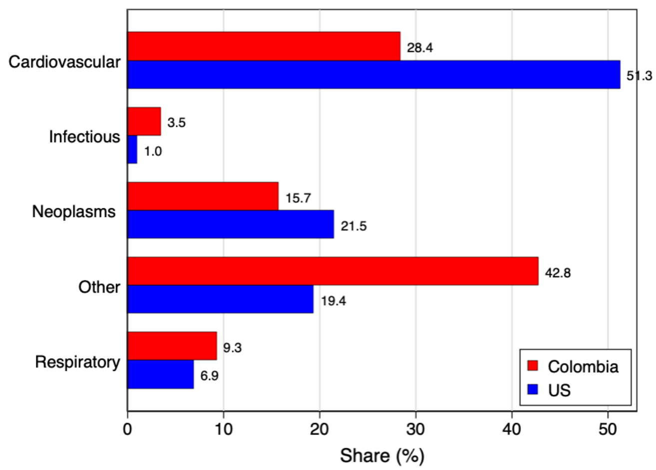
Figure 2.4: Distribution of Daily Average Temperature by Elevation over Time

Mountain Distribution Sea-Level Distribution



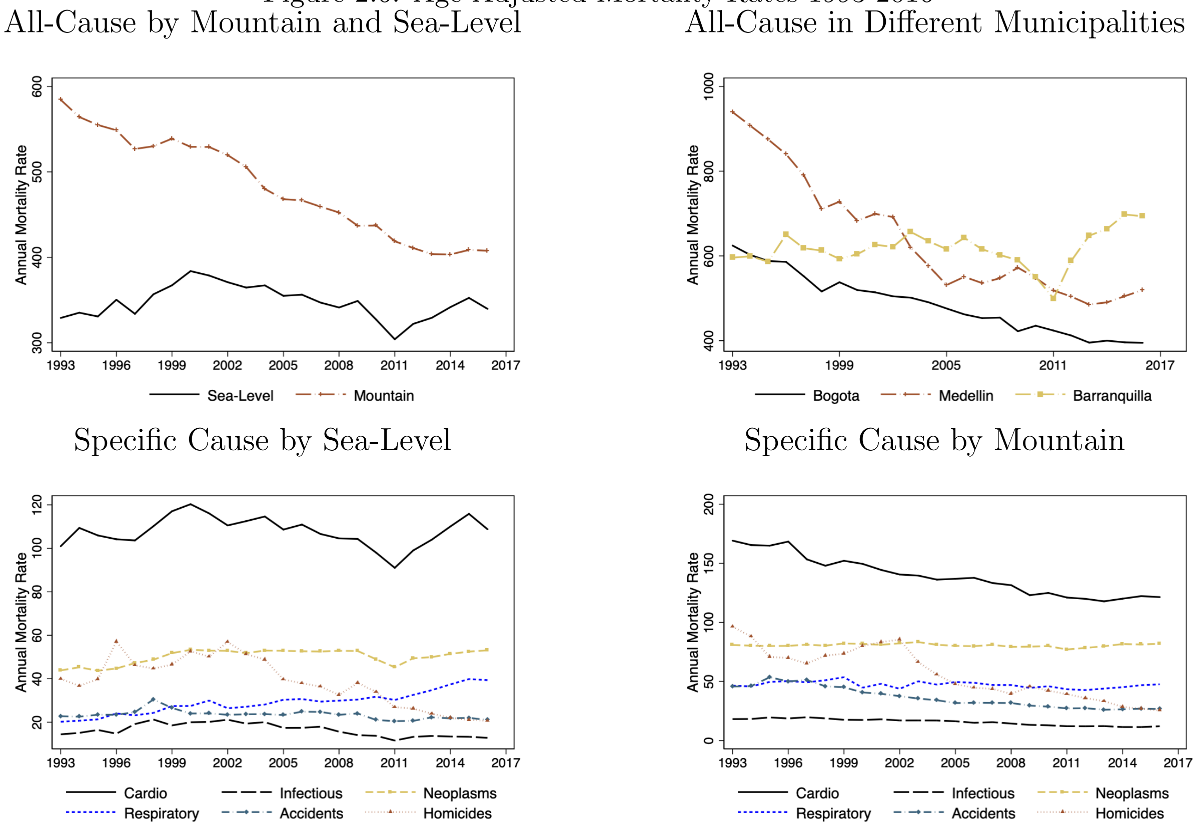
Notes: Annual temperature distribution by elevation over two time periods: 1993-2005 and 2006-2016.

Figure 2.5: Mortality Rates: Comparison Colombia and U.S.



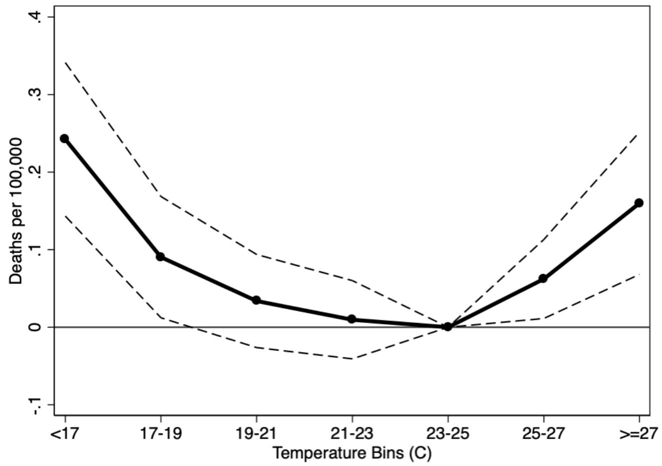
Notes: U.S. mortality data from [17]. Colombian data grouped in five main categories.

Figure 2.6: Age-Adjusted Mortality Rates 1993-2016



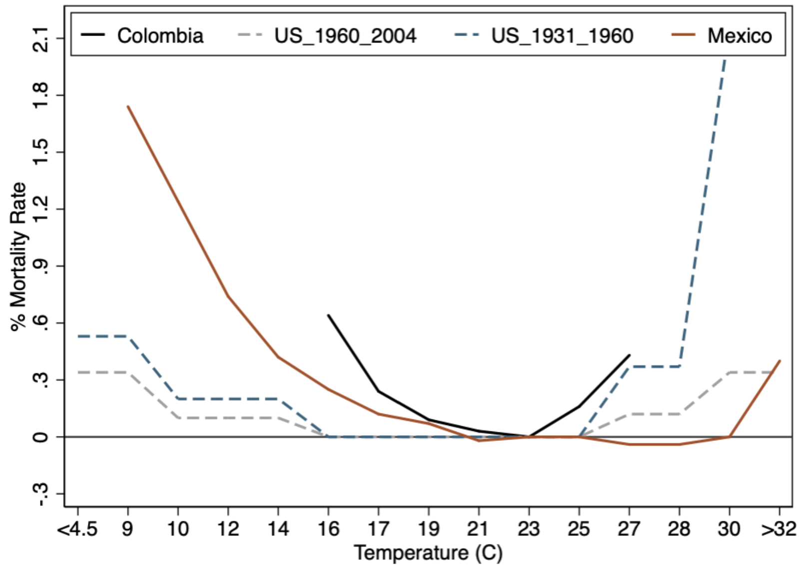
Notes: All entries are age-adjusted to 2005 population. Observations are weighted by total population in the municipality in the respective year.

Figure 2.7: Cumulative Dynamic Effect Exposure Window Five Months



Notes: Dynamic cumulative effects for each temperature bin plotted in the figure. Cumulative effects are calculated based on 4 lags that correspond to a temperature exposure window of 5 months. Cumulative estimates using municipality-year and month-year fixed effects. 90% confidence intervals constructed with standard errors clustered at the municipality level. All regressions are weighted by population and control for precipitation shocks.

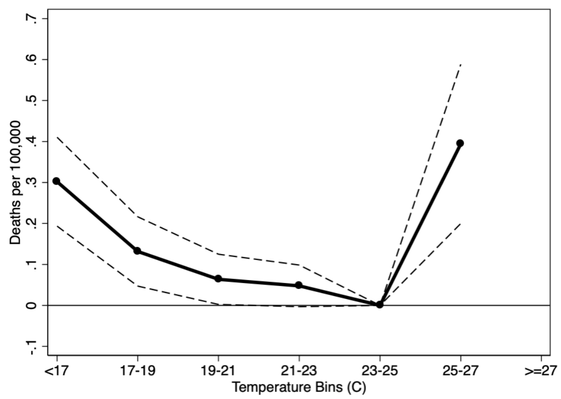
Figure 2.8: Comparison to the Literature



Notes: U.S estimates from [5] using cumulative dynamic effects with an exposure window of two months. Mexico estimates from [9] with cumulative effects after one month. Estimates for Colombia correspond to cumulative dynamic effect for five months.

Figure 2.9: Heterogeneous Effects by Elevation

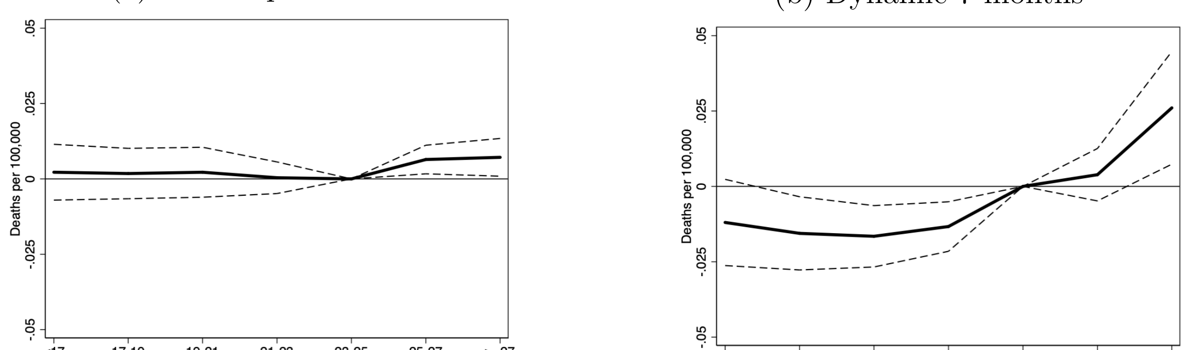
(a) Mountain Municipalities (b) Sea-Level Municipalities



Notes: Dynamic cumulative effects for each temperature bin plotted in the figures. Reference temperature bin 23-25°C. Cumulative effects after an exposure window of 5 months. Estimates using municipality-year and month-year fixed effects. 90% confidence intervals constructed with standard errors clustered at the municipality level. All regressions are weighted by population and control for precipitation shocks.

Figure 2.10: Infectious Diseases

(a) Contemporaneous (b) Dynamic 7 months

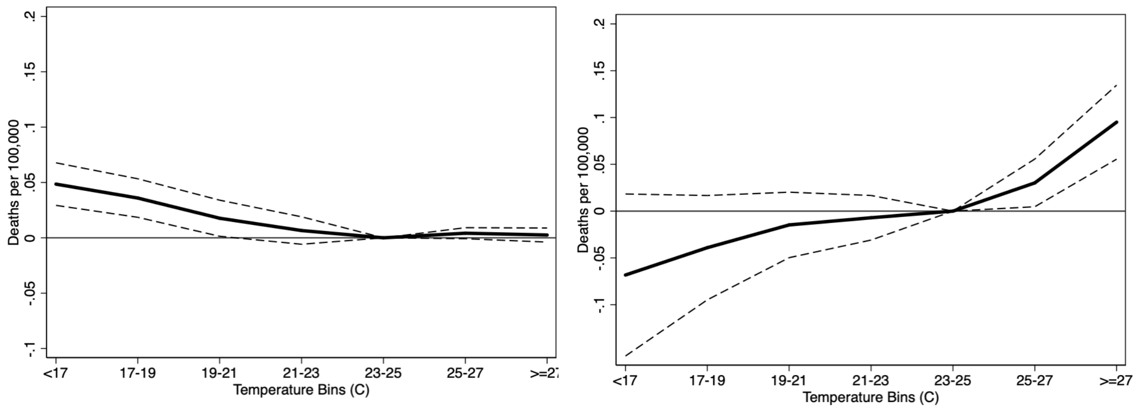


Notes: Contemporaneous and dynamic cumulative effects for each temperature bin plotted in each panel. Cumulative effects are calculated based on 6 lags that correspond to a temperature exposure window of 7 months. Cumulative estimates using municipality-year and month-year fixed effects. 90% confidence intervals constructed with standard errors clustered at the municipality level. All regressions are weighted by population and control for precipitation shocks.

Figure 2.11: Respiratory

(a) Contemporaneous

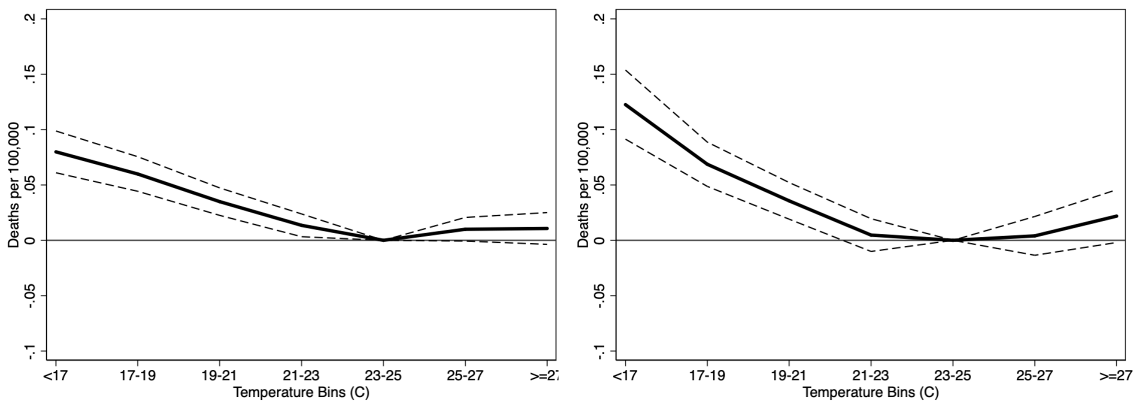
(b) Dynamic 9 months



Notes: Contemporaneous and dynamic cumulative effects for each temperature bin plotted in each panel. Cumulative effects are calculated based on 8 lags that correspond to a temperature exposure window of 9 months. Cumulative estimates using municipality-year and month-year fixed effects. 90% confidence intervals constructed with standard errors clustered at the municipality level. All regressions are weighted by population and control for precipitation shocks.

Figure 2.12: Cardiovascular

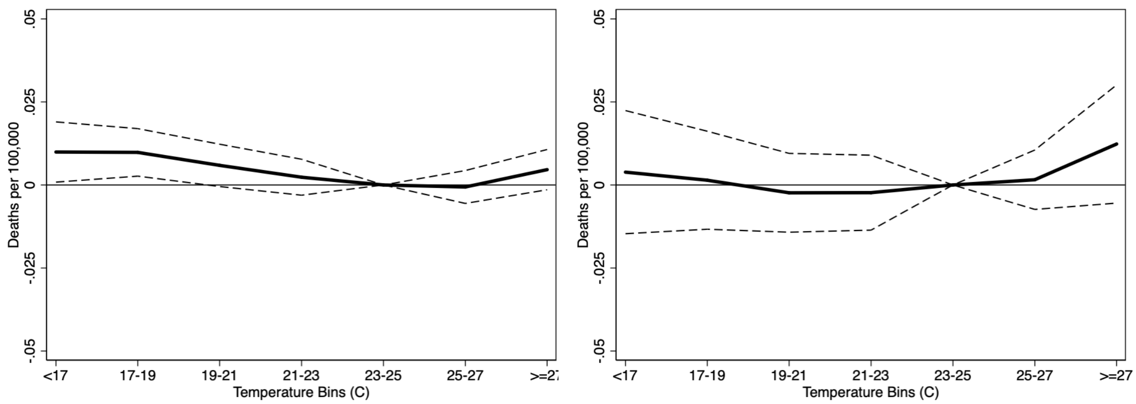
(a) Contemporaneous (b) Dynamic 5 months



Notes: Contemporaneous and dynamic cumulative effects for each temperature bin plotted in each panel. Cumulative effects are calculated based on 4 that correspond to a temperature exposure window of 5 months. Cumulative estimates using municipality-year and month-year fixed effects. 90% confidence intervals constructed with standard errors clustered at the municipality level. All regressions are weighted by population and control for precipitation shocks.

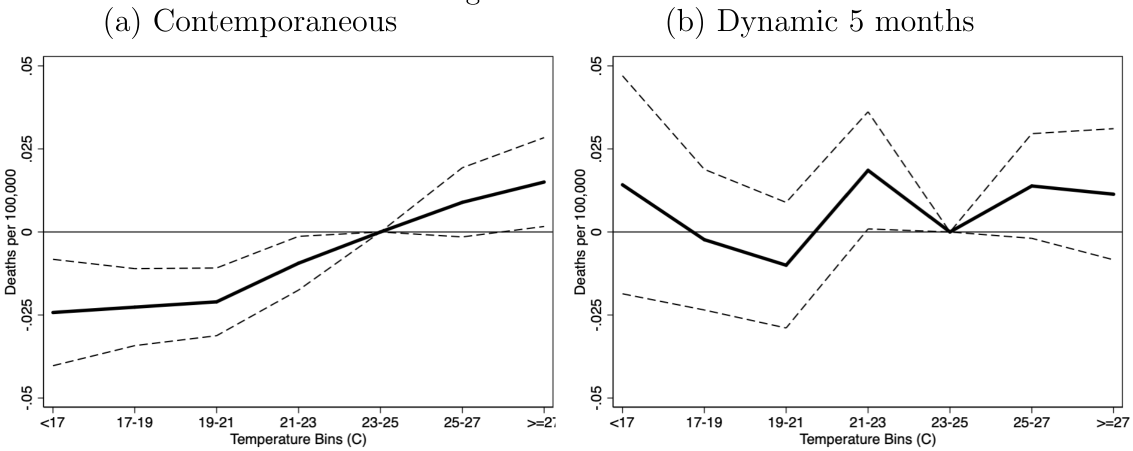
Figure 2.13: Neoplasms

(a) Contemporaneous (b) Dynamic 5 months



Notes: Contemporaneous and dynamic cumulative effects for each temperature bin plotted in each panel. Cumulative effects are calculated based on 4 that correspond to a temperature exposure window of 5 months. Cumulative estimates using municipality-year and month-year fixed effects. 90% confidence intervals constructed with standard errors clustered at the municipality level. All regressions are weighted by population and control for precipitation shocks.

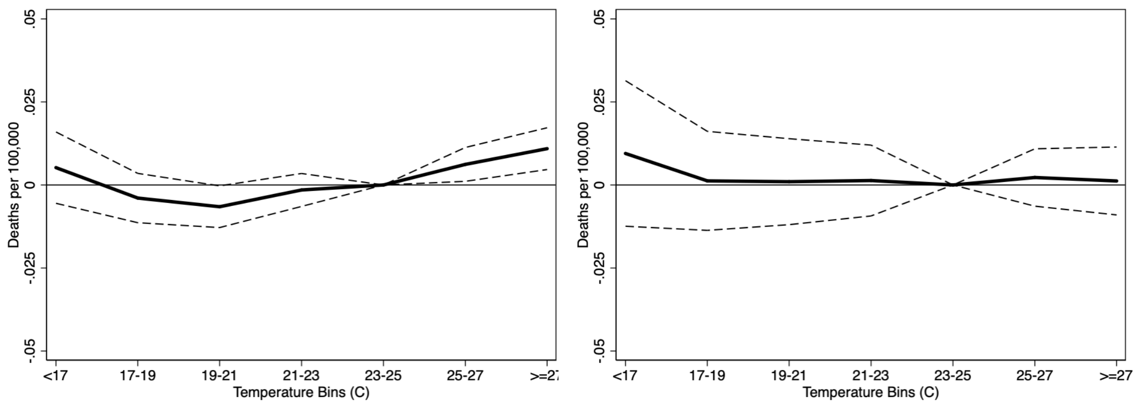
Figure 2.14: Homicides



Notes: Contemporaneous and dynamic cumulative effects for each temperature bin plotted in each panel. Cumulative effects are calculated based on 4 that correspond to a temperature exposure window of 5 months. Cumulative estimates using municipality-year and month-year fixed effects. 90% confidence intervals constructed with standard errors clustered at the municipality level. All regressions are weighted by population and control for precipitation shocks.

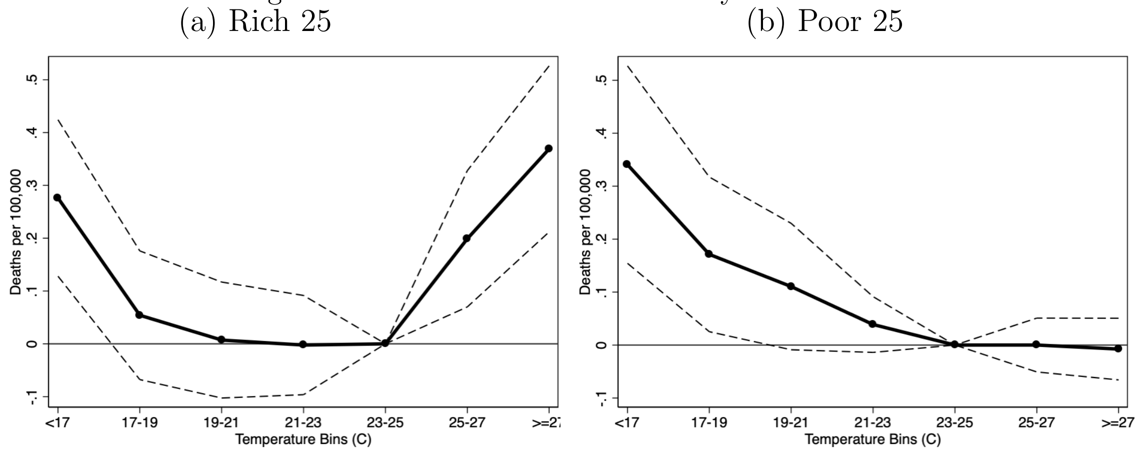
Figure 2.15: Accidents

(a) Contemporaneous (b) Dynamic 5 months



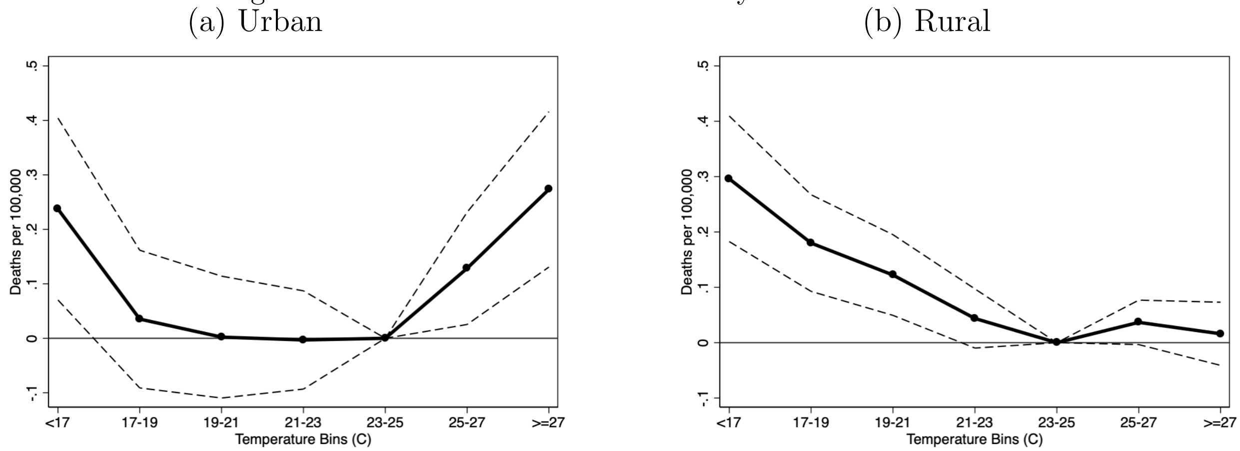
Notes: Contemporaneous and dynamic cumulative effects for each temperature bin plotted in each panel. Cumulative effects are calculated based on 4 that correspond to a temperature exposure window of 5 months. Cumulative estimates using municipality-year and month-year fixed effects. 90% confidence intervals constructed with standard errors clustered at the municipality level. All regressions are weighted by population and control for precipitation shocks.

Figure 2.16: Rich-Poor Cumulative Dynamic 5 Months



Notes: Income groups defined based on the Multidimensional Poverty Index. Panel (a) correpond to the top 75th percentile or 25th richest municipalities. Panel (b) municipalities between the 25th and 75th percentile of the poverty distribution. Panel (c) to the poorest 25th percentile. All figures plot estimates for each temperature bin interacted with the income group. Estimates from a single regression fully interacted with income groups (including fixed effectes) using four lags. Regressions control for precipitation and standard errors clustered at the municipality level. Separate estimates for the contemporaneous effects fully interatect reveal no differences between the groups: F-Test p-values: 0.597 0.888 0.820 0.437 0.494 0.301

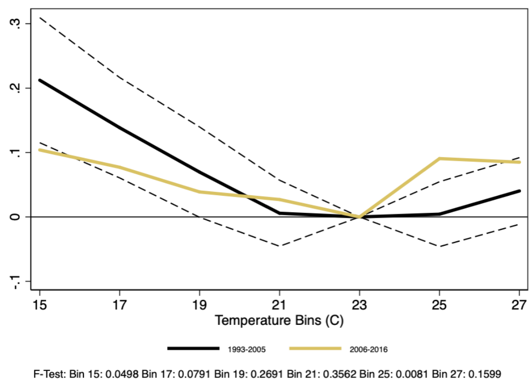
Figure 2.17: Urban-Rural Cumulative Dynamic 5 Months



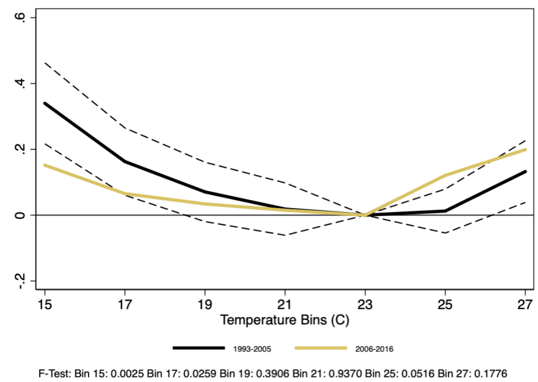
Notes: Urban-Rural groups defined based on the classification by the Colombian government based on population density and access to services. All figures plot estimates for each temperature bin interacted with urbanization group. Estimates from a single regression fully interacted with urbanization (including fixed effectes) using four lags. Regressions control for precipitation and standard errors clustered at the municipality level. Separate estimates for the contemporaneous effects fully interatect reveal no differences between the groups.

Figure 2.18: Mortality-Temperature by Decade

(a) Contemporaneous



(b) Cumulative 5 months



Notes: Contemporaneous and cumulative dynamic effects after 5 months of exposure for each temperature bin plotted in the figures for two different time perios. 95% confidence interval for period 1993-2005. Standard errors for the second period not reported for clarity, but p-values for F-tests on differences shown for each temperature bin. Regressions control for precipitation and municipality, municipality-year and month-year fixed effects.

Table 2.1: Annual Mortality Rate and Share of Specific Cause of Death by Age Group

	Age Group										
	All	0-4	5-9	10-19	20-29	30-39	40-49	50-59	60-69	70-79	80+
Infectious Diseases	3.64	10.20	6.23	2.43	4.27	6.58	5.48	3.48	2.42	1.98	1.75
Neoplasms	15.71	1.93	13.79	5.27	4.89	11.33	21.21	25.95	24.66	20.05	12.48
Endocrine and Nutritional	4.35	4.38	2.37	0.89	0.85	1.59	3.18	5.11	5.95	5.72	5.17
Cardiovascular Diseases	28.40	1.37	4.35	3.17	3.85	9.52	21.29	31.58	37.58	41.89	44.39
Respiratory Diseases	9.28	12.50	6.80	2.38	1.76	2.56	4.04	6.21	9.00	12.04	15.80
Other Diseases	18.31	61.38	23.15	11.08	9.17	11.60	13.72	14.62	14.71	15.13	16.55
Accidentes	7.68	7.60	33.75	21.96	19.75	16.81	11.53	6.53	3.75	2.56	2.29
Homicides	11.67	0.65	8.65	48.49	51.93	37.66	17.98	5.72	1.56	0.44	1.46
Suicides	0.96	0.00	0.92	4.35	3.53	2.35	1.56	0.80	0.37	0.17	0.10
Death Rate × 100,000	457.3	357.4	33.0	116.8	209.2	217.8	301.3	601.1	1339.4	3052.6	9099.5

Notes: Specific causes of death classified according to ICD-10 WHO. The last row of the table corresponds to the annual crude death rate per 100,000 for the whole country, weighted by population. All other entries correspond to shares of specific cause of death for all sample and by age group.

Table 2.2: Dynamic Causal Effect Age-Adjusted All-Cause Mortality Rates

	Monthly Mortality Rate per 100,000			
	(Contemporaneous)	(Cum 5)	(Cum 7)	(Cum 9)
Base Temperature: $\in$ [23C,25C) [73F,77F)				
Temperature < 17	0.172***	0.242***	0.023	-0.031
	(0.038)	(0.060)	(0.079)	(0.142)
Temperature $\in$ [17,19)	0.110***	0.090*	-0.003	-0.039
	(0.032)	(0.048)	(0.050)	(0.108)
Temperature $\in$ [19,21)	0.052*	0.034	-0.015	0.028
	(0.029)	(0.036)	(0.038)	(0.077)
Temperature $\in$ [21,23)	0.019	0.010	-0.020	0.040
	(0.022)	(0.031)	(0.034)	(0.055)
Temperature $\in$ [25,27)	0.050**	0.062**	0.062	0.069
	(0.016)	(0.031)	(0.038)	(0.053)
Temperature ≥ 27	0.061**	0.160**	0.253***	0.233**
	(0.020)	(0.056)	(0.068)	(0.082)
25th Precipitation Pctile	-0.114	-0.327	-0.122	-0.140
	(0.094)	(0.229)	(0.309)	(0.375)
75th Precipitation Pctile	0.027	0.437**	0.932***	1.233***
	(0.093)	(0.193)	(0.222)	(0.273)
Observations	301,656	301,588	301,554	301,520
Mean Mortality Rate	37.58			
SD Mortality Rate	19.75			
Municipality × Year FE	Yes	Yes	Yes	Yes
Year × Month FE	Yes	Yes	Yes	Yes

Notes: ***p-value < 0.001, **p-value < 0.01, *p-value < 0.05. Standard errors clustered at the municipality level reported in parenthesis. All regressions are weighted by population. Each column is a separate regression. Column Contemporaneous present estimates using no lags. Cum 5 estimated the dynamic model using 4 lags, meaning results correspond to cumulative dynamic effects after an exposure window of 5 months.

Table 2.3: All Cause By Age-Group All Sample % Effect

Age-Group	Dynamic 5 Months		Mean Mortality Rate
	< 17	≥ 27	
0-4	0.26	1.32**	26.05
5-9	0.49	1.17**	2.47
10-19	1.28**	-0.20	8.2
20-29	0.14	0.31	16.96
30-39	0.44	0.76***	17.45
40-49	0.33	0.07	22.98
50-59	0.09	0.14	45.12
60-69	0.20	0.54***	105.12
70-79	0.72***	0.31	249.45
80+	1.22***	0.63**	778.89

Notes: Estimates in each row comes from separate regressions by age group. Dynamic cumulative effect with an exposure window of 5 months. The entries under each temperature bin are calculated by taking point estimates and dividing them by average monthly mortality rates for each age group. ***p-value < 0.001, **p-value < 0.01, *p-value < 0.05 from point estimates in each regression.

Table 2.4: Contemporaneous by Urban Rural Classification

	Monthly Mortality Rate per 100,000		
	(Urban)	(Semi-Urban)	(Rural)
Base Temperature: $\in$ [23C,25C) [73F,77F)			
Temperature < 17	0.170**	0.227***	0.143***
	(0.064)	(0.055)	(0.038)
Temperature $\in$ [17,19)	0.091*	0.146**	0.088**
	(0.053)	(0.048)	(0.031)
Temperature $\in$ [19,21)	0.050	0.059	0.041
	(0.049)	(0.045)	(0.025)
Temperature $\in$ [21,23)	0.029	-0.014	0.001
	(0.036)	(0.041)	(0.018)
Temperature $\in$ [25,27)	0.058*	0.013	0.037*
	(0.030)	(0.030)	(0.020)
Temperature ≥ 27	0.067**	0.012	0.059**
	(0.034)	(0.033)	(0.023)
25th Precipitation Pctile	-0.182	0.029	0.058
	(0.132)	(0.172)	(0.140)
75th Precipitation Pctile	0.036	0.112	-0.050
	(0.133)	(0.126)	(0.120)
Observations	32,256	83,784	185,616
Mean Mortality Rate	43.54	30.27	24.52
SD Mortality Rate	15.2	20.31	23.54
Municipality $\times$ Year FE	Yes	Yes	Yes
Year $\times$ Month FE	Yes	Yes	Yes

Notes: ***p-value < 0.001, **p-value < 0.01, *p-value < 0.05. Standard errors clustered at the municipality level reported in parenthesis. All regressions are weighted by population. Each column is a separate regression.

Table 2.5: Cumulative Dynamic 5 Months by Urban Rural

	Monthly Mortality Rate per 100,000		
	(Urban)	(Semi-Urban)	(Rural)
Base Temperature: ∈ [23C,25C) [73F,77F)			
Temperature < 17	0.237**	0.315**	0.296***
	(0.102)	(0.106)	(0.069)
Temperature ∈ [17,19)	0.035	0.147*	0.180***
	(0.077)	(0.081)	(0.053)
Temperature ∈ [19,21)	0.002	0.041	0.122**
	(0.068)	(0.069)	(0.044)
Temperature ∈ [21,23)	-0.003	-0.002	0.044
	(0.055)	(0.067)	(0.032)
Temperature ∈ [25,27)	0.128**	-0.018	0.037
	(0.063)	(0.067)	(0.024)
Temperature ≥ 27	0.273**	0.026	0.016
	(0.087)	(0.067)	(0.035)
25th Precipitation Pctile	-0.207	-0.800*	-0.087
	(0.334)	(0.481)	(0.406)
75th Precipitation Pctile	0.646**	0.180	0.220
	(0.274)	(0.355)	(0.316)
Observations	32,256	83,760	185,572
Mean Mortality Rate	43.54	30.27	24.53
SD Mortality Rate	15.2	20.31	23.53
Municipality × Year FE	Yes	Yes	Yes
Year × Month FE	Yes	Yes	Yes

Notes: ***p-value < 0.001, **p-value < 0.01, *p-value < 0.05. Standard errors clustered at the municipality level reported in parenthesis. All regressions are weighted by population. Each column is a separate regression.

Table 2.6: Cumulative Dynamic 7 Months by Urban Rural

	Monthly Mortality Rate per 100,000		
	(Urban)	(Semi-Urban)	(Rural)
Base Temperature: $\in$ [23C,25C) [73F,77F)			
Temperature < 17	-0.154	0.396**	0.276**
	(0.115)	(0.161)	(0.093)
Temperature $\in$ [17,19)	-0.126*	0.208	0.184**
	(0.070)	(0.130)	(0.076)
Temperature $\in$ [19,21)	-0.091	0.100	0.127*
	(0.059)	(0.117)	(0.066)
Temperature $\in$ [21,23)	-0.050	0.021	0.037
	(0.058)	(0.111)	(0.043)
Temperature $\in$ [25,27)	0.098	-0.015	0.060*
	(0.081)	(0.081)	(0.034)
Temperature ≥ 27	0.355**	0.053	0.067
	(0.107)	(0.091)	(0.047)
25th Precipitation Pctile	0.214	-0.953	0.152
	(0.460)	(0.696)	(0.504)
75th Precipitation Pctile	1.266***	0.583	0.488
	(0.283)	(0.476)	(0.407)
Observations	32,256	83,748	185,550
Mean Mortality Rate	43.54	30.27	24.53
SD Mortality Rate	15.2	20.31	23.53
Municipality $\times$ Year FE	Yes	Yes	Yes
Year $\times$ Month FE	Yes	Yes	Yes

Notes: ***p-value < 0.001, **p-value < 0.01, *p-value < 0.05. Standard errors clustered at the municipality level reported in parenthesis. All regressions are weighted by population. Each column is a separate regression.

Chapter 3

Temperature and Morbidity in Colombia

3.1 Introduction

The changing climate has spurred an interest in quantifying the economic damages associated to this environmental risk.[1] Economic damages often include, but are not limited to, loses in agricultural productivity, property damages due to extreme weather events, and human health [3]. The costs associated to human health have been of particular interest given that health is not only valuable in itself because it's an indicator that people are living better lives, but because health has a productive side. Better health implies that people can work harder and longer, eventually translating into higher incomes. In fact, a large literature has focused on the cost of climate change in terms of mortality risk based on empirically founded estimates of the relationship between short-term variations in temperature and mortality ([2], [7]). However, the effects of temperature shocks on demand for healthcare services and alternative health outcomes that do not

[1] see [1] and [2] for a review.

result in death (i.e. morbidity) have received less attention ([10], [11], [21]). This is important for many reasons but one of them is that ignoring morbidity, might lead to underestimates of the costs of climate change. Moreover, health systems might see an increase in demand and an additional burden after temperature changes, but they could also serve as a mediating factor between climate and mortality.

This paper estimates the relationship between temperature and health services usage, using the universe of services provided in the health system in Colombia over the period 2009 to 2016. I use a unique data set that combines information on four morbidity outcomes: (i) hospitalizations, (ii) emergency room (ER) visits, (iii) consultations, and (iv) procedures by type of diagnosis, with daily weather data from reanalysis models to produce a balanced panel with close to 8,000 observations. With data at the annual-municipality level and panel regressions, the main specification includes municipality and department-by-year fixed effects to account for most sources of unobserved heterogeneity (departments are equivalent to U.S. states). Identification comes from municipality-specific deviations in weather with respect to municipality averages after controlling for flexible time trends common to all municipalities within a department.

I find that hospitalization rates monotonically increase with temperature over the entire distribution observed in Colombia. Exchanging a day in the reference bin 23-25°C for a single day above 27°C increases hospitalization cases by 29.6 per 100,000, equivalent to 0.86% of the average annual hospitalization rate, whereas an additional day below 17°C leads to a decrease of 21.7 hospitalizations per 100,000 (0.63%). I also document increases in emergency room visits and procedures rates, whereas overall consultation rates seem to be associated with additional days in ‘colder’ temperatures relative to 23-25°C.

To provide insights on the mechanisms at work, I explore heterogeneous responses in the four morbidity outcomes by diagnoses. The increasing relationship between hospitalization rates and temperature is, in general terms, common across all categories.

However, increased hospitalizations due to infectious diseases, pregnancies and childbirth, respiratory, circulatory, as well as external factors drive this result. I further dig into sub-categories associated with infectious and pregnancy-related diagnoses not only because of the magnitudes of the effects, but because these haven't been extensively documented in the literature. Moreover, these diseases affect children and women to a greater extent.

As for infectious diseases I show that all four morbidity outcomes (hospitalizations, ER visits, consultations and procedures) within the sub-categories of (i) arthropod-borne viral fevers such as dengue, zika, yellow fever, or ebola, (ii) protozoal diseases like malaria, or leishmaniasis, and (iii) viral infections including mumps, mononucleosis or coronavirus infection (pre COVID-19), increase with temperature. These results are consistent with findings in the epidemiological literature that suggest that higher than average temperature shocks aid in the replication of microbes causing human diseases, and subsequently increase viral transmission. For example, [16] show that dengue incidence increased succeeding higher temperatures in Singapore. This is especially true in tropical countries given the absence of winter temperatures, resulting in more hospitable environments for human diseases [15].

Though the literature has documented increases in ER visits and hospitalizations after exposure to extreme heat and cold ([10], [11], [21] for example), the findings in this paper depart from the mechanisms identified so far, namely external factors, cardiovascular, endocrine, diabetes and conditions originating in the perinatal period. Results regarding increases in demand for health services of patients diagnosed with infectious diseases, are consistent with my findings in Chapter 2 that relate hot temperature shocks with increased mortality rates from these diseases.

Pregnancy-related morbidity outcomes also increase throughout the temperature distribution, indicating that women and likely fetal health is negatively affected by hot temperature shocks. Maternal care related to fetus health (fetus hereafter), as well as maternal disorders like genitourinary infections, diabetes mellitus and malnutrition, mainly explain why women seek care.[2]. Both of these diagnoses exhibit the largest relative effects of exchanging a day in the reference bin 23-25°C for an additional day with average temperature above 27°C, of approximately 1.2% and 1.5% respectively. Pregnancies with abortive outcomes, either planned or unplanned, also exhibit consistent increasing relationships in temperature in all of the four morbidity outcomes.[3]

This paper contributes to the literature that aims at quantifying costs of climate change with empirically founded estimates of the relationship between weather and health outcomes ([1], [7], [4]). Unlike much of the estimates that rely on death counts, I focus on alternative health outcomes that are rarely available especially in middle and low income countries. Evidence on how morbidity outcomes react to changes in temperature is limited, except for [10], [11] and [13] that focus on emergency room visits and hospitalizations from California, Germany and three U.S. states respectively. The epidemiological literature is wider, but the geogrpahical scope is small as they rely on a handful of cities mostly located in the U.S., Canada and Europe ([22], [23], [24], [21], [25], [26]). Nonetheless, all agree that extreme heat increases hospitalizations and emergency room visits, but mechanisms at work in terms of diagnoses vary from context to context.

Even less, however, is known about morbidity effects following temperature shocks in developing countries. I extend the literature by providing further evidence on the effects of temperature shocks on the demand for health services, not necessarily at extreme temperatures. Detailed information on type of access and principal diagnosis allows me to confirm that hospitalizations increase even at the narrow temperature distribution

[2]Fetal health include damages to fetus from viral diseases experienced by the mother, from drugs and alcohol use, and poor fetal growth, hypoxia or false labor.

[3]Abortion is only legal in Colombia under the following three circumstances: (i) continuation of pregnancy endangers the mother's life or health, (ii) existence of life-threatening fetal malformations, or (iii) pregnancy is the result of rape, non-consensual artificial insemination or incest.

observed in Colombia[4], meaning that effects are triggered not necessarily at extreme heat. Moreover, I provide new insights on the potential mechanisms that explain these findings.

This paper also speaks to another strand of literature that documents the effects of fetal exposure to heat and long-term human capital, by affecting, among others, long-term cognitive ability and adult earnings (Include references). However, as pointed out by [13], the effects of exposure on maternal health is still unclear and this might impose further costs that have not been yet documented. In fact, most of the literature on the effect of extreme heat on maternal health and pregnancy outcomes focuses on birth outcomes, including birth weight, stillbirth, almost neglecting the health of women (see [22] for a review). An exception is [13] who find that extreme heat increases the likelihood that a woman is hospitalized during pregnancy using data from three U.S. states: Arizona, New York and Washington. My findings corroborate these results in a very different context, but in addition to hospitalizations I am able to capture impacts on other health insults that not necessarily lead to hospital o emergency room visits.

Using observational data on how Colombia's temperature distribution has changed over time, I link estimates from variations in weather to the potential costs of climate change. Assuming temperatures will continue to rise in upcoming years as has been recently observed, and that no further adaptation measures are undertaken, I estimate that the shift in the temperature distribution results in 1,161.3 additional hospitalizations per 100,000 inhabitants per year (33.6% of the average annual rate of 3458.87). These results suggest an important increase in demand for health services as temperatures continue to rise, but they also shed light on the importance on access to mitigate the adverse effects.

The paper proceeds as follows. Section 2 provides details on the institutional back-

[4] 17°C to 27°C given Colombia's closeness to the Equator

ground and the health system in Colombia. Section 3 describes the data sources, and some descriptive statistics. Section 4 outlines the econometric models used to estimate the temperature-morbidity response function. Section 5 discusses the main results from fitting the regressions, and heterogeneous findings. Section 6 concludes.

3.2 Institutional Background

Colombia undertook an ambitious health reform in 1993 to address, among others, low coverage levels and inequalities in access to health services. As of 1992, approximately 25% of the population had health insurance, and only one out of six individuals in the poorest quintile seek medical treatment ([27], [28]). The reform established mandatory health insurance, so that all individuals could access a pre-established package of basic health services regardless of their economic means.

In transitioning to universal coverage, the system was and currently is divided into two regimes that have a common structure but differ in target populations: (i) the contributory regime (henceforth CR), and (ii) the subsidized regime (henceforth SR). Formal and self-employed workers above a pre-determined minimum income must enroll in CR, and contribute 12.5% of their income. The employer is responsible for two-thirds of the contribution, and the employee pays for the rest. This contribution is collected by the worker's insurer of choice, who uses it to pay for the enrollee's stipulated premium, and transfers the difference to a public fund that subsidizes those whose difference is negative or in other regimes.

SR targets low-income individuals with no formal work, and eligibility is means tested using an index based on household's socioeconomic characteristics (SISBEN - Beneficiary Identification System). The law mandates that those individuals with the lowest SISBEN scores, as well as vulnerable groups like children under five and pregnant women are prioritized. Individuals make no insurance contributions, but have access to the basic basket of services. Funding for SR comes from cross subsidies from CR, and transfers from local and the central government. Primary, some inpatient, and emergency care are covered under SR (see [29], [30], and [27] for a more detailed description of the reform and the system).

Since the reform in 1993, coverage reached almost 91% of the population with access to at least the basic bundle of services in 2016. Throughout the study period in this paper, 2009 to 2016, the average share of the population covered in either regime was 90.45%, with a 50-50 distribution between CR and SR (figure B.1 in Appendix B). Most municipalities exhibit coverage over 70%. The remaining uninsured population still has access to public facilities through the public health intervention package, where they receive preventive and emergency care.

3.3 Data and Descriptive Trends

This section describes the data used in the analysis and characterizes the temperature distribution and the morbidity profile in Colombia over the period 2009-2016.

Weather Data: Temperature and rainfall data are drawn from the European Centre for Medium-Range Weather Forecasts (ECMWF), which periodically uses forecast models and data assimilation systems to produce climate reanalysis data in the ERA-Interim product.[5] ERA-Interim data is available on a $0.125° \times 0.125°$ quadrilateral grid daily since January 1979.[6] The key variables for the analysis are daily average temperature and daily total precipitation. Daily average temperature corresponds to the average of four readings per day reported at different times during the day.[7] Daily grid-level data is

[5] The data can be downloaded from http://apps.ecmwf.int/datasets/data/interim-full-daily/levtype=sfc/

[6] This corresponds to grids of approximately $16km \times 16km$

[7] Daily total precipitation is the sum of all the readings per day.

aggregated at the municipality level by taking an area-weighted average of the weather variable of interest in each municipality.[8] The weights are defined by the area of each grid that belongs to a particular municipality.[9] I use daily weather data to construct a panel consisting of approximately 8350 municipality-year observations for the period 2009-2016.

The empirical analysis considers a discrete version of the annual distribution of temperature. I define fine temperature categories to guarantee enough variation within municipality to identify effects on morbidity (i.e. 2°C temperature categories). Colombia's closeness to the Equator implies that populations are exposed to an almost constant temperature throughout the year, supporting this definition of narrow temperature categories. Panel (a) in figure 3.1 shows the average annual distribution of daily mean temperature from 1993-2016 grouped across seven temperature categories or bins.[10] These bins represent daily temperatures of less than 17°C, higher than 27°C and five 2°C wide bins in between. The average number of days in a year in the modal bin 17-19°C is 120. Most of the distribution is concentrated around this bin, and only a few days are observed in the extreme bins: 25 per year in the less than 17°C and 30 in the greater than 27°C bin. Average annual temperature is 20.9°C. This distribution constitutes the main explanatory variables in the empirical analysis. This strategy preserves the daily variation in temperature to capture non-linearities in the temperature-mortality relationship *a la* [4].

Panels (b) and (c) in figure 2.2 presents a key feature of the temperature data: the temperature distribution depends on elevation. As countries get closer to the Equator,

[8]Municipalities are the smallest administrative area, grouped in Departments, where the latter can be though of as States in the United States. There are currently 1,222 municipalities, each one led by an elected mayor and administered by a municipal council.

[9]Shape files for Colombian municipalities are superposed over the grid weather data file extracted from ERA-Interim that contains Colombia, to aggregate at the municipality level

[10]This is a discretized version of the continuous distributions of temperature

differences in temperature across municipalities are determined by their elevation relative to sea-level, with average temperature declining as altitude increases. To highlight the elevation-temperature gradient, I group municipalities in two elevation groups: mountain and sea-level. The former corresponds to those located more than 1000 meters above sea-level and the latter, to those below this threshold.[11] In municipalities closer to sea level, average daily temperature below 21°C are not observed, whereas average temperatures above 25°C are rare in mountainous areas. Panels (b) and (c) in figure 2.2 plot the average annual distribution for both groups. This implies that the effect of exposure to 'colder' temperatures on morbidity will be identified by municipalities in higher elevations, while the effect of hotter temperatures is driven by those closer to sea-level. It is worth highlighting that approximately 75% of the Colombian municipalities and population are located in the mountainous region.

Morbidity Data: Data on the use of medical services are taken from the SISPRO system compiled by the Ministry of Health and Social Protection of Colombia. The files available in SISPRO contain the universe of services provided in the health system by number people treated and total cases reported at the municipality-year level for the period 2009-2016.[12] Access can be measured by type of service provided, namely, (i) consultations, (ii) procedures, (iii) emergencies, and (iv) hospitalizations. Consultations refer to meetings between a physician and a patient either at a medical center or at a patient's home, as a preventive measure or to obtain a diagnosis/treatment for a particular case. Procedures are defined as any 'activity directed at or performed on an individual with the object of improving health, treating disease or injury, or making a diagnosis'.[13] They are either surgical or non-surgical. Emergencies refer to visits to

[11] This is a typical classification of mountainous areas

[12] Cases reported are usually higher than number of people accessing the health system, because a person can access the system more than once.

[13] Taken from Wikipedia

the emergency room and, hospitalizations include inpatient visits whether through the emergency department or not.

I combine this information with population data drawn from the National Statistics Department of Colombia (DANE) to construct consultation, procedure, emergencies and hospitalization rates per 100,000 inhabitants.[14] These rates are calculated by dividing the total number of people or cases in a municipality on a given year, by the total population in that municipality-year. Each type of service can also be classified by diagnosis. The diagnosis codes correspond to the tenth revision of the International Statistical Classification of Diseases and Related Health Problems by the World Health Organization (ICD-10 WHO).

Table 3.1 presents the total number of cases per type of service, as well as the share of each type of diagnosis over the period 2009-2016. The data contains 725.4 million consultations, 524 million procedures, 38.4 million visits to the emergency room and 12.8 million hospitalizations. For consultation and procedures, the leading diagnosis are diseases of the digestive and circulatory system, followed by respiratory diseases. As for emergencies respiratory and infectious diseases are the leading diagnoses.

3.4 Empirical Strategy

This section presents the model used to estimate the temperature-morbidity response function. To quantify the effect of weather on access to health services in any given year and location, I estimate fixed-effects linear regressions. Specifically, I fit variants of the following specification:

[14]Population data in each municipality comes from the series produced by DANE based on census records and projections.

$$MR_{iy} = \sum_{j=1}^{6} \beta_j BinTemp_{jiy} + \sum_{k=1}^{10} \gamma_k BinPrec_{kiy} + \eta_i + \psi_{dy} + \varepsilon_{iy} \tag{3.1}$$

where MR_{iy} the morbidity rate per 100,000 inhabitants at the municipality i and year y level. MR_{iy} includes four different outcomes: (i) number of consultations, (ii) procedures, (iii) hospitalizations, and (iv) emergencies. Temperature variables are constructed using a discrete version of the annual distribution, which allows to capture a flexible non-linear relationship with morbifity following [4]. As such, the variables $BinTemp_{imy}$ denote the number of days in municipality i in year y in which the average daily temperature is in the j^{th} bin of the seven 2°C bin described in Figure 2.2. Since the number of days in a year is constant and the temperature variables add up to this constant, temperature bin 23-25°C (73.4-77°F) is excluded from estimation and used as a reference bin. This means that the coefficient of interest β_j on the variable temperature bin j is interpreted as the effect on each morbidity outcome from exchanging a day in the reference bin to a day in temperature bin j.

The equation includes a full set of controls for precipitation, denoted by variables $BinPrec_{kiy}$ in equation (3.1). These are indicators based on annual rainfall in municipality i in year t, to capture a discrete version of the annual precipitation distribution. Each variable $BinPrec_{kiy}$ counts the number of days in a year total daily rainfall fell in precipitation bin k. There are 10 of these 3-millimeter (mm) bin rainfall variables, with precipitation between 3-6mm excluded from estimation.[15]

The last term of equation (3.1), ε_{iy} is a stochastic error term. η_i denotes a full set of municipality fixed-effects, and ψ_{dy} department-by-year fixed effects.[16] Municipality

[15]This specification assumes that temperature and precipitation are independent. I am considering specifications with interactions between the two. Also I plan to obtain data for humidity.

[16]There are 32 departments, equivalent to States in the United States, in Colombia. Each department

fixed-effects absorb all unobserved time invariant municipality-specific determinants of morbidity. This captures factors like permanent differences in health conditions that are specific to the municipality, or availability and quality of health services in each municipality. The department-by-year fixed effects account for time-varying differences in morbidity rates that are common across all municipalities in a specific department.

By conditioning on this structure of fixed-effects, identification of the parameters of interest β_j,comes from municipality-specific deviations in weather from municipality averages after controlling for precipitation, and time-trends specific to each department. The empirical validity of this specification relies on the identifying assumption that conditional on the fixed effects structure, weather variables are not correlated with the idiosyncratic error term. This implies that:

$$E(BinTemp_{jiy}\varepsilon_{iy}|BinTemp_{-jiy}, BinPrec_{kiy}, \eta_i, \psi_{dy}) = 0$$

Due to the randomness of weather variations, the assumption is reasonable and widely made in the literature. Variations in weather are likely orthogonal to unobserved determinants of morbidity. Standard errors are clustered at the municipality level to account for correlation within municipality over time. Weather is highly localized given Colombia's rugged geography, providing an additional reason to cluster standard errors at the municipality level.

The lack of seasonality and spatial distribution of temperature within this context implies that the effect of exposure to 'colder' temperatures on mortality is identified by municipalities in higher elevations, while the effect of hotter temperatures is driven by those closer to sea-level. To explore the existence of heterogeneous responses at narrower ranges of temperature, I also estimate equation 3.1 separately for two elevation groups;

is comprised by a group of municipalities.

those above 1000 meters referred to as mountain and those below 1000 meters referred to as sea level. To that end, the temperature bins for the mountainous area range from below 17°C to 25°C. The 'hottest' two bins are grouped in one given that temperatures above 27°C are rarely observed at higher elevations. For municipalities located closer to sea-level, temperature bins are defined between below 23°C and 27°C. In both cases, temperature bin 23-25°C (73.4-77°F) is excluded from estimation for comparison purposes.

3.5 Results

3.5.1 All Diagnoses

Figure 3.2 presents estimates for the preferred specification described in equation (3.1) for four annual morbidity outcomes: Consultation, Hospitalization, Procedures and Emergency Room Visit Rates per 100,000 inhabitants. Each panel plots the coefficients associated to each temperature bin, interpreted as the estimated impact on morbidity of exchanging one day in temperature bin j with respect to the reference bin 23-25°C. Tables 3.2, 3.3, 3.4, and 3.5 report point estimates for the preferred specification in column (2), as well as for alternative specifications of the fixed-effects structure and alternative sub-samples of elevation groups to assess robustness of results and provide further insights.

The results reveal that hospitalization rates monotonically increase with temperature. Panel (a) in figure 3.2 shows that exchanging a day in the reference bin 23-25°C for a single day below 17°C leads to a decrease of 21.7 hospitalizations per 100,000. This impact correspond to 0.63% as compared to the mean annual hospitalization rate of 3458.8 per 100,000 reported in the preferred specification in column (2) in table 3.2.

On the contrary, an additional day above 27°C increases hospitalization cases by 29.6 per 100,000, equivalent to 0.86% of the average annual hospitalization rate. Including a linear time trend allowed to vary at the municipality level yields almost indistinguishable point estimates from the baseline specification, as reported in column (3). Columns (Mountain) and (Sea-Level) explore differences by elevation, by estimating equation (3.1) separately by municipalities located above and below 1000m. Hospitalization rates increase with temperature at both groups of municipalities, with no statistical difference between them for the common temperatures (p-value for F-test of difference 0.20 and 0.22 for temperature bin 21-23°C and 25-27°C respectively).

For reference, these findings are consistent with those in [10] and [11], though not strictly comparable for reasons such as the frequency of the data used. At the temperature ranges observed both in the U.S, Germany and in Colombia, both papers find an increasing relationship between hospital usage and temperature.

Emergency room (ER) visits exhibit an imprecisely estimated U-shape in temperature as observed in panel (b) in figure 3.2 and column (2) in table 3.3. However, alternative specifications using log of ER rate per 100,000 and separately by elevation group, reveal that this morbidity risk is higher at the end points of the temperature distribution especially in the hot part (columns (Log) and (Sea-Level) in table 3.3). Particularly, an additional day above 27°C with respect to a day in the reference category 23-25°C increases ER visits rate by 0.6%. Procedures rate per 100,000 also increase with an additional day above 27°C, consistently across specifications as shown in panel (d) in figure 3.2 and table 3.5.

Consultation rate to health services decline with temperature, though imprecisely estimated at conventional levels. Panel (c) in figure 3.2 shows that exchanging a day in the reference bin 23-25°C for a single day below 17°C leads to an increase of 529.7 consults per 100,000. This impact correspond to 0.26% as compared to the mean annual consultation rate of 196,389.7 per 100,000 reported in the preferred specification in column (2) in table 3.4. The effect becomes smaller for temperatures closer to the reference bin, and some significant at conventional levels. Separating the analysis by elevation shows that in both sets of municipalities the relationship in temperature is decreasing. For example, an additional day in temperature bin of less than 21°C relative to a day in 23-25°C in sea level municipalities increase consultations per 100,000 inhabitants by 413.6 (0.27%) as shown in column (5) in table 3.4.

Taken together these results indicate that a day with average temperature over 27°C, relative to a 23-25°C day, increases hospitalizations, emergency room visits and procedures rates, whereas higher consultation rates seem to be associated with additional days in 'colder' temperatures relative to 23-25°C. The section that follows, explores heterogeneity by disease in these relationships to provide further insights on the mechanisms at work.

3.5.2 By Disease

To explore the potential mechanisms that drive the temperature-morbidity relationship described in the previous section, in this I separate the analysis by disease type. I estimate equation (3.1) for 19 patient's principal diagnoses classified according to ICD-10 that explain almost 95% of hospitalizations and ER visits, 80% of consultations and 64% of procedures.[17]

Figure 3.3 summarizes the results for each of the four outcomes considered: (a) Hospitalization, (b) Emergencies, (c) Consultations and, (d) Procedures rates. Each panel plots the coefficients associated to each temperature bin for all 19 disease categories. For exposition purposes confidence intervals are not presented, but the full set of estimates

[17] I only use 19 out of the 21 described in table 3.1 because I merge injuries and trauma with external factors, given the low incidence of the latter. According to (ICD-10)-WHO category 'Factors influencing health status and contact with health services' should not be used for international comparisons.

are displayed in Appendix B tables B.1, B.2, B.3, and B.4 respectively. Additionally, each plot highlights different disease categories with colors and markers that shed light on the most relevant diseases that react to temperature. Light grey lines represent the rest of diseases and diagnoses. Most of the highlighted categories coincide throughout the four different outcomes, namely, infectious, pregnancy-related, circulatory, and respiratory among the biological reasons for seeking care, and external factors including injuries and trauma.

Panel (a) in figure 3.3 shows that the increasing relationship between hospitalization rates and temperature previously documented, is in general terms common across all categories. However, increased hospitalizations due to infectious diseases, pregnancies, respiratory, circulatory, and genitourinary, as well as external factors mainly explain this result. Together these categories comprise approximately 66% of the reasons for hospitalizations. Infectious diseases present the highest effects relative to average hospitalization rates in this category, though not the biggest point estimates as depicted in the figure. Particularly, an additional day above 27°C with respect to a day in the reference category 23-25°C increases hospitalization rates caused by infectious diseases by 1.7 cases per 100,000, equivalent to 1.1% of the average annual rate of 165.8. An additional day on the 'coldest' temperature bin reduces hospitalizations by 2.3 per 100,000 (1.4%), tracing an increasing relationship throughout the temperature distribution. All point estimates are significant at conventional levels.

Within the infectious category, hospitalizations due to (i) intestinal infectious diseases (cholera, typhoid, amoebiasis, gastroenteritis, etc.), (ii) arthropod-borne viral fevers such as dengue, zika, yellow fever, or ebola, (iii) protozoal diseases like malaria, or leishmaniasis, and (iv) skin and other viral infections including varicella, smallpox, measles, mumps, mononucleosis or coronavirus infection (pre COVID-19), mainly explain the increasing relationship in temperature. Panel (a) in figure 3.4 shows estimates for 19 of the sub-categories comprised in the infectious disease group, highlighting the ones with the biggest effects. The mentioned sub-categories explain around 72% of total cases attributed to infectious diseases. In relative terms the biggest effects come from diseases such as malaria, but point estimates are bigger for intestinal and arthropod-borne.

Emergencies, procedures and consultation rates within the infectious disease category also increase with temperature in the sub-categories of arthropod-borne, viral infections such as mumps or mononucleosis, and protozoal diseases like malaria, or leishmaniasis (panels (b), (c) and (d) 3.4). Together with increased hospitalization rates, these results are consistent with findings in the epidemiological literature that suggest that higher than average temperature shocks aid in the replication of microbes causing human diseases, and subsequently increase viral transmission. For example, [16] show that dengue incidence increased succeeding higher temperatures in Singapore. Tropical environments tend to be more hospitable to human diseases, given the absence of winter temperatures ([15]), partly explaining why these findings depart from the evidence in the economics literature that mainly focuses on countries located in the temperate region ([10] and [11]).

Hospitalizations and procedures rate due to circulatory and respiratory illness, exhibit the same pattern though relative effects are somewhat smaller than for infectious diseases (panels (a) and (d) in figure 3.3). For the two categories, exchanging a day in the reference bin 23-25°C for an additional day in the hottest temperature bin increases hospitalizations by 0.9%. Hospitalizations and emergency room visits consequence of external causes, mainly injuries and trauma, also monotonically increase in temperature with relative effects similar to those described for circulatory and respiratory diseases. [10] finds that emergency room visits due to injuries increase after hot temperature shocks, also consistent with the literature that suggests that warmer conditions might encourage individuals to engage in outdoor activities such as swimming and driving increasing the likelihood of accidents, as well as increased conflicts that result in higher mortality ([17],

[20]).

So far, these findings support the temperature-mortality analysis previously described for Colombia in Chapter 2 of this dissertation. I show that mortality risks are higher at the end points of the narrow temperature distribution observed in Colombia. Deaths attributed to infectious diseases and respiratory illnesses drive the relationship in the hot part of the distribution, affecting children aged 0-5 primarily. Moreover, I show that mortality not only reacts to unusually hot days contemporaneously, but peak after an exposure window of seven months before stabilizing at that level, suggesting no evidence of a 'harvesting' effect after hot temperature shocks as has been documented in other contexts [17]. The use of annual morbidity data in this paper and aggregated daily temperature, should be sufficient to capture the full dynamic relationship between access to health care and temperature [4].

Further analysis for other diagnoses helps uncover additional risks that not necessarily result in death. Hospitalizations related to pregnancy and childbirth also increase in temperature across the entire distribution. An additional day in the 'coldest' temperature bin relative to a warmer day of 23-25°C decreases pregnancy hospitalizations by 1.4%, while a hotter day increases them by 0.73%. To address the concern that deliveries and childbirth hospitalizations would have happened regardless of weather shocks, I separately estimate equation (3.1) by sub-categories within pregnancy and childbirth. Panel (a) in figure 3.5 plots temperature estimates for the eight sub-categories (full set of results in tables B.11, B.12, B.13, and B.14 in Appendix B). Deliveries account for approximately 30% of hospitalizations and other access to health care, followed by maternal care related to fetus and amniotic cavity that include damages to fetus from viral diseases experienced by the mother, from drugs and alcohol use, and poor fetal growth, hypoxia or false labor (fetus hereafter); as well as other maternal disorders like genitourinary infections, diabetes mellitus and malnutrition that together account for approximately

36% of hospitalizations and 53% of emergencies respectively (B.10 in appendix). Both fetus and other maternal disorders exhibit the largest relative effects after an additional day in the hottest temperature bin relative to a day in 23-25°C, of approximately 1.2% and 1.5% respectively.

These results are echoed in the other pregnancy-related morbidity outcomes: emergency room visits, consultations and procedures. The biggest effects (point-estimates and in relative terms) on emergency room visits comes from women seeking maternal care related to fetus, and other maternal disorders (panel (b) in figure 3.5). Similar results replicate for these two sub-categories in the temperature-consultation rate and temperature-procedures rate (panels (c) and (d) in figure 3.5). Finally, pregnancies with abortive outcomes, either planned or unplanned, also exhibit increasing relationships in temperature in all of the four morbidity outcomes. These contribute to around 11% diagnosis within the pregnancy and childbirth category. Together the results for pregnancy and childbirth category indicate that maternal and likely fetal health are compromised after hot temperature shocks, regardless of the morbidity measure used. Most of the literature on the effects of extreme heat on pregnancy outcomes focus on birth outcomes, almost neglecting maternal health to the exception of [13]. They also find that extreme heat increases the likelihood that a woman is hospitalized during pregnancy in three U.S. states: Arizona, New York and Washington.

Overall estimates for emergencies, consultation and procedures rates are less precise, but provide further insights on the specific diagnoses reacting to changes in temperature. Unlike hospitalizations, there is heterogeneity in responses to temperature among certain diseases and sub-categories.This is especially true for emergency room visits, where a non-precise U-shape relationship between temperature and this morbidity risk is traced across the temperature distribution observed in Colombia. As previously described, the effects on the hottest side of the distribution are mainly explained by pregnancy-related, and infectious diseases with relative effects of 0.32%, 0.28% respectively. However, some other diseases, including respiratory and musculoskeletal related, react to additional days in the colder side of the temperature distribution (Panel (b) in figure 3.3).

Exchanging a day in the reference bin 23-25°C for a day below 17°C increases not only ER visits but consultations related to musculoskeletal diseases, including arthritis, by 1.13% and 0.33% respectively. The medical literature provides some suggestive evidence that rheumatoid arthritis patients show weather sensitivity, including experiencing higher pain during cold days [31]. Visits to the the emergency room due to respiratory illness also increase by 0.64% during colder days, as has been documented in other contexts [10]. It is worth noting, however, the much 'milder' temperatures at which these effects arise as compared to those documented in the U.S. (additional days below 4.4°C).

Despite these effects on the cold side of the distribution, overall, additional days in hotter temperature bins translate into more usage and demand of health services. Increased access due to infectious diseases and pregnancy-related care mainly explain these results, suggesting an important effect for children and women. Though access to services are not available by age, analyses using mortality data indicate that children are more prone to infectious diseases (Chapter 2 Into the tropics: Temperature and Mortality in Colombia).

3.6 Costs and Implications for Climate Change

This section estimates the potential effects of climate change based on how Colombia's temperature distribution has changed over the past years, and assuming no further adaptation measures are undertaken. Figure 3.6 displays how the full distribution of daily mean temperature behaved over two different time periods. The dark bars represent the average number of days in each temperature bin that the average person experienced over the period 1985-2008. The light grey bars show how the average temperature distribution between 2009 and 2016. The light pink bars report the change in the number of days experienced between the two time periods. The most important changes in the distribution were observed at mild temperatures, rather than at the extremes. For example, the data shows that the typical person experienced 38.2 additional days in temperature bin 19-21°C over the latter period relative to the previous 20 years. The average number of days above 27°C also increased, though to a lesser extent: 18.7 days.

Assuming these trends in temperature will be maintained over the next years and the distribution will continue to shift at the pace observed, I estimate the the potential effect of climate change on morbidity outcomes, particularly on hospitalization rates. I multiply the observed change in the number of days in a given temperature bin by the corresponding estimate in column (2) in table 3.2 ($\hat{\beta}_j$), then sum across these products as follows:

$$\Delta HospitalizationRate = \sum_{j=1}^{6} \hat{\beta}_j \times \Delta DaysBinTemp_j \tag{3.2}$$

where $\Delta HospitalizationRate$ denotes the change in annual hospitalization rate and $\Delta DaysBinTemp_j$ the change in number of days in each temperature bin from the periods: 1985-2008 and 2009-2016. I find that this shift in the temperature distribution results in 1322.1 additional hospitalizations per 100,000 inhabitants per year.[18]. Compared to an average annual rate of 3458.87, this effect implies an increase of 38.2%. Using the more conservative estimates of column (3) in table 3.2, the shift in temperature distribution implies an increase of 1161.3 hospitalizations per 100,000 per year (33.6%).

[18]Standard errors under construction

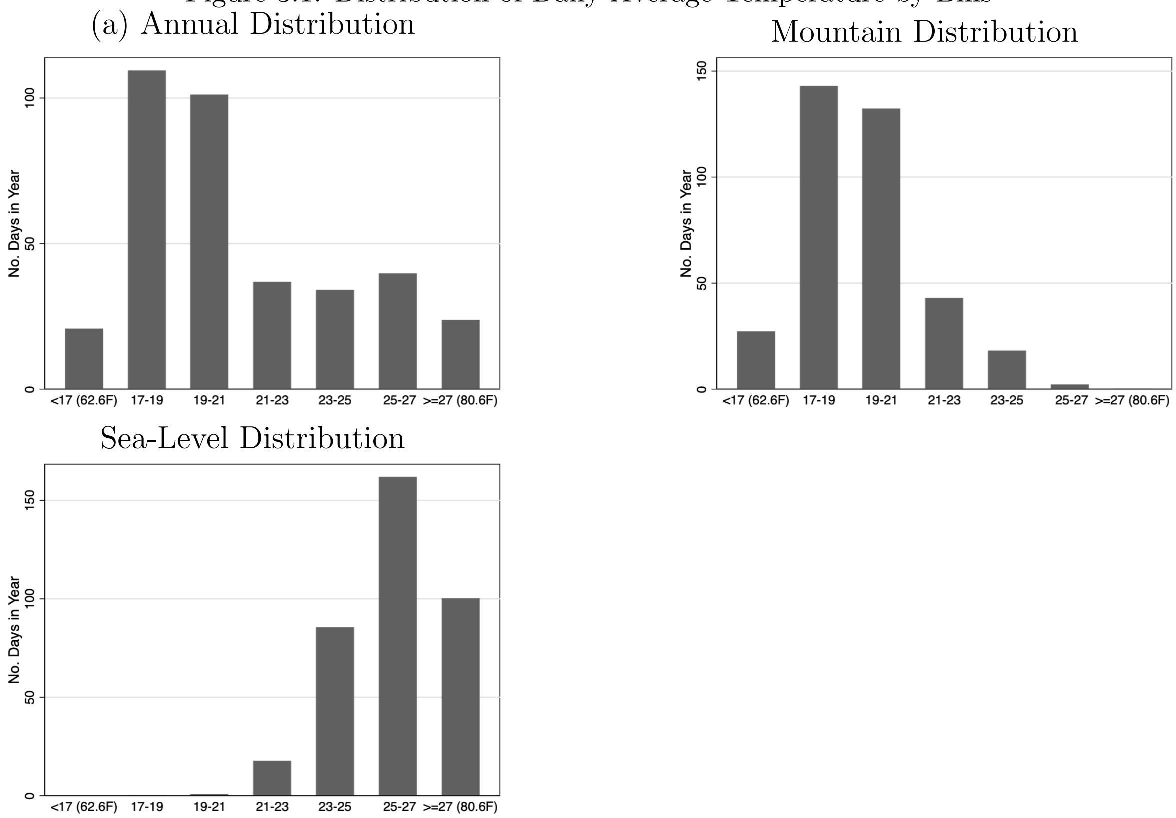
3.7 Discussion

This paper provides evidence on how health services usage increase after the occurrence of hot temperature shocks. Using detailed information on four morbidity outcomes for over 1000 Colombian municipalities, I find that hospitalization rates monotonically increase with temperature. Exchanging a day in the reference bin 23-25°C for a single day above 27°C increases hospitalization cases by 29.6 per 100,000, equivalent to 0.86% of the average annual hospitalization rate, whereas an additional day below 17°C leads to a decrease of 21.7 hospitalizations per 100,000 (0.63%).

Infectious diseases and maternal-related care mainly explain these results. Digging further within each of these two sub-categories reveals that not only hospitalizations, but other morbidity outcomes such as emergency room visits, and consultations also increase with temperature. Vector-borne diseases (e.g. dengue, zika, yellow fever, or malaria) and certain viral infections within the infectious disease category lead individuals to seek care. Maternal care related to fetus health, as well as maternal disorders like genitourinary infections, diabetes mellitus and malnutrition, rather than delivery, mainly explain increases in morbidity outcomes by women. These results shed light on the populations that may be more at risk after experiencing changes in temperature, namely children, fetus in utero, and women.

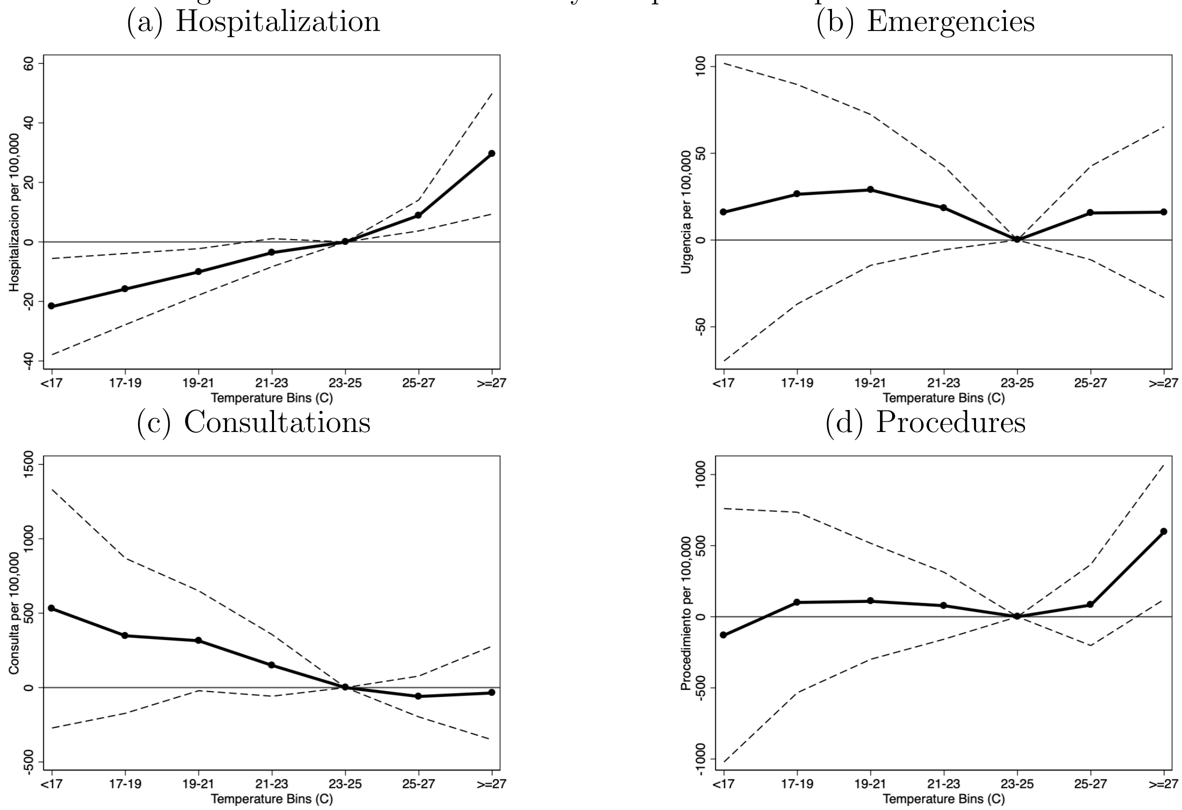
Assuming temperatures will continue to rise in upcoming years as has been recently observed in Colombia, and that no further adaptation measures are undertaken, I link estimates associated to weather variations to the potential costs of climate change. I find that a shift in the temperature distribution in upcoming years result in 1,161.3 additional hospitalizations per 100,000 inhabitants per year (33.6% of the average annual rate of 3458.87). These results suggest an important increase in demand for health services as temperatures continue to rise, but they also shed light on the importance on access to mitigate the adverse effects. In future work, I will translate these estimates to money terms by using data on the costs of hospital usage and determine the financial burden on the health system. Moreover, I will further investigate the role of health care access in mitigating the negative effects associated to rising temperatures.

Figure 3.1: Distribution of Daily Average Temperature by Bins



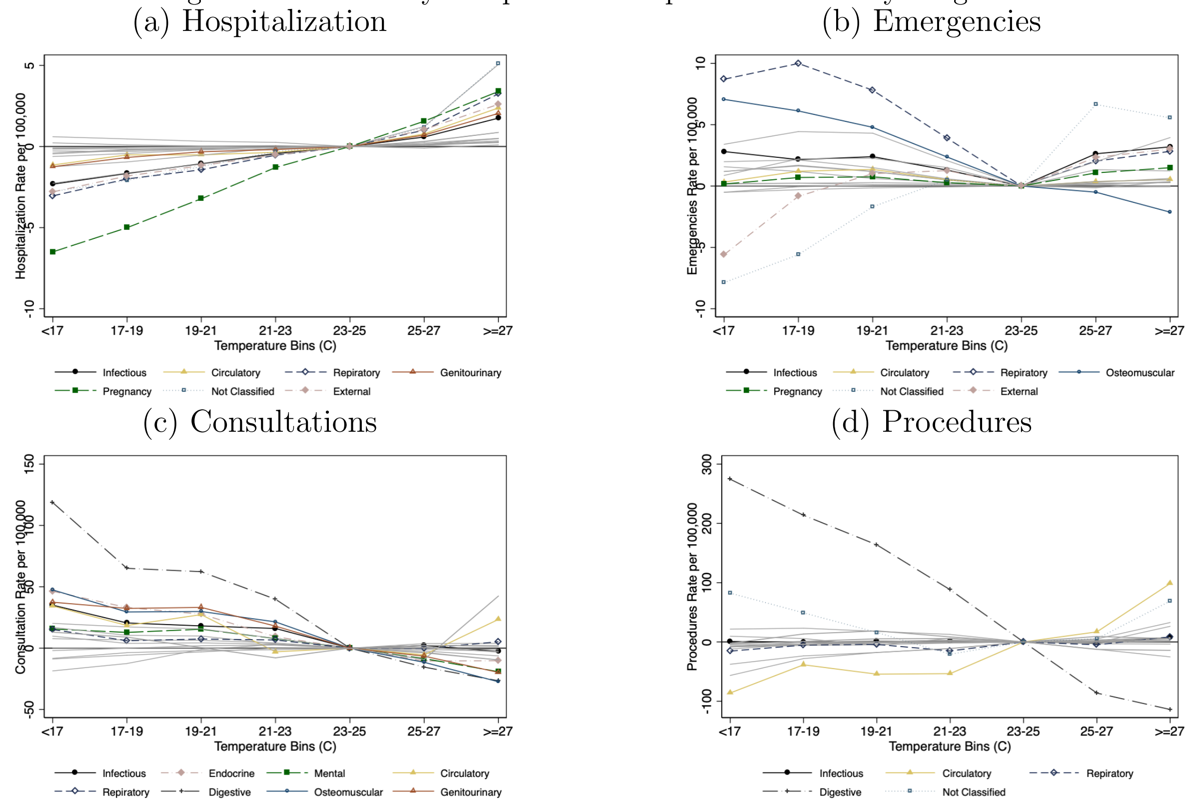
Notes: Panel (a) shows the annual temperature distribution across seven 2°C temperature bins. Observations are weighted by total population in the municipality in the respective year, so that the bars represent the number of days per year in each bin that an average person experiences. Panel (b) presents the average annual temperature distribution for municipalities located in the mountanous area above 1000m. Panel (c) depicts the distribution for municipalities at lower elevations, below 1000m.

Figure 3.2: Estimated Morbidity-Temperature Response Function



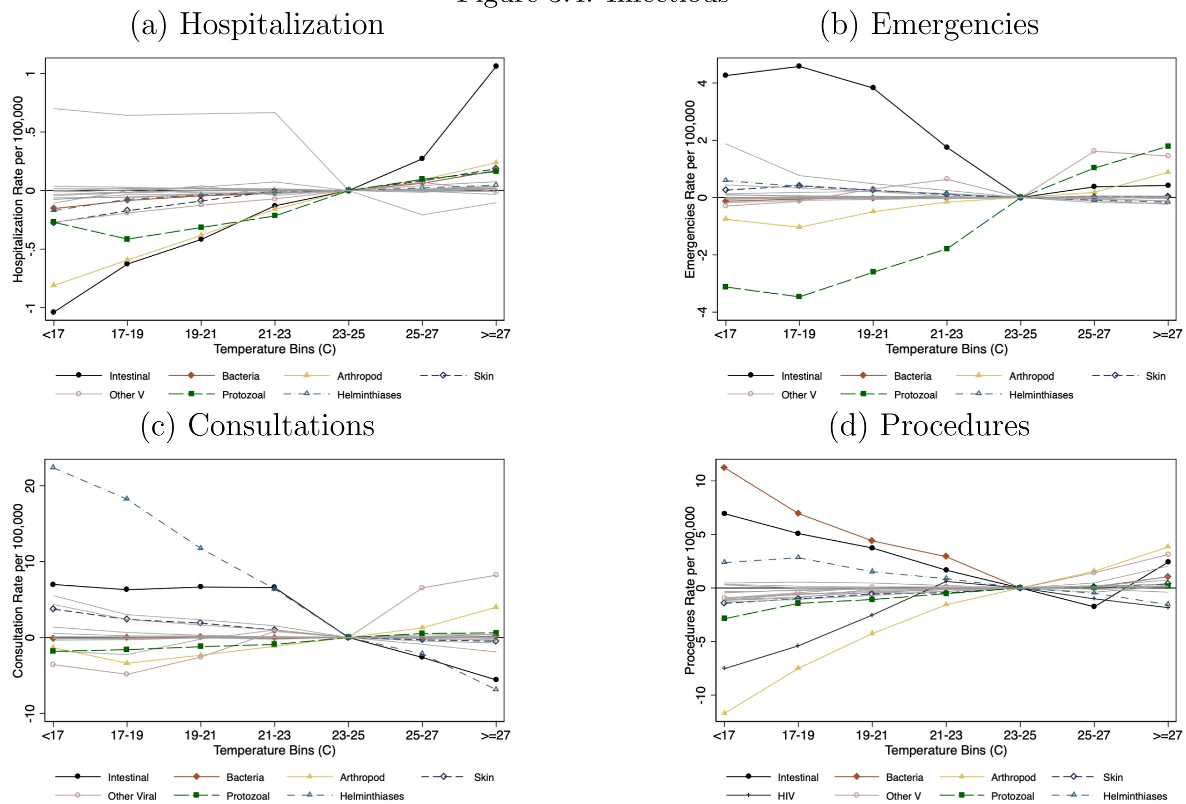
Notes: Each panel plots the response function between an annual morbidity rate outcome (per 100,000) and temperature. Equation (3.1) is fitted separetely for Consultation, Hospitalization, Procedure and Emergencie Rate respectively. Dahsed lines represent 95% confidence intervals. Standard errors clustered at the municipality. Regressions control for precipitation, municipality and department-by-year fixed effects. Estimates weighted by population in each municipality.

Figure 3.3: Morbidity-Temperature Response Function by Diagnosis



Notes: Annual morbidity rate outcome (per 100,000) and temperature. Equation (3.1) fitted separately for Consultation, Hospitalization, Procedure and Emergencies Rate respectively by diagnosis. Standard errors clustered at the municipality. Regressions control for precipitation, municipality and department-by-year fixed effects. Estimates weighted by population in each municipality.

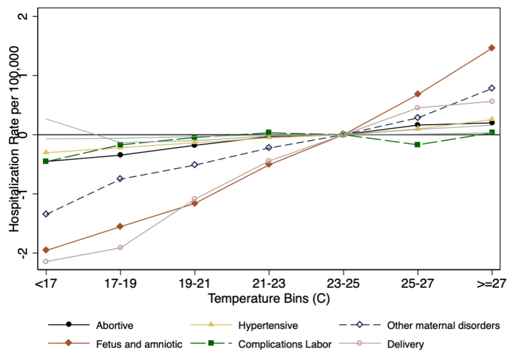
Figure 3.4: Infectious



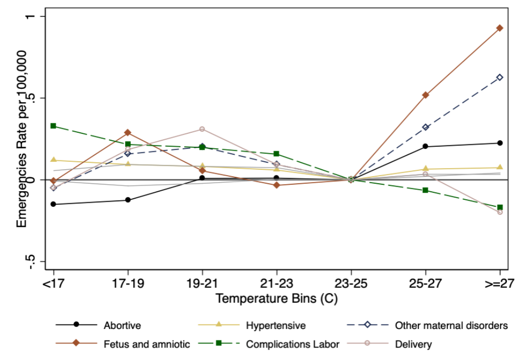
Notes: annual morbidity rate outcome (per 100,000) and temperature. Equation (3.1) is fitted separately for Consultation, Hospitalization, Procedure and Emergencies Rate respectively by diagnosis. Standard errors clustered at the municipality. Regressions control for precipitation, municipality and department-by-year fixed effects. Estimates weighted by population in each municipality.

Figure 3.5: Pregnancy and Child Birth

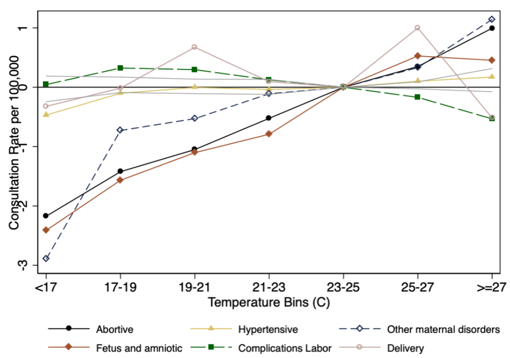
(a) Hospitalization



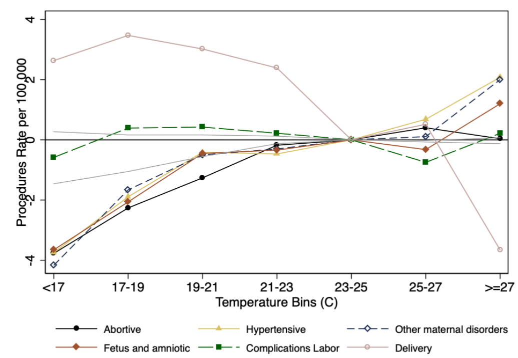
(b) Emergencies



(c) Consultations

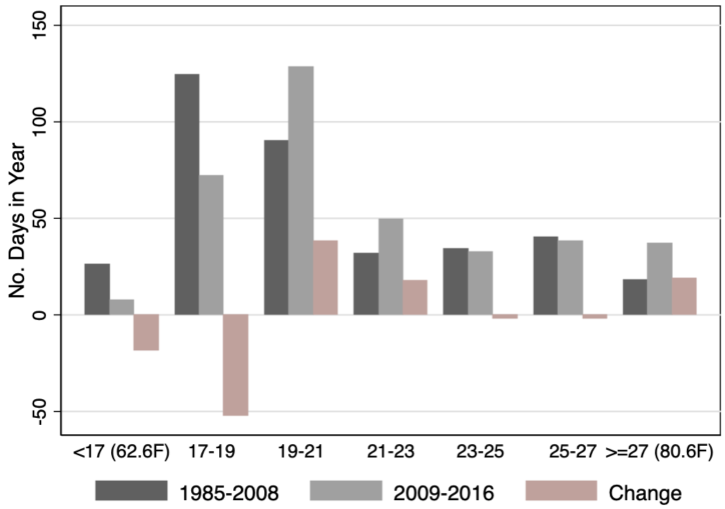


Procedures



Notes: annual morbidity rate outcome (per 100,000) and temperature. Equation (3.1) is fitted separately for Consultation, Hospitalization, Procedure and Emergencies Rate respectively by diagnosis. Standard errors clustered at the municipality. Regressions control for precipitation, municipality and department-by-year fixed effects. Estimates weighted by population in each municipality.

Figure 3.6: Annual Temperature distribution 1985-2008 and 2009-2016



Notes: Average number of days per year in each temperature bin for two time periods: 1985-2008 and 2009-2016. Averages are weighted by population in a municipality-year. Change defined as the difference in the average number of days in 2009-2016 and 1985-2008 in each temperature bin.

Table 3.1: Total and Share of Diagnosis by Type of Service

	Share			
	Consultation	Procedures	Emergencies	Hospitalization
Infectious Diseases	4.80	2.22	10.54	4.70
Neoplasms	1.44	2.03	0.64	4.92
Blood	0.53	0.49	0.35	0.71
Endocrine and Nutritional	5.01	3.88	1.01	1.87
Mental	1.62	1.31	0.79	2.44
Nervous	2.15	1.43	2.38	1.51
Eye	3.18	1.01	0.98	0.77
Ear	1.52	0.73	2.08	0.63
Cardiovascular Diseases	8.92	7.23	2.79	6.05
Respiratory Diseases	7.49	3.89	14.81	10.55
Digestive	12.92	11.27	5.13	6.93
Skin	2.83	0.99	2.98	3.29
Osteomuscular	7.18	4.60	5.81	3.04
Genitourinary	6.32	4.63	6.19	7.48
Pregnancy	0.91	1.66	4.36	13.40
Perinatal	0.19	0.35	0.24	2.14
Malformations	0.50	0.40	0.07	0.58
Not Classified	9.69	12.29	22.53	14.71
Injuries Trauma	3.38	3.04	10.81	8.12
External Factores	0.37	0.36	0.75	0.65
Factors	19.02	36.20	4.76	5.53
Total Cases (Millions)	725.4	542.0	38.4	12.8

Notes: Total cases per type of service over the period 2009-2016. Each column Specific causes of death classified according to ICD-10 WHO.

Table 3.2: Hospitalization

	Rate per 100,000					
	(1)	(2)	(3)	(Log)	(Mountain)	(Sea-Level)
Base: $\in$ [23C,25C) [73F,77F)						
Temperature < 17	39.071***	-21.721**	-16.347*	-0.010**	-19.327**	
	(7.604)	(8.248)	(9.734)	(0.004)	(7.456)	
Temperature $\in$ [17,19)	28.715***	-15.845**	-16.169**	-0.008**	-14.843**	
	(5.322)	(6.099)	(7.643)	(0.003)	(5.648)	
Temperature $\in$ [19,21)	18.394***	-10.073**	-9.649*	-0.005**	-10.604**	
	(4.488)	(3.984)	(5.532)	(0.002)	(3.720)	
Temperature $\in$ [21,23)	7.992**	-3.605	-5.248	-0.001	-6.165**	10.416
	(2.553)	(2.399)	(3.711)	(0.001)	(2.248)	(13.187)
Temperature $\in$ [25,27)	0.712	8.905***	12.187**	0.002*	6.469**	15.549**
	(2.898)	(2.654)	(5.133)	(0.001)	(2.838)	(6.950)
Temperature ≥ 27	5.388	29.641**	26.491**	0.009***		37.904**
	(6.329)	(10.344)	(9.516)	(0.002)		(18.839)
Observations	8,344	8,343	8,343	8,343	6,334	1,985
Mean Rate		3458.87			3619.95	2926.52
SD Rate		2091.85			1900.26	2547.1
Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes					
Department $\times$ Year FE	No	Yes	Yes	Yes	Yes	Yes
Linear Municip. Trend	No	No	Yes	No	No	No

Notes: ***p-value < 0.001, **p-value < 0.01, *p-value < 0.05. Each column reports point estimates for temperature variables on variations of the baseline specification described in equation (3.1) and presented in column (2). Column (1) only allows for municipality and year fixed effects. Column (3) adds a linear time trend that varies by municipality to column (2). Column (4) uses log morbidity rate as dependent variable. Columns (Mountain) and (Sea-Level) estimates equation (3.1) separately municipalities located above and below 1000m. All regressions control for precipitation and weighted by population. Standard errors clustered at the municipality level reported in parenthesis.

Table 3.3: Emergencies

	Rate per 100,000					
	(1)	(2)	(3)	(Log)	(Mountain)	(Sea-Level)
Base: $\in$ [23C,25C) [73F,77F)						
Temperature < 17	64.753*	16.062	52.247	0.001	46.151	
	(36.988)	(43.754)	(41.340)	(0.004)	(58.878)	
Temperature $\in$ [17,19)	58.479**	26.379	34.929	0.003	52.065	
	(24.443)	(32.260)	(30.328)	(0.003)	(44.098)	
Temperature $\in$ [19,21)	40.801**	28.886	33.633	0.003	47.057	
	(16.655)	(22.174)	(21.351)	(0.002)	(29.850)	
Temperature $\in$ [21,23)	20.325*	18.477	13.181	0.001	29.250*	21.045
	(11.651)	(12.279)	(13.624)	(0.001)	(15.438)	(30.386)
Temperature $\in$ [25,27)	17.617	15.600	8.748	0.004**	1.402	39.621**
	(13.090)	(13.767)	(16.920)	(0.002)	(31.054)	(17.684)
Temperature ≥ 27	43.830**	16.073	10.172	0.006**		59.623*
	(18.331)	(25.112)	(29.661)	(0.002)		(33.085)
Observations	8,347	8,345	8,345	8,345	6,338	1,983
Mean Rate		10459.31			10258.27	10788.74
SD Rate		9182.940000000001			8990.74	9685.790000000001
Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes					
Department $\times$ Year FE	No	Yes	Yes	Yes	Yes	Yes
Linear Municip. Trend	No	No	Yes	No	No	No

Notes: ***p-value $<$ 0.001, **p-value $<$ 0.01, *p-value $<$ 0.05. Each column reports point estimates for temperature variables on variations of the baseline specification described in equation (3.1) and presented in column (2). Column (1) only allows for municipality and year fixed effects. Column (3) adds a linear time trend that varies by municipality to column (2). Column (4) uses log morbidity rate as dependent variable. Columns (Mountain) and (Sea-Level) estimates equation (3.1) separately municipalities located above and below 1000m. All regressions control for precipitation and weighted by population. Standard errors clustered at the municipality level reported in parenthesis.

Table 3.4: Consultation

	Rate per 100,000					
	(1)	(2)	(3)	(Log)	(Mountain)	(Sea-Level)
Base: $\in$ [23C,25C) [73F,77F)						
Temperature $<$ 17	2083.743***	529.715	1010.717**	-0.001	434.271	
	(495.926)	(408.839)	(429.513)	(0.002)	(511.346)	
Temperature $\in$ [17,19)	1230.002***	348.242	307.662	-0.000	280.233	
	(259.404)	(265.865)	(266.057)	(0.002)	(357.978)	
Temperature $\in$ [19,21)	665.846***	314.684*	180.036	-0.000	256.517	
	(171.898)	(171.219)	(183.592)	(0.001)	(237.256)	
Temperature $\in$ [21,23)	390.584***	149.128	4.447	-0.000	67.914	413.637**
	(114.281)	(105.639)	(126.150)	(0.001)	(145.592)	(170.572)
Temperature $\in$ [25,27)	-105.991	-59.892	-84.700	0.000	-60.466	-16.618
	(88.913)	(70.011)	(128.950)	(0.001)	(106.049)	(114.530)
Temperature $\geq$ 27	27.368	-36.256	31.009	0.002		-66.201
	(183.128)	(160.569)	(246.860)	(0.001)		(236.623)
Observations	8,382	8,382	8,382	8,382	6,352	2,006
Mean Rate		196389.71			209184.61	154872.49
SD Rate		103028.72			103753.32	90085.89
Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes					
Department $\times$ Year FE	No	Yes	Yes	Yes	Yes	Yes
Linear Municip. Trend	No	No	Yes	No	No	No

Notes: ***p-value $<$ 0.001, **p-value $<$ 0.01, *p-value $<$ 0.05. Each column reports point estimates for temperature variables on variations of the baseline specification described in equation (3.1) and presented in column (2). Column (1) only allows for municipality and year fixed effects. Column (3) adds a linear time trend that varies by municipality to column (2). Column (4) uses log morbidity rate as dependent variable. Columns (Mountain) and (Sea-Level) estimates equation (3.1) separately municipalities located above and below 1000m. All regressions control for precipitation and weighted by population. Standard errors clustered at the municipality level reported in parenthesis.

Table 3.5: Procedures

	Rate per 100,000					
	(1)	(2)	(3)	(Log)	(Mountain)	(Sea-Level)
Base: $\in$ **[23C,25C) [73F,77F)**						
Temperature < 17	989.985**	-130.276	31.228	-0.002	175.874	
	(428.334)	(454.437)	(396.995)	(0.004)	(483.585)	
Temperature $\in$ [17,19)	599.088*	100.408	-0.041	0.001	310.869	
	(309.469)	(323.643)	(285.476)	(0.003)	(337.672)	
Temperature $\in$ [19,21)	489.391**	108.610	84.609	-0.000	237.934	
	(212.107)	(208.104)	(192.712)	(0.002)	(224.587)	
Temperature $\in$ [21,23)	382.024**	77.501	118.368	0.000	140.962	-143.055
	(150.679)	(120.004)	(115.795)	(0.001)	(139.546)	(301.248)
Temperature $\in$ [25,27)	40.972	82.345	78.912	0.000	17.144	5.985
	(158.590)	(145.430)	(152.698)	(0.001)	(235.825)	(244.897)
Temperature ≥ 27	1051.626***	596.458**	572.116*	0.005**		296.046
	(245.897)	(242.216)	(294.709)	(0.002)		(401.358)
Observations	8,370	8,370	8,370	8,370	6,352	1,994
Mean Rate		147078.97			155511.50	121821.04
SD Rate		104005.92			103032.7	104746.68
Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes					
Department $\times$ Year FE	No	Yes	Yes	Yes	Yes	Yes
Linear Municip. Trend	No	No	Yes	No	No	No

Notes: ***p-value < 0.001, **p-value < 0.01, *p-value < 0.05. Each column reports point estimates for temperature variables on variations of the baseline specification described in equation (3.1) and presented in column (2). Column (1) only allows for municipality and year fixed effects. Column (3) adds a linear time trend that varies by municipality to column (2). Column (4) uses log morbidity rate as dependent variable. Columns (Mountain) and (Sea-Level) estimates equation (3.1) separately municipalities located above and below 1000m. All regressions control for precipitation and weighted by population. Standard errors clustered at the municipality level reported in parenthesis.

Chapter 4

Gender dimensions of climate change: Testing for gender-differentiated effects of weather shocks in sub-Saharan Africa

4.1 Introduction

There is a growing consensus that the changing climate will affect human health in a number of ways: through its effect on disease environment, changes in average and variability of temperature, through the prevalence of extreme weather events such as droughts, hurricines, and flood, etc. In fact, a vast strand of literature has focused on documenting the effect of exposure to extreme temperatures on health, primarily using mortality as an outcome (see [2] for a review, [7]). However, the effects of temperature shocks on alternative health outcomes that do not result in death (i.e. morbidity) and children's nutritional status have received less attention ([10], [11], [21], [32], [12]). Understanding the effect on nutritional outcomes is important because these have been linked to households's economic conditions and human capital formation in the long run ([33], [34]). Even less is known about the distributional impacts of temperature shocks, and whether certain population groups within already vulnerable areas will disproportionately bear the costs of climate change, enhancing pre-existing inequality [35].

In this paper we investigate whether variations in temperature impact children's health, and further ask if they differentially affect nutritional outcomes by gender. There are reasons to suspect that males and females might respond differently to temperature anomalies, including but not limited to, biological, cultural norms and preferences by caregivers. For instance, differences in how boys and girls are raised (henceforth socialization) may explain differential outcomes. For example, if boys participate in outdoor labor more, or more physical play, they may become more accustomed to heat exposure. Alternatively, if girls spend more time indoors, exposed to indoor air pollution, they may be more vulnerable to other shocks. While these socialization differences lead to a divergence in biophysical responses to weather shocks, they are a function of gender behavior as opposed to physical responses only. A second reason might be related to parental preferences that lead scarce resources to be differentially directed toward boys or girls. When households face income shocks, the reallocation of resources may not be symmetric. In particular, if boys are favored (based either on pure preferences or expected returns on investment), then girls may bear a disproportionate share of the costs of weather shocks. Finally, the composition of household income across parents can also lead to differential responses. If male and female caregivers have different preferences around the allocation of resources and income flows into the home are both gender differentiated and differentially vulnerable to weather shocks, then imperfect risk pooling in the home may lead to differences in the allocation of resources by child gender (and also adult gender) [36].

Using a rich dataset of individual health records from the Demographic and Health Surveys (DHS) paired with high-resolution weather outcomes at the subnational level for 21 sub-Saharan African countries, we start by showing that biophysical measures of child health are affected by weather shocks. Exploiting temperature variation within administrative units in each country, we find that weight-for-height monotonically decrease with temperature for temperatures above 20°C. Exchanging a day in the reference category 15-20°C for a single day above 35°C decreases weight-for-height by 0.013 standard deviations of the worldwide distribution, equivalent to 6% of the average score of -0.21 in our sample of children aged 12 to 60 months. Allowing for cumulative effects and the possibility that temperature shocks take time to fully translate into health outcomes, we find that weight-for-height decreases even further, by 0.018 (8.6%) after six months. Both girls and boys are negatively affected by changes in temperature, but results are stronger for girls in the extreme of the hottest part of the temperature distribution. In other temperature bins, we cannot discern any significant difference, if any boys appear to be slightly worse off.

Height-for-age, considered a longer-term measure of nutritional status, also reacts negatively to temperature shocks but only after children are exposed for more than six months. Effects are stronger for younger children aged 12 to 36 months, with girls experiencing a significant decline after additional days above 35°C. That is, most of the effect appears to be driven exclusively by girls, with a decline in height-for-age of 0.025 standard deviations (equivalent to an effect of 1.4% of the average score in the sample). Boys on the other hand, experience a non-significant at conventional levels increase of 0.006 standard deviations. On the cold extreme end of the temperature distribution, we also find that additional days below 15°C negatively affects height for both girls and boys aged 12 to 60 months, though they appear to be stronger for older children (aged 36 to

60 months).

This paper contributes to the economic analysis of health, temperature, and eventually climate change in developing countries. Most of this literature focuses on the effect of extreme heat or exposure *in-utero* on infant mortality ([37], [38], [39]). Using multiple or single country analyses, these papers find that hot days increase infant mortality, with effect sizes that are generally orders of magnitude larger in developing country contexts [37]. For rural India, [39] show that extreme heat during pregnancy increases infant mortality likely due to reduced agricultural yields, wages and disease prevalence. However, few focus on the effect of temperature on children's health through anthropometric measures, and doing so is important because nutritional status has been linked to long-term educational and labor outcomes ([40], [41], [42]). Measures of height, in particular, are considered good predictors of human capital, while weight is mostly associated to current economic conditions of households.

The literature analyzing the effects of weather shocks on children's health in the developing world focuses primarily on severe precipitation/floods and drought measures. Most of the papers document adverse effects on weight and height at birth and infancy ([43], [44], [45], [46]). An exception is [32] who explore the role of heat exposure on children's nutrition aged 3 to 36 months in five West African countries. They find that extreme heat increases the prevalence of chronic and acute malnutrition in this population group.Their focus on these West African countries is partly explained by the finding that mortality effects are more salient above a 32°C threshold, therefore they choose to focus only in this geographical area where such temperatures are observed.

Temperature shocks in other developing countries have received less attention, likely because they tend to be located in tropical latitudes. Temperature in these latitudes is often not considered a critical factor in agriculture due to the lack of seasonality, and little variation within or across years is registered [43]. However, changes in temperature affect not only agricultural yields but the prevalence of diseases that can impact health directly ([15], [16]). Chapters 2 and 3 of this disseration provide evidence that even small changes in temperature in Colombia, a tropical country closely located to the Equator, affect human mortality and morbidity. Also using data from Colombia, [47] find, as in [12], that exposure to heat waves during the third trimester of pregnancy reduces weight at birth. Most of the papers reviewed so far focus on the broad effects on children, with either no heterogeneous analysis by gender or without any noticeable difference between boys and girls. This paper extends the analysis to a broad set of countries in an understudied region, focusing on the effect of temperature and gender differences.

Gender-differentiated effects of weather shocks have been found in the context of sub-Saharan Africa and South East Asia, but after the occurrence of higher than average rainfall or droughts. [34] find that exposure to higher than average rainfall during the first year of life improves women well being in adulthood in Indonesia. They are less likely to self-report poor health, more likely to be taller, and achieve higher educational levels. [48] find that drought shocks increase the probability of child marriage and early fertility in sub-Saharan Africa, especially in countries where the majority of the population belongs to ethnic groups that traditionally make bride price payments at marriage instead of dowry. This paper finds that temperature shocks are also important in shaping the health response functions by gender. With further analysis on the mechanisms underlying the preliminary results of gender differences in this paper, we also hope to contribute to a thin literature examining the distributional impacts of weather shocks [35].

The paper proceeds as follows. Section 4.2 describes the data sources, and some descriptive statistics. Section 4.3 outlines the econometric models used to estimate the temperature-health response function, and differentiated impacts by gender. Section 4.4 discusses the main findings. Section 4.5 discusses the results and future analysis.

4.2 Data

This section describes the two main sources of data used for the analysis, namely Demographic and Health Surveys (DHS) for 21 Sub-Saharan African countries and weather from the Global Meteorological Forcing Dataset for land surface modeling (GMFD v3).

Health Outcomes: Data on children and women health comes from the DHS, which are nationally representative household surveys carried out in a myriad of low and middle income countries since the 1980s. We use all publicly available data from IPUMS-DHS for 71 surveys across 21 sub-Saharan African countries with at least two surveys between 1990 and 2016.[1] The sample contains only surveys for which geographical coordinates of the primary sampling unit (group of villages or urban neighborhoods usually referred to as clusters) are available, because this will allow us to combine individual outcomes with weather data at the subnational level.

DHS interviews women of childbearing age (usually 15 to 49 years), and collects information on weight and height for children under five. Followig the norm in the literature we use z-scores to approximate health status of children ([33], [43], [49]). We use two main outcomes for children's health: (i) weight-for-height z-score (WHZ), and (ii) height-for-age z-score (HAZ). Weight-for-*height* z-score compares the child's weight to the median weight of a reference population of the same *height* and sex, expressing the difference in terms of standard deviations from the reference population's distribution. Height-for-*age* z-score compares the child's height to the median height of a reference population with the same *age*. The reference population distribution corresponds to that constructed by the World Health Organization (WHO) based on a sample of infants and children across the world, with no known illness or socioeconomic constraints on growth

[1] Countries and number of surveys include Benin (3), Burundi (2), Cameroon (3), Congo (2), Ethiopia (4), Ghana (5), Guinea (3), Ivory Coast (3), Kenya (3), Madagascar (2), Malawi (4), Mali (4), Niger (2), Nigeria (4), Rwanda (3), Senegal (7), Zimbabwe (4), Uganda (4), Tanzania (3), Burkina Faso (4), Zambia (2).

[49].[2]

The outcome measures selected for the analysis capture two different dimensions of health. WHZ summarizes current nutritional status and is often considered as health investment flow. Low weight-for-height (wasting or thinness) indicates in most cases a recent and severe process of weight loss, often associated with acute starvation and/or severe disease. Wasting may also be the result of a chronic unfavorable condition [49]. HAZ better captures long term nutritional status (e.g. health stock), and has been linked to long-term outcomes. Low height-for-age reflect (stunted growth) reflects a process of failure to reach linear growth potential as a result of suboptimal health and/or nutritional conditions [49].

Table 4.1 presents summary statistics for the approximately 380,000 children aged 0 to 5 years in the sample, and separately by different age groups and gender. To interpret z-scores, consider that 2 standard deviations below the median for the reference population are associated with severe acute malnutrition for WHZ and stunting for HAZ. A z-score of zero represents the median for the global reference population. In our sub-Saharan African sample children are below the median both in WHZ and HAZ, with an average of -0.27 and -1.49 standard deviations respectively. Separating the analysis by gender, reveals that for the entire sample girls are closer to the mean of the reference population than boys. The first row in panel (A) shows that on average, boys are 0.3 standard deviations under weight of the reference mean, while girls are 0.26 below. These differences between girls and boys appear consistent with what [43] document for Nigeria.

Younger children aged 12 to 24 months are further from the mean of the global reference population in terms of WHZ. Boys are 0.5 standard deviations below the mean, while girls are 0.4 standard deviations below the mean. However, this gap of 0.1 standard

[2] As a robustness check we also consider Weight-for-*age* z-score, similarly defined as the other two outcome variables.

deviations in WHZ between boys and girls vanishes as children grow. By age group 48 to 60 months, girls are more underweight than boys, with an average WHZ of -0.27 for girls and -0.2 for boys. Panel (B) in table 4.1 shows that on average boys in the sample are 1.6 standard deviations shorter than the reference population, while girls are 1.4 standard deviations shorter. The difference is statistically significant and though it is maintained throughout age groups, it declines as age increases.

Weather Data: Temperature and precipitation are drawn from GMFD, which combines reanalysis and observational data to produce daily variables at the $0.25° \times 0.25°$ resolution. We aggregate grid cells into observations at the subnational level, weighting by a 2011 cross sectional estimate of gridded population from Landscan. The empirical analysis considers a discrete version of the monthly distribution of temperature. We classify average daily temperature in one of six 5°C temperature bins and count the number of days in a month within each one. The extreme categories include temperatures below 15°C and above 35°C. This strategy preserves the daily variation in temperature to capture non-linearities in the temperature-health relationship *a la* [4]. It is worth noting that we compute non-linearities (e.g. binning) at the grid cell level before aggregating across space to mitigate aggregation bias [50].

We use location coordinates for each DHS cluster and month-year of interview to match sample observations to weather variables corresponding to the second-order administrative division units (i.e. adm2, henceforth administrative or subnational units) where they are located.[3] While cluster locations are available at higher spatial resolution than administrative units, we cannot observe the same cluster repeatedly. Higher resolution geography (e.g. grid cells) would imply few repeated observations, generating a noisy estimate of average conditions for the population in a given location via fixed

[3]DHS clusters are usually smaller than the subnational level we are using to aggregate variables in the analysis.

effects. Administrative regions allows us to capture many more observations over time for the same population, allowing for a more precise estimate using panel methodologies.

The sample includes 2253 subnational units spread across 21 countries. Figure (4.1) presents the average number of days within each subnational unit in the sample in each temperature category. Panels (a) and (b) show that most of the days above 35°C and between 30-35°C are concentrated in the countries bordering North Africa and the tropic of cancer: Mali, Niger, Senegal, Ivory Coast, Ghana, Burkina Faso, Nigeria and Ethiopia. The rest of the countries, given their closeness to the Equator, exhibit average temperatures 20 and 30°C (panels (c) and (d)). The coldest days below 20°C are mostly located in Ethiopia and subnational units located in mountain ranges (panels (e) and (f)).

4.3 Empirical Strategy

This section presents the models used to estimate the effect of temperature on children's health and differential effects by gender, contemporaneously and allowing for cumulative dynamic effects. This will allow us to explore the possibility that health outcomes might take time to react to changes in environmental conditions.

4.3.1 Contemporaneous Effect

To quantify the contemporaneous effect of weather on children's health, we fit variants of the following specification:

$$y_{ijmt} = \sum_{k=1}^{T} \beta_k T_{kjmt} + \psi_1 P_{jmt} + \psi_2 P_{jmt}^2 + \alpha_1 Female_{ijmt} + \alpha_2 Age_{ijmt} + \delta_j + \gamma_{ct} + \nu_m + \varepsilon_{ijmt} \tag{4.1}$$

where y_{ijmt} is either WHZ or HAZ for child i, located in subnational region j in country c, during month and year of interview m and t respectively. Temperature variables are constructed using a discrete version of the monthly distribution of daily average temperature, which allows for a flexible non-linear relationship with children's health following [4]. The variables T_{kjmt} denote the number of days in the k^{th} 5°C temperature bin in subnational region m and month and year of interview mt. Since the number of days in a month is constant and temperature variables add up to this constant, temperature bin 15-20°C (59-68°F) is excluded from estimation and used as a reference bin. This means that the coefficient of interest β_k on the variable temperature bin k is interpreted as the effect on WHZ or HAZ from exchanging a day in the reference bin to a day in temperature bin k. Equation (4.1) also includes controls for total monthly precipitation and a quadratic term (P_{jmt}, P^2_{jmt}), as well as child's characteristics such as gender and age in months at the time of interview ($Female_{ijmt}$, Age_{ijmt}).

The last term of equation (4.1), ε_{ijmt} is a stochastic error term. δ_j denotes a full set of subnational region fixed-effects, γ_{ct} country-by-year fixed-effects and ν_m a set of month fixed-effects. Subnational fixed-effects absorb all unobserved time invariant administrative-specific determinants of children's health. This captures factors like permanent differences in health conditions and facilities that are specific to each administrative unit. The country-by-year fixed effects account for time-varying differences in health outcomes that are common across all subnational units in a specific country. Month of year fixed-effects should capture seasonal patterns.

By conditioning on this structure of fixed-effects, identification of the parameters of interest, β_k, comes from subnational unit-specific deviations in weather from subnational averages after controlling for precipitation, time-trends specific for each country and seasonality common across the sample. The empirical validity of this specification relies on the identifying assumption that conditional on the fixed effects structure, weather variables are not correlated with the idiosyncratic error term. Due to the randomness of weather variations, the assumption is reasonable. Variations in weather are likely orthogonal to unobserved determinants of health. The repeated cross-section nature of DHS and the uneven cluster sample across years could be of concern for identification purposes. However, we do not believe the types and characteristics of people sampled within an administrative unit are different in month-years with different weather (i.e. that sampling is correlated with the climate).

Standard errors are clustered at the subnational level to account for correlation within each unit over time. The fact that weather could be highly localized, justify clustering at the subnational level. We will also explore additional controls and alternative fixed-effects structures as robustness checks.

4.3.2 Dynamic Effect

The relationship between temperature shocks and health is likely to be dynamic, as weather shocks could take time to fully translate into nutritional outcomes especially in the measures of height. To investigate this possibility, we allow for lags of weather variables and fit the following dynamic specification:

$$y_{ijmt} = \sum_{k=1}^{T}\sum_{l=0}^{L}\beta_{kl}T_{kj(mt-l)} + \sum_{l=0}^{L}\psi_{1l}P_{j(mt-l)} + \sum_{l=0}^{L}\psi_{2l}P^2_{j(mt-l)} + \alpha_1 Female_{ijmt} + \alpha_2 Age_{ijmt} + \delta_j + \gamma_{ct} + \nu_m + \varepsilon_{ijmt} \quad (4.2)$$

This model allows the effect of weather variables up to L months in the past to affect health outcomes in the current month. To that end, the contemporaneous effect of temperature bin k is β_{k0}, while the dynamic causal effect comes from summing all of the coefficients on temperature bin k: $\sum_{l=0}^{L}\beta_{kl}$. If weather shocks have a temporary effect in nutritional status, a contemporary change in the outcome measure should be expected to be followed by a compensatory change in subsequent months. If on the contrary weather shocks have delayed and permanent effects on nutritional outcomes, estimates accumulate over time (e.g. $\sum_{l=0}^{L}\beta_{kl} > \beta_{j0}$ or $\sum_{l=0}^{L}\beta_{kl} < \beta_{j0}$.)

4.3.3 Gender-Differentiated Effects

To investigate if temperature shocks impact males and females differently, we estimate the contemporaneous and dynamic effects in the following interacted specification with a dummy variable for gender:

$$\begin{aligned} y_{ijmt} = & \sum_{k=1}^{T}\sum_{l=0}^{L}\beta_{klM}T_{kj(mt-l)} + \sum_{k=1}^{T}\sum_{l=0}^{L}\beta_{klDiff}\mathbb{1}\{i=female\}\times T_{kj(mt-l)} + \\ & \sum_{l=0}^{L}\psi_{1lM}P_{j(mt-l)} + \sum_{l=0}^{L}\psi_{1lDiff}\mathbb{1}\{i=female\}\times P_{j(mt-l)} + \\ & \sum_{l=0}^{L}\psi_{2lM}P^2_{j(mt-l)} + \sum_{l=0}^{L}\psi_{2lDiff}\mathbb{1}\{i=female\}\times P^2_{j(mt-l)} + \\ & \alpha_1 Female_{ijmt} + \alpha_2 Age_{ijmt} + \alpha_{2Diff}\mathbb{1}\{i=female\}\times Age_{ijmt} + \delta_j + \gamma_{ct} + \nu_m + \varepsilon_{ijmt} \end{aligned} \tag{4.3}$$

For temperature bin k, $\sum_{l=0}^{L}\beta_{klM}$ represent the cumulative dynamic effect of an additional day in temperature bin k relative to a day in the reference category 15-20°C for males. $\sum_{l=0}^{L}\beta_{klDiff}$ is the cumulative difference with females.

4.4 Results

4.4.1 Weight-for-Height z-score

Table 4.2 presents contemporaneous and cumulative dynamic effects using WHZ score as an outcome for children aged 12 to 60 months. We fit equations 4.1 and 4.3.2 using different exposure windows up to nine months (i.e. using 1 lag up to 8 lags). Column (Contemp) in table 4.2 reveals that for most part of the temperature distribution, weight-for-height monotonically decrease with temperature contemporaneously. Exchanging a day in the reference bin 15-20°C for a single day above 35°C leads to a 0.013 standard deviations decline in the WHZ score. This impact corresponds to 6% of the mean Z-score of -0.210 in the sample. Panel (a) in figure (4.2) plots the contemporaneous estimates for each temperature bin, tracing the relationship between WHZ score and temperature along the entire distribution.

Estimated effects remain unchanged or become larger when considering that temperature shocks can take time to fully translate into health outcomes. Columns (2m), (5m), and (6m) presents estimates for equation 4.3.2 using one, four and five lags that correspond to an exposure window of two, five and six months respectively. The effect of an additional day above 35°C accumulates up to -0.018 after six months (8.6%) (i.e. $\sum_{l=0}^{5} \beta_{kl} < \beta_{k0}$), though not significant at conventional levels. It is likely that including lags over a temperature bin with few observations (i.e. >35°C), reduces precision of estimates. However, effects in temperature bin 30-35°C accumulate up to a significant drop of 0.025 standard deviations in WHZ score (11.0% of the mean WHZ score). Panel (b) in figure (4.2) plots cumulative dynamic effects for six months, indicating that the decreasing relationship between temperature and weight-for-height remains and peak at this point. After six months effects are imprecisely estimated and not statistically different than the ones after five or six months (columns (8m) and (9m)).

These results are consistent with what [32] find for children aged 3 to 36 months in five West African countries, though they only find effects at the range of 30-35°C. They find that an additional exposure of 100 hours the 30-35°C bin relative to a reference category of 25°C over the three month period previous to the survey date, decreases WHZ by 0.1 standard deviations. Though not strictly comparable in terms of magnitudes given differences in the empirical strategy, we find almost identical magnitudes when translating our cumulative dynamic estimates from an additional day to an additional 100 hours.[4]

Tables (4.3) and (4.4) explore heterogeneous effects by age groups. We split the sample by children aged 12 to 36 months, and older than 36. Weight-for-height z-score mainly declines in temperature for both age groups, but effects as percentage of the mean z-score for each group are higher for older children. Contemporaneously, an additional day above 35°C relative to the reference category decreases WHZ score by 0.011 standard deviations for children aged 12 to 36 months, and 0.012 for those aged 36 to 60 months. However, compared to to the mean z-score for each group, the effect for younger children is 3.9% while 10.9% for the older group. As for the entire sample, negative effects peak after six months, with bigger effects documented in temperature bin 30-35°C (columns (6m)). For children aged 12 to 36 months negative effects accumulate up to -0.018 (6.43%) and to -0.03 (27.3%) for those aged 36 to 60.[5]

We next disaggregate the analysis by gender, estimating equation 4.3.3 with different exposure windows to temperature shocks. Table (4.5) shows that increases in temperature negatively affect weight-by-height z-score both for girls and boys aged 12 to 60 months, but differences in response arise at the hottest end of the temperature distribution. Additional days above 35°C relative to a day in the reference bin 15-20°C impacts more severely WHZ scores for girls, and the difference becomes bigger as effects accu-

[4]Multiply our estimates for the 30-35°C: 0.025 by 4.2

[5]Similar results are observed when estimating equations 4.1 and 4.3.2 using Weight-for-Age z-score as an outcome. Tables (C.1), (C.2), and (C.3) in Appendix C present the results.

mulate over time. Contemporaneously the difference is -0.004, but as lags are included in estimation it increases to -0.026 standard deviations. The impacts are also somewhat higher for girls in the coldest part of the temperature distribution (≤15°C), though not significant at conventional levels.

Gender differences in other temperature ranges, especially in bin 30-35°C, are small but in favor of girls. While an additional day with average temperature 30-35°C reduces WHZ score in 0.029 standard deviations for boys, for girls the fall is 0.021. These heterogeneous responses suggest there might be additional factors at play that in some cases favor boys and in others either there is no difference, or benefits girls (e.g. cultural norms, preferences for one gender, socialization dynamics, type of income shock experienced by the household, etc.). The possibility that girls are somewhat less affected than boys for certain temperature categories is consistent with the findings in [34], where women are benefited by higher than average rainfall.

Analysis by age groups and using weight-for-*age* z-score as an outcome variable show similar results. Biophysical measures of health are negatively affected by exposure to hotter than average days, but extreme heat effects are stronger for girls. When using weight-for-age, the differences favoring boys seem to be higher for age group 12 to 36 months (Tables (C.7), (C.8), (C.4), (C.5), and (C.6) in the Appendix C).

4.4.2 Height-for-Age z-score

We now turn to the longer term measure of health status: height-for-age z-score. Table 4.6 presents estimates for children aged 12 to 60 months. We fit equations 4.1 and 4.3.2 using different exposure windows up to nine months (i.e. using 1 lag up to 8 lags). Column (Contemp) and panel (a) in figure 4.3 show that HAZ does not react immediately to temperature shocks, as all estimates are close to zero and not significant at conventional levels. Accumulating the effect over the following nine months, does not seem to significantly affect height except in the coldest end of the temperature distribution. Allowing an exposure window of nine months (column (9m)), an additional day below 15°C relative to the reference category 15-20°C reduces HAZ by 0.056 standard deviations (3.13% of the mean HAZ score for the sample).

Splitting the sample by age group reveal that temperature shocks might affect younger and older children differently, especially in the hot end of the temperature distribution. Tables 4.7 and 4.8 show that after nine months HAZ decreases after an additional day below 15°C (0.055 and 0.061 standard deviations for 12-36 and 36-60 months respectively). To the best of our knowledge, these effects on the cold side of the distribution for sub-Saharan African countries are new to the literature. However, temperatures above 20°C appear to have a negative effect on HAZ for children 12 to 36, but not for those aged 36 to 60 months. An additional day with average temperature between 30-35°C reduces HFA by 0.029 standard deviations (column (9m) in table 4.7). These results are in line to those estimated by [32] and magnitudes appear to be similar, when translating our estimates to the effects of an additional 100 hours.

Overall, table 4.9 reveal no evident difference in the effect of temperature shocks in HAZ between girls and boys aged 12 to 60 months. But narrowing the analysis to younger children (12 to 36 months) shows that after an exposure window of eight months an additional day above 35°C reduces HAZ for girls by 0.025 standard deviations while for boys the effect is not statistically significant at 0.006 (column (8m) in table 4.10).

Given the longer-term nature of this measure of health, we are exploring alternative specifications to capture the shocks in a broader window of time or alternative specification of the shocks. But this initial set of results seem to suggest that temperature shocks, both cold and hot, affect children's height aged 12 to 36 months after being exposed for more than eight months. At the hottest end of the temperature distribution, girls appear to bear more of the effect.

4.5 Discussion

This paper estimates the effects of temperature shocks on two biophysical measures of health in sub-Saharan African children: weight-for-height and height-for-age. The former is considered as a short-term measure of health status, while the latter as a variable capturing health stock and longer term impacts. We find that weight-for-height monotonically decreases with temperature contemporaneously, but shocks take up to six months to fully translate into health effects. Both girls and boys are negatively affected by changes in temperature, but results are stronger for girls in the extreme of the hottest part of the temperature distribution. For other temperature ranges, we don't observe significant differences and if anything, boys appear to bear a slightly higher effect.

Height-for-age, considered a longer-term measure of nutritional status, reacts negatively to temperature shocks only after children are exposed for more than six months. Effects are stronger for younger children aged 12 to 36 months, with girls experiencing a significant decline after additional days above 35°C and bearing almost all of the effect. Considering that height is a measure that can take time to react, future analysis will investigate alternative specifications that will allow us to determine how far along the effects extend over time. On the cold extreme end of the temperature distribution, we also find that additional days below 15°C negatively affects height for both girls and boys aged 12 to 60 months, though they appear to be stronger for older children (aged 36 to 60 months).

Having established that children's anthropometric measures react to temperature and that with extreme hot temperature shocks girls seem to bear a higher impact, in future work we will further ask if this heterogeneity arises for reasons that go beyond different biophysical responses to warmer temperatures. These include, for instance, differences in socialization patterns, or parental preferences that lead scarce resources to be differentially directed towards boys or girls. Composition of household income across parents can also lead to differential responses. If male and female caregivers have different preferences around the allocation of resources and income flows into the home are both gender differentiated and differentially vulnerable to weather shocks, then imperfect risk pooling in the home may lead to differences in the allocation of resources by child gender. Economic conditions and income shocks, likely associated to weather, along with these preferences, cultural norms or socialization patterns may result in either girls or boys bearing a higher health cost.

To test the relevance of these channels we will consider the importance of shocks during the growing season (income channel) relative to shocks at other times of the year. We will also differentiate between urban and rural households in this analysis, with the idea that rural households will have a larger share of their income in agriculture. If the differential effects are higher in households that experience more severe income shocks, it could be indicative of preferences favoring a specific group. We will also construct measures of whether agricultural production is gender differentiated using ethnographic information, i.e. if there are traditionally male and female crops in a region. Restricting the sample to rural households, we will examine shocks to gender differentiated income during the growing season versus other times of the year. A bigger effect in gender differentiated production during the growing season is suggestive of the relevance of the channel of intrahousehold allocation of resources based on the distribution of income.

Within Sub-Saharan Africa there are significant differences in cultural norms, for example in terms of inheritance of land, or marriage and family dynamics that could explain inequitable preferences between daughters and sons [51]. Patrilocality, in which a married couple lives near or with husband's parents, or patrilineality, where names and properties pass to the next generation through male descendants is prevalent in certain places and could bias preferences in favor of sons. On the contrary, other areas follow matrilineal systems that could shape preferences differently. Additionally, it is customary in many places that in prearranged marriages the groom or his family pay a bride price to the bride's family, unlike the custom of dowry payments followed in countries like India. This could favor preferences for nurturing girls health, so there might be important heterogeneities to explore that could explain why for some ranges of temperatures girls are worse off while for others boys are.

We will also explore the role of cultural norms and gender preferences by constructing measures of preferences and direction of marital payments using ethnographic atlas information by George Peter Murdock ([52]) merged by geography with the DHS data.. Differences in these traditions might result in some areas favoring boys, while others might favor girls, causing temperature shocks to have opposing effects on children's health. Ignoring such considerations in estimation might explain why for many temperature bins we find no discernible differences.

Finally, we will further explore the role of infectious diseases in explaining the health impacts of temperature shocks. It might be the case that weight loss is caused by illness rather than malnutrition or lack of food due to income shocks. In that case, both girls and boys are exposed to such risk, likely explaining the similar patterns we are observing for both. Even socialization norms, can protect or expose more a gender to the disease burden.

Table 4.1: Average Boys and Girls

	Age Groups in Months				
	(All)	(12-24)	(24-36)	(36-48)	(48-60)
Male	-0.291	-0.505	-0.173	-0.111	-0.199
	(0.003)	(0.007)	(0.007)	(0.007)	(0.007)
Female	-0.258	-0.396	-0.126	-0.117	-0.265
	(0.003)	(0.007)	(0.007)	(0.007)	(0.007)
Difference p-value	0.000	0.000	0.000	0.528	0.000
Observations	375,389	88,187	74,155	68,699	58,852
Male	-1.578	-1.792	-2.019	-1.839	-1.719
	(0.004)	(0.008)	(0.008)	(0.008)	(0.008)
Female	-1.405	-1.502	-1.849	-1.765	-1.679
	(0.004)	(0.008)	(0.008)	(0.008)	(0.008)
Difference p-value	0.000	0.000	0.000	0.000	0.001
Observations	380,140	89,170	75,091	69,622	59,691

Notes: Each panel presents descriptive statistics for variables: (A) WHZ, and (B) HAZ respectively, for the entire sample of children and by age group in months. The rows Male and Female is the average for boys and girls respectively. p-value for the test statistic on the Ho: Male = Female is reported in the row Difference p-value.

Table 4.2: Weight-for-Height Z score and Temperature

	Age Group 12 to 60 Months					
	(Contemp)	(2m)	(5m)	(6m)	(8m)	(9m)
Base Temperature: $\in$ [15,20)						
Temperature $<$ 15	-0.002	-0.001	-0.008	-0.006	-0.010	-0.012
	(0.004)	(0.004)	(0.008)	(0.007)	(0.009)	(0.011)
Temperature $\in$ [20,25)	-0.003**	-0.003**	-0.004*	-0.004	0.003	0.001
	(0.001)	(0.001)	(0.003)	(0.003)	(0.004)	(0.005)
Temperature $\in$ [25,30)	-0.007***	-0.009***	-0.010**	-0.011**	0.004	0.002
	(0.002)	(0.002)	(0.004)	(0.005)	(0.007)	(0.007)
Temperature $\in$ [30,35)	-0.007***	-0.009***	-0.022***	-0.025***	-0.007	-0.009
	(0.002)	(0.002)	(0.005)	(0.007)	(0.010)	(0.011)
Temperature $\geq$ 35	-0.013***	-0.016**	-0.008	-0.018	-0.012	-0.014
	(0.004)	(0.006)	(0.012)	(0.016)	(0.022)	(0.025)
Total Month Precipitation	-0.000	-0.000	0.000	0.001	0.001	0.001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
Precipitation Squared	0.000**	0.000**	0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Female	0.026***	0.026***	0.026***	0.025***	0.025***	0.025***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)
Age	0.007***	0.007***	0.007***	0.007***	0.007***	0.007***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	257,558	256,826	245,776	238,298	225,181	220,044
Mean	-0.210					
SD	1.34					
Adm2 FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Country $\times$ year	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The first column (Contemp) fits the contemporaneous relationship between temperature and WHZ. Each column adds lags of temperature in equation 4.3.3. Columns 2m, 5m, 6m, 8m, and 9m include 1, 4, 5, 7 and 8 lags respectively. Stars correspnd to significance of the cumulative dynamic effect. Standard errors clustered at administrative/sub-national (adm2) level.

Table 4.3: Weight-for-Height z-score and Temperature (12-36 Months)

	Age Group 12 to 36 Months					
	(Contemp)	(2m)	(5m)	(6m)	(8m)	(9m)
Base Temperature: ∈ [15,20)						
Temperature < 15	0.003	0.005	-0.003	0.002	0.000	0.003
	(0.005)	(0.005)	(0.012)	(0.011)	(0.013)	(0.015)
Temperature ∈ [20,25)	-0.002	-0.002	0.001	0.001	0.005	-0.002
	(0.002)	(0.002)	(0.003)	(0.004)	(0.006)	(0.006)
Temperature ∈ [25,30)	-0.007***	-0.008***	-0.003	-0.004	0.006	-0.003
	(0.002)	(0.002)	(0.004)	(0.006)	(0.008)	(0.009)
Temperature ∈ [30,35)	-0.007**	-0.009**	-0.018**	-0.018**	-0.003	-0.017
	(0.002)	(0.003)	(0.006)	(0.007)	(0.011)	(0.013)
Temperature ≥ 35	-0.011**	-0.012*	0.005	-0.007	-0.016	-0.037
	(0.004)	(0.006)	(0.013)	(0.018)	(0.024)	(0.027)
Total Month Precipitation	-0.000	-0.000	0.000	0.001	0.001*	0.001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
Precipitation Squared	0.000	0.000**	0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Female	0.074***	0.074***	0.074***	0.072***	0.074***	0.073***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.008)	(0.008)
Age	0.024***	0.024***	0.024***	0.023***	0.023***	0.022***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	145,190	144,768	138,750	134,593	126,806	123,426
Mean	-0.280					
SD	1.39					
Adm2 FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Country × year	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The first column (Contemp) fits the contemporaneous relationship between temperature and WHZ. Each column adds lags of temperature in equation 4.3.3. Columns 2m, 5m, 6m, 8m, and 9m include 1, 4, 5, 7 and 8 lags respectively. Stars correspnd to significance of the cumulative dynamic effect. Standard errors clustered at administrative/sub-national (adm2) level.

Table 4.4: Weight-for-Height z-score and Temperature (36-60 months)

	Age Group 36 to 60 Months					
	(Contemp)	(2m)	(5m)	(6m)	(8m)	(9m)
Base Temperature: ∈ [15,20)						
Temperature < 15	-0.008	-0.007	-0.014	-0.013	-0.020*	-0.029**
	(0.005)	(0.006)	(0.009)	(0.009)	(0.011)	(0.013)
Temperature ∈ [20,25)	-0.004**	-0.005**	-0.011***	-0.010**	0.003	0.006
	(0.001)	(0.002)	(0.003)	(0.004)	(0.005)	(0.006)
Temperature ∈ [25,30)	-0.006**	-0.008***	-0.016**	-0.016**	0.006	0.011
	(0.002)	(0.002)	(0.005)	(0.006)	(0.008)	(0.009)
Temperature ∈ [30,35)	-0.006**	-0.009**	-0.026***	-0.030**	-0.005	0.005
	(0.003)	(0.003)	(0.007)	(0.009)	(0.012)	(0.014)
Temperature ≥ 35	-0.012**	-0.022**	-0.024	-0.024	0.005	0.018
	(0.006)	(0.009)	(0.019)	(0.024)	(0.034)	(0.038)
Total Month Precipitation	-0.000	-0.000	-0.000	0.000	0.000	0.001
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)
Precipitation Squared	0.000**	0.000***	0.000**	0.000	0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Female	-0.038***	-0.038***	-0.037***	-0.039***	-0.040***	-0.039***
	(0.007)	(0.007)	(0.007)	(0.008)	(0.008)	(0.008)
Age	-0.010***	-0.010***	-0.009***	-0.009***	-0.009***	-0.009***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	112,347	112,037	107,005	103,686	98,358	96,601
Mean	-0.110					
SD	1.26					
Adm2 FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Country × year	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The first column (Contemp) fits the contemporaneous relationship between temperature and WHZ. Each column adds lags of temperature in equation 4.3.3. Columns 2m, 5m, 6m, 8m, and 9m include 1, 4, 5, 7 and 8 lags respectively. Stars correspnd to significance of the cumulative dynamic effect. Standard errors clustered at administrative/sub-national (adm2) level.

Table 4.5: Weight-for-Height z-score Gender (12 to 60 Months)

	Age Group 12 to 60 Months					
	(Contemp)	(2m)	(5m)	(6m)	(7m)	(8m)
Base Temperature: $\in$ [15,20)						
Temperature $<$ 15 Male	-0.000	0.000	-0.005	-0.003	-0.010	-0.007
	(0.004)	(0.004)	(0.009)	(0.009)	(0.009)	(0.010)
Temperature $\in$ [20,25) Male	-0.003**	-0.004**	-0.005*	-0.004	-0.001	0.004
	(0.001)	(0.002)	(0.003)	(0.003)	(0.004)	(0.004)
Temperature $\in$ [25,30) Male	-0.007***	-0.009***	-0.010**	-0.011**	-0.005	0.003
	(0.002)	(0.002)	(0.004)	(0.005)	(0.006)	(0.007)
Temperature $\in$ [30,35) Male	-0.009***	-0.011***	-0.025***	-0.029***	-0.021**	-0.010
	(0.002)	(0.002)	(0.005)	(0.007)	(0.008)	(0.010)
Temperature $\geq$ 35 Male	-0.011**	-0.012**	-0.002	-0.005	-0.004	0.000
	(0.004)	(0.005)	(0.012)	(0.017)	(0.021)	(0.023)
Temperature $<$ 15 $\times$ Female	-0.003	-0.002	-0.008	-0.005	-0.003	-0.006
	(0.005)	(0.005)	(0.007)	(0.007)	(0.006)	(0.007)
Temperature $\in$ [20,25) $\times$ Female	0.001	0.001	0.001	0.001	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Temperature $\in$ [25,30) $\times$ Female	0.001*	0.002**	0.001	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Temperature $\in$ [30,35) $\times$ Female	0.004***	0.005***	0.006***	0.008***	0.006**	0.006**
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
Temperature $\geq$ 35 $\times$ Female	-0.004	-0.010**	-0.012*	-0.026**	-0.026**	-0.026**
	(0.004)	(0.005)	(0.007)	(0.009)	(0.010)	(0.012)
Observations	257,558	256,826	245,776	238,298	231,034	225,181
Mean	-0.210					
SD	1.34					
Adm2 FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Adm0 $\times$ year	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The first column (Contemp) fits the contemporaneous relationship between temperature and WHZ. Each column adds lags of temperature in equation 4.3.3. Columns 2m, 5m, 6m, 7m, and 8m include 1, 4, 5, 6 and 7 lags respectively. Stars correspond to significance of the cumulative dynamic effect. Standard errors clustered at administrative/sub-national (adm2) level. Controls for precipitation, age and gender.

Table 4.6: Height-for-Age z-score (12 to 60 Months)

	Age Group 12 to 60 Months					
	(Contemp)	(2m)	(5m)	(6m)	(8m)	(9m)
Base Temperature: $\in$ [15,20)						
Temperature $<$ 15	-0.005	-0.006	-0.021**	-0.028**	-0.045***	-0.056***
	(0.005)	(0.006)	(0.010)	(0.010)	(0.014)	(0.014)
Temperature $\in$ [20,25)	0.001	-0.000	0.005	0.009**	-0.002	-0.005
	(0.001)	(0.002)	(0.003)	(0.004)	(0.005)	(0.006)
Temperature $\in$ [25,30)	0.001	0.001	0.007	0.013**	-0.000	-0.004
	(0.002)	(0.002)	(0.005)	(0.005)	(0.007)	(0.008)
Temperature $\in$ [30,35)	-0.004	-0.004	0.008	0.017**	-0.003	-0.009
	(0.002)	(0.003)	(0.006)	(0.007)	(0.011)	(0.012)
Temperature $\geq$ 35	-0.002	0.009	0.004	0.013	0.005	0.007
	(0.005)	(0.007)	(0.014)	(0.019)	(0.024)	(0.028)
Total Month Precipitation	-0.000*	-0.000**	-0.000	-0.001**	-0.002**	-0.001*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
Precipitation Squared	0.000	0.000	0.000	0.000*	0.000**	0.000*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Female	0.169***	0.169***	0.172***	0.173***	0.172***	0.171***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Age	-0.004***	-0.004***	-0.004***	-0.004***	-0.003***	-0.003***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	261,316	260,584	249,534	242,056	228,939	223,802
Mean	-1.790					
SD	1.61					
Adm2 FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Country $\times$ year	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The first column (Contemp) fits the contemporaneous relationship between temperature and HAZ. Each column adds lags of temperature in equation 4.3.3. Columns 2m, 5m, 6m, 8m, and 9m include 1, 4, 5, 7 and 8 lags respectively. Stars correspnd to significance of the cumulative dynamic effect. Standard errors clustered at administrative/sub-national (adm2) level.

Table 4.7: Height-for-Age z-score (12 to 36 Months)

	Age Group 12 to 36 Months					
	(Contemp)	(2m)	(5m)	(6m)	(8m)	(9m)
Base Temperature: $\in$ [15,20)						
Temperature $<$ 15	-0.003	-0.004	-0.021	-0.024	-0.043**	-0.055**
	(0.007)	(0.007)	(0.014)	(0.014)	(0.020)	(0.020)
Temperature $\in$ [20,25)	0.001	-0.000	0.008*	0.009*	-0.005	-0.009
	(0.002)	(0.002)	(0.005)	(0.005)	(0.007)	(0.008)
Temperature $\in$ [25,30)	0.000	-0.000	0.007	0.010	-0.006	-0.010
	(0.002)	(0.003)	(0.006)	(0.007)	(0.010)	(0.011)
Temperature $\in$ [30,35)	-0.005*	-0.005	0.007	0.011	-0.016	-0.029*
	(0.003)	(0.003)	(0.008)	(0.009)	(0.013)	(0.016)
Temperature $\geq$ 35	-0.002	0.003	-0.009	0.003	-0.011	-0.018
	(0.005)	(0.007)	(0.016)	(0.021)	(0.027)	(0.033)
Total Month Precipitation	-0.000**	-0.000*	0.000	-0.001	-0.002**	-0.001
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)
Precipitation Squared	0.000	0.000	0.000	0.000	0.000**	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Female	0.247***	0.247***	0.249***	0.249***	0.245***	0.246***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Age	-0.028***	-0.028***	-0.027***	-0.027***	-0.027***	-0.027***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	147,136	146,714	140,696	136,539	128,752	125,372
Mean	-1.800					
SD	1.69					
Adm2 FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Country $\times$ year	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The first column (Contemp) fits the contemporaneous relationship between temperature and HAZ. Each column adds lags of temperature in equation 4.3.3. Columns 2m, 5m, 6m, 8m, and 9m include 1, 4, 5, 7 and 8 lags respectively. Stars correspnd to significance of the cumulative dynamic effect. Standard errors clustered at administrative/sub-national (adm2) level.

Table 4.8: Height-for-Age z-score (36 to 60 Months)

	Age Group 36 to 60 Months					
	(Contemp)	(2m)	(5m)	(6m)	(8m)	(9m)
Base Temperature: $\in$ [15,20)						
Temperature $<$ 15	-0.007	-0.008	-0.025**	-0.039***	-0.052***	-0.061***
	(0.006)	(0.007)	(0.010)	(0.012)	(0.014)	(0.016)
Temperature $\in$ [20,25)	-0.001	-0.002	0.001	0.009**	0.003	0.002
	(0.002)	(0.002)	(0.004)	(0.004)	(0.006)	(0.007)
Temperature $\in$ [25,30)	0.001	0.001	0.004	0.016**	0.007	0.006
	(0.002)	(0.003)	(0.005)	(0.006)	(0.008)	(0.009)
Temperature $\in$ [30,35)	-0.004	-0.005	0.008	0.023**	0.010	0.016
	(0.003)	(0.004)	(0.007)	(0.009)	(0.013)	(0.014)
Temperature $\geq$ 35	-0.002	0.020	0.031	0.027	0.039	0.064
	(0.009)	(0.015)	(0.022)	(0.027)	(0.036)	(0.040)
Total Month Precipitation	-0.000	-0.000	0.000	-0.001	-0.002*	-0.001
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)
Precipitation Squared	0.000	0.000	-0.000	0.000	0.000*	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Female	0.067***	0.067***	0.071***	0.073***	0.076***	0.074***
	(0.008)	(0.008)	(0.008)	(0.009)	(0.009)	(0.009)
Age	0.005***	0.005***	0.005***	0.005***	0.005***	0.005***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	114,159	113,849	108,817	105,498	100,170	98,413
Mean	-1.780					
SD	1.51					
Adm2 FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Country $\times$ year	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The first column (Contemp) fits the contemporaneous relationship between temperature and HAZ. Each column adds lags of temperature in equation 4.3.3. Columns 2m, 5m, 6m, 8m, and 9m include 1, 4, 5, 7 and 8 lags respectively. Stars correspnd to significance of the cumulative dynamic effect. Standard errors clustered at administrative/sub-national (adm2) level.

Table 4.9: Height for Age z-score Gender - 12 to 60 Months

	Age Group 12 to 60 Months					
	(Contemp)	(2m)	(5m)	(6m)	(7m)	(8m)
Base Temperature: $\in$ [15,20)						
Temperature $<$ 15 Male	-0.007	-0.007	-0.022**	-0.029**	-0.044***	-0.045***
	(0.005)	(0.006)	(0.010)	(0.010)	(0.011)	(0.013)
Temperature $\in$ [20,25) Male	0.000	-0.001	0.004	0.008**	0.005	-0.003
	(0.002)	(0.002)	(0.003)	(0.004)	(0.005)	(0.005)
Temperature $\in$ [25,30) Male	0.001	0.000	0.008	0.013**	0.010	-0.000
	(0.002)	(0.002)	(0.005)	(0.005)	(0.006)	(0.007)
Temperature $\in$ [30,35) Male	-0.004	-0.004	0.009	0.017**	0.013	-0.003
	(0.003)	(0.003)	(0.006)	(0.008)	(0.009)	(0.011)
Temperature $\geq$ 35 Male	-0.001	0.010	0.009	0.013	0.015	0.013
	(0.005)	(0.007)	(0.015)	(0.020)	(0.022)	(0.024)
Temperature $<$ 15 $\times$ Female	0.004	0.003	0.001	0.001	0.001	-0.001
	(0.005)	(0.005)	(0.006)	(0.006)	(0.006)	(0.006)
Temperature $\in$ [20,25) $\times$ Female	0.001	0.001	0.001	0.002	0.003**	0.003**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Temperature $\in$ [25,30) $\times$ Female	0.001	0.000	-0.001	-0.000	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Temperature $\in$ [30,35) $\times$ Female	-0.000	0.000	0.000	-0.000	0.001	0.002
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.003)
Temperature $\geq$ 35 $\times$ Female	-0.001	-0.003	-0.010	0.001	-0.003	-0.014
	(0.004)	(0.005)	(0.009)	(0.011)	(0.012)	(0.013)
Observations	261,316	260,584	249,534	242,056	234,792	228,939
Mean	-1.790					
SD	1.61					
Adm2 FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Adm0 $\times$ year	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The first column (Contemp) fits the contemporaneous relationship between temperature and HAZ. Each column adds lags of temperature in equation 4.3.3. Columns 2m, 5m, 6m, 7m, and 8m include 1, 4, 5, 6 and 7 lags respectively. Stars correspond to significance of the cumulative dynamic effect. Standard errors clustered at administrative/sub-national (adm2) level. Controls for precipitation, age and gender.

Table 4.10: Height for Age z-score Gender - 12 to 36 Months

	Age Group 12 to 36 Months					
	(Contemp)	(2m)	(5m)	(6m)	(7m)	(8m)
Base Temperature: $\in$ [15,20)						
Temperature $<$ 15 Male	-0.003	-0.004	-0.020	-0.024	-0.031*	-0.040**
	(0.008)	(0.008)	(0.014)	(0.015)	(0.017)	(0.019)
Temperature $\in$ [20,25) Male	0.001	-0.000	0.007	0.008	0.003	-0.007
	(0.002)	(0.002)	(0.005)	(0.005)	(0.006)	(0.007)
Temperature $\in$ [25,30) Male	-0.000	-0.000	0.008	0.009	0.007	-0.008
	(0.002)	(0.003)	(0.006)	(0.007)	(0.009)	(0.010)
Temperature $\in$ [30,35) Male	-0.005	-0.005	0.006	0.010	0.001	-0.022
	(0.003)	(0.004)	(0.008)	(0.010)	(0.011)	(0.013)
Temperature $\geq$ 35 Male	0.001	0.007	0.001	0.009	0.010	0.006
	(0.005)	(0.007)	(0.018)	(0.022)	(0.027)	(0.029)
Temperature $<$ 15 $\times$ Female	-0.001	-0.002	-0.008	-0.009	-0.010	-0.015
	(0.008)	(0.008)	(0.010)	(0.011)	(0.011)	(0.011)
Temperature $\in$ [20,25) $\times$ Female	-0.000	-0.001	-0.001	-0.001	0.001	0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Temperature $\in$ [25,30) $\times$ Female	-0.001	-0.001	-0.002	-0.002	-0.001	-0.001
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
Temperature $\in$ [30,35) $\times$ Female	-0.002	-0.001	-0.001	-0.002	-0.001	0.003
	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.004)
Temperature $\geq$ 35 $\times$ Female	-0.006	-0.007	-0.014	-0.006	-0.013	-0.031*
	(0.005)	(0.006)	(0.012)	(0.016)	(0.017)	(0.018)
Observations	141,552	141,147	135,378	131,390	127,301	123,865
Mean	-1.800					
SD	1.69					
Adm2 FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Adm0 $\times$ year	Yes	Yes	Yes	Yes	Yes	Yes

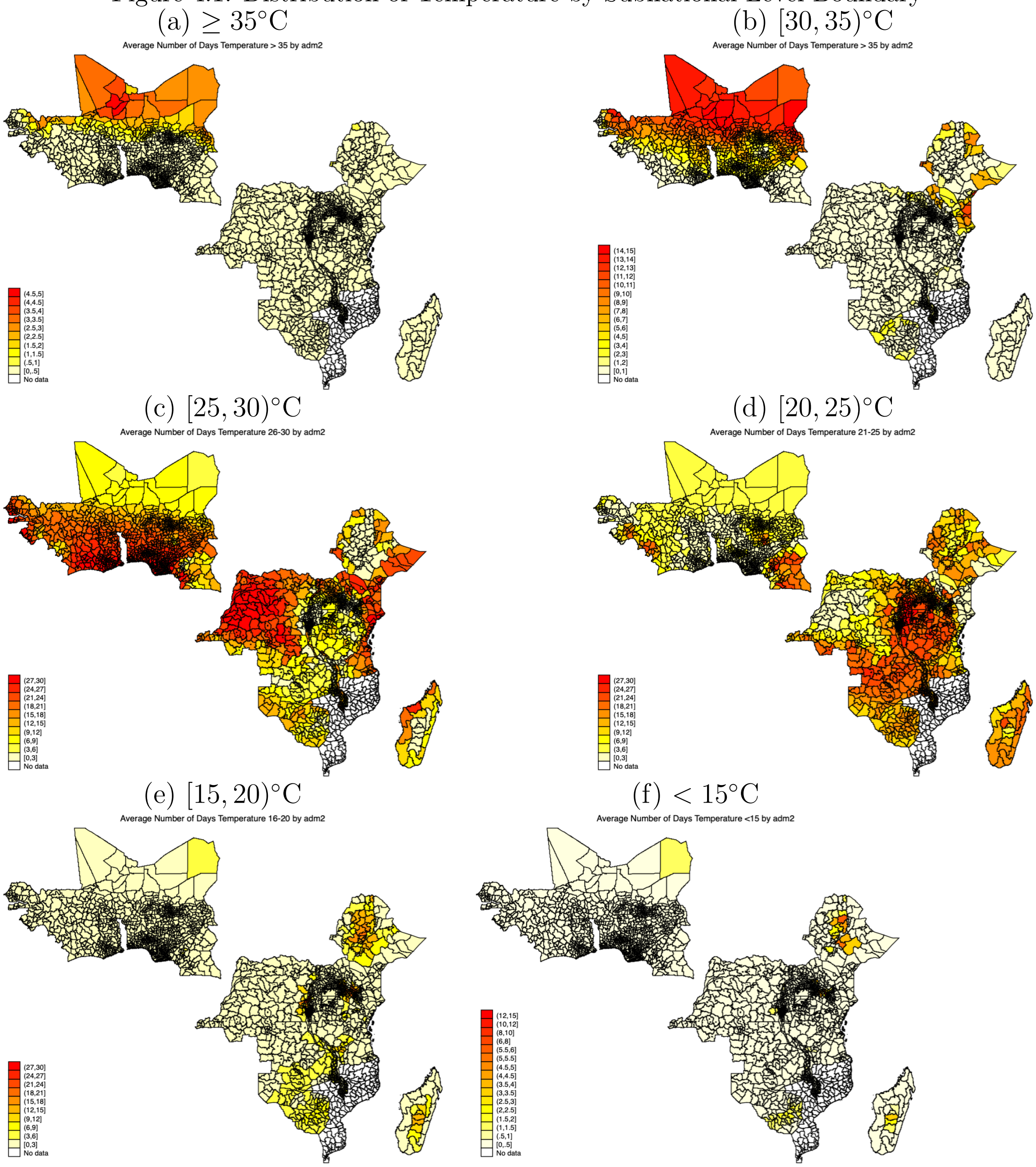
Notes: The first column (Contemp) fits the contemporaneous relationship between temperature and HAZ. Each column adds lags of temperature in equation 4.3.3. Columns 2m, 5m, 6m, 7m, and 8m include 1, 4, 5, 6 and 7 lags respectively. Stars correspond to significance of the cumulative dynamic effect. Standard errors clustered at administrative/sub-national (adm2) level. Controls for precipitation, age and gender.

Table 4.11: Height for Age z-score Gender - 36 to 60 Months

	Age Group 36 to 60 Months					
	(Contemp)	(2m)	(5m)	(6m)	(7m)	(8m)
Base Temperature: $\in$ **[15,20)**						
Temperature $<$ 15 Male	-0.011	-0.012	-0.027**	-0.042**	-0.063***	-0.055***
	(0.007)	(0.007)	(0.011)	(0.013)	(0.014)	(0.015)
Temperature $\in$ [20,25) Male	-0.003	-0.004*	-0.001	0.007	0.007	0.001
	(0.002)	(0.002)	(0.004)	(0.004)	(0.005)	(0.006)
Temperature $\in$ [25,30) Male	-0.000	-0.001	0.004	0.015**	0.013*	0.006
	(0.002)	(0.003)	(0.005)	(0.006)	(0.007)	(0.008)
Temperature $\in$ [30,35) Male	-0.004	-0.006	0.008	0.022**	0.022**	0.011
	(0.003)	(0.004)	(0.007)	(0.009)	(0.010)	(0.013)
Temperature $\geq$ 35 Male	-0.007	0.021	0.034	0.026	0.029	0.038
	(0.009)	(0.015)	(0.022)	(0.028)	(0.031)	(0.037)
Temperature $<$ 15 $\times$ Female	0.007	0.008	0.005	0.005	0.005	0.005
	(0.006)	(0.006)	(0.007)	(0.008)	(0.008)	(0.008)
Temperature $\in$ [20,25) $\times$ Female	0.004**	0.004**	0.004**	0.005**	0.005**	0.005**
	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Temperature $\in$ [25,30) $\times$ Female	0.002*	0.002	0.001	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
Temperature $\in$ [30,35) $\times$ Female	0.001	0.002	0.001	0.001	0.002	-0.000
	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.004)
Temperature $\geq$ 35 $\times$ Female	0.011	-0.003	-0.007	0.002	0.003	0.002
	(0.008)	(0.012)	(0.017)	(0.022)	(0.023)	(0.024)
Observations	114,159	113,849	108,817	105,498	102,478	100,170
Mean	-1.780					
SD	1.51					
Adm2 FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Adm0 $\times$ year	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The first column (Contemp) fits the contemporaneous relationship between temperature and HAZ. Each column adds lags of temperature in equation 4.3.3. Columns 2m, 5m, 6m, 7m, and 8m include 1, 4, 5, 6 and 7 lags respectively. Stars correspond to significance of the cumulative dynamic effect. Standard errors clustered at administrative/sub-national (adm2) level. Controls for precipitation, age and gender.

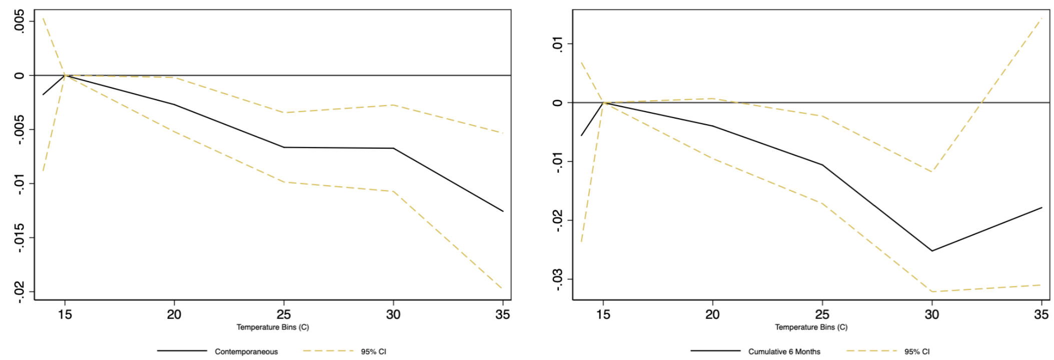
Figure 4.1: Distribution of Temperature by Subnational-Level Boundary



Notes: Average number of days in administrative or subnational (adm2) level during survey years

Figure 4.2: Weight-for-Height z-score

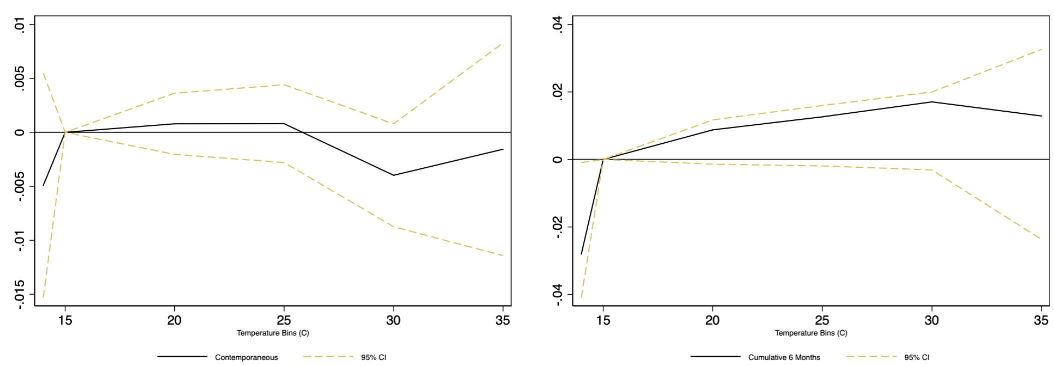
(a) Contemporaneous (b) Cumulative 6 months



Notes: Plot of the estimated coefficients for each temperature bin for all children aged 12 to 60 months. Estimators are interpreted based on the reference temperature between 15-20C.

Figure 4.3: Height-for-Age z-score

(a) Contemporaneous (b) Cumulative 6 months



Notes: Plot of the estimated coefficients for each temperature bin for all children aged 12 to 60 months. Estimators are interpreted based on the reference temperature between 15-20C.

Appendix A

Appendix for Chapter 2

A.1 Appendix Figures and Tables

Table A.1: Dynamic Causal Effect Age-Adjusted All-Cause Mortality Rates Mountain

	Monthly Mortality Rate per 100,000		
	(Contemporaneous)	(Dynamic 5 Months)	(Dynamic 9 Months)
Base Temperature: $\in$ **[23C,25C) [73F,77F)**			
Temperature < 17	0.162***	0.298***	-0.031
	(0.046)	(0.067)	(0.155)
Temperature $\in$ [19,21)	0.045	0.060	-0.012
	(0.036)	(0.039)	(0.077)
Temperature $\in$ [21,23)	0.024	0.043	0.010
	(0.027)	(0.033)	(0.055)
Temperature ≥ 25	0.130***	0.330**	0.178
	(0.039)	(0.107)	(0.178)
25th Precipitation Pctile	0.008	-0.168	0.313
	(0.100)	(0.303)	(0.473)
75th Precipitation Pctile	0.074	0.576**	1.166***
	(0.102)	(0.246)	(0.320)
Observations	228,960	228,920	228,880
Mortality Rate	40.28		
SD Mortality Rate	18.86		
Municipality FE	Yes	Yes	Yes
Municipality $\times$ Month FE	No	No	No
Municipality $\times$ Year FE	Yes	Yes	Yes
Year $\times$ Month FE	Yes	Yes	Yes

Notes: ***p-value < 0.001, **p-value < 0.01, *p-value < 0.05. Standard errors clustered at the municipality level reported in parenthesis. All regressions are weighted by population. Each column is a separate regression and the header indicate the number of lags included in the model.

Table A.2: Dynamic Causal Effect Age-Adjusted All-Cause Mortality Rates Sea

	Monthly Mortality Rate per 100,000		
	(Contemporaneous)	(Dynamic 5 Months)	(Dynamic 9 Months)
Base Temperature: $\in$ [23C,25C) [73F,77F)			
Temperature < 23	-0.010	-0.032	0.052
	(0.027)	(0.040)	(0.095)
Temperature $\in$ [25,27)	0.044**	0.039	0.084
	(0.017)	(0.031)	(0.064)
Temperature ≥ 27	0.045*	0.125**	0.241**
	(0.025)	(0.063)	(0.119)
25th Precipitation Pctile	-0.298**	-0.752*	-0.574
	(0.133)	(0.396)	(0.726)
75th Precipitation Pctile	-0.068	-0.159	0.827
	(0.153)	(0.375)	(0.568)
Observations	72,696	72,668	72,640
Mortality Rate	28.84		
SD Mortality Rate	20.03		
Municipality FE	Yes	Yes	Yes
Municipality $\times$ Month FE	No	No	No
Municipality $\times$ Year FE	Yes	Yes	Yes
Year $\times$ Month FE	Yes	Yes	Yes

Notes: ***p-value < 0.001, **p-value < 0.01, *p-value < 0.05. Standard errors clustered at the municipality level reported in parenthesis. All regressions are weighted by population. Each column is a separate regression and the header indicate the number of lags included in the model.

Table A.3: Cardiovascular, Respiratory, Neoplasms: Mountain

	Cardiovascular		Respiratory		Neoplasms	
	(0 Lags)	(4 Lags)	(0 Lags)	(4 Lags)	(0 Lags)	(4 Lags)
Base Temperature: $\in$ **[23C,25C) [73F,77F)**						
Temperature $<$ 17	0.076***	0.139***	0.054***	0.046**	0.005	0.002
	(0.013)	(0.020)	(0.015)	(0.017)	(0.006)	(0.012)
Temperature $\in$ [19,21)	0.032***	0.044***	0.022*	0.019	0.003	-0.004
	(0.009)	(0.010)	(0.011)	(0.013)	(0.004)	(0.007)
Temperature $\in$ [21,23)	0.015**	0.017*	0.012	0.012	0.001	-0.003
	(0.007)	(0.010)	(0.009)	(0.011)	(0.004)	(0.007)
Temperature $\geq$ 25	0.033**	0.065**	0.026**	0.092**	0.002	0.018
	(0.014)	(0.032)	(0.008)	(0.036)	(0.006)	(0.019)
25th Precipitation Pctile	-0.004	-0.023	0.028	0.007	-0.026	-0.214**
	(0.041)	(0.129)	(0.036)	(0.095)	(0.028)	(0.076)
75th Precipitation Pctile	0.038	0.139	-0.023	-0.047	0.037*	0.141*
	(0.052)	(0.101)	(0.024)	(0.077)	(0.022)	(0.073)
Observations	228,960	228,920	228,960	228,920	228,960	228,920
Mortality Rate	11.58		3.97		6.71	
SD Mortality Rate	6.79		3.23		4.29	
Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes
Municipality $\times$ Month FE	No	No	No	No	No	No
Municipality $\times$ Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Year $\times$ Month FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: ***p-value $<$ 0.001, **p-value $<$ 0.01, *p-value $<$ 0.05. Standard errors clustered at the municipality level reported in parenthesis. All regressions are weighted by population.

Table A.4: Infectious, Homicides, Accidents: Mountain

	Infectious		Homicides		Accidents	
	(0 Lags)	(4 Lags)	(0 Lags)	(4 Lags)	(0 Lags)	(4 Lags)
Base Temperature: $\in$ **[23C,25C) [73F,77F)**						
Temperature < 17	0.004	0.009	-0.036***	0.013	0.005	0.009
	(0.006)	(0.007)	(0.009)	(0.021)	(0.007)	(0.017)
Temperature $\in$ [19,21)	0.003	-0.001	-0.028***	-0.016	-0.006	0.001
	(0.006)	(0.005)	(0.006)	(0.011)	(0.004)	(0.010)
Temperature $\in$ [21,23)	0.000	-0.003	-0.012**	0.013	-0.000	0.002
	(0.004)	(0.005)	(0.005)	(0.009)	(0.003)	(0.009)
Temperature $\geq$ 25	0.010**	0.021**	0.019*	0.038*	0.014**	0.018
	(0.004)	(0.009)	(0.011)	(0.022)	(0.005)	(0.013)
25th Precipitation Pctile	-0.007	0.045	0.009	0.105	0.041*	-0.025
	(0.013)	(0.037)	(0.037)	(0.103)	(0.025)	(0.071)
75th Precipitation Pctile	-0.005	0.017	0.010	0.238**	-0.031	-0.089
	(0.010)	(0.034)	(0.039)	(0.091)	(0.031)	(0.083)
Observations	228,960	228,920	228,960	228,920	228,960	228,920
Mortality Rate	1.28		4.71		2.99	
SD Mortality Rate	1.54		6.92		4.29	
Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes
Municipality $\times$ Month FE	No	No	No	No	No	No
Municipality $\times$ Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Year $\times$ Month FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: ***p-value < 0.001, **p-value < 0.01, *p-value < 0.05. Standard errors clustered at the municipality level reported in parenthesis. All regressions are weighted by population.

Table A.5: Cardiovascular, Respiratory, Neoplasms: Sea

	Cardiovascular		Respiratory		Neoplasms	
	(0 Lags)	(4 Lags)	(0 Lags)	(4 Lags)	(0 Lags)	(4 Lags)
Base Temperature: $\in$ [23C,25C) [73F,77F)						
Temperature $<$ 23	0.005	-0.021	-0.004	-0.021**	0.001	0.002
	(0.011)	(0.015)	(0.005)	(0.010)	(0.006)	(0.012)
Temperature $\in$ [25,27)	0.009	0.004	0.003	0.000	-0.001	0.000
	(0.008)	(0.013)	(0.003)	(0.007)	(0.004)	(0.006)
Temperature $\geq$ 27	0.006	0.025	0.006	0.019	0.001	0.006
	(0.012)	(0.021)	(0.005)	(0.014)	(0.005)	(0.014)
25th Precipitation Pctile	-0.121	-0.194	-0.102**	0.062	0.002	-0.130
	(0.078)	(0.204)	(0.040)	(0.103)	(0.047)	(0.095)
75th Precipitation Pctile	-0.027	-0.159	0.030	0.081	-0.031	-0.066
	(0.056)	(0.158)	(0.037)	(0.076)	(0.039)	(0.117)
Observations	72,696	72,668	72,696	72,668	72,696	72,668
Mortality Rate	8.80		2.43		4.08	
SD Mortality Rate	6.91		3.01		4.08	
Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes
Municipality $\times$ Month FE	No	No	No	No	No	No
Municipality $\times$ Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Year $\times$ Month FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: ***p-value < 0.001, **p-value < 0.01, *p-value < 0.05. Standard errors clustered at the municipality level reported in parenthesis. All regressions are weighted by population.

Table A.6: Infectious, Homicides, Accidents: Sea

	Infectious		Homicides		Accidents	
	(0 Lags)	(4 Lags)	(0 Lags)	(4 Lags)	(0 Lags)	(4 Lags)
Base Temperature: $\in$ [23C,25C) [73F,77F)						
Temperature < 23	0.001	-0.013**	-0.009	0.027	-0.004	0.004
	(0.005)	(0.005)	(0.014)	(0.028)	(0.006)	(0.010)
Temperature $\in$ [25,27)	0.005*	0.005	0.005	0.013	0.006	0.002
	(0.003)	(0.005)	(0.007)	(0.013)	(0.004)	(0.007)
Temperature $\geq$ 27	0.005	0.020**	0.002	0.001	0.012**	0.008
	(0.004)	(0.010)	(0.011)	(0.020)	(0.005)	(0.009)
25th Precipitation Pctile	-0.007	0.010	0.022	-0.417**	0.012	0.090
	(0.019)	(0.077)	(0.068)	(0.200)	(0.031)	(0.086)
75th Precipitation Pctile	0.006	-0.003	-0.024	-0.106	-0.021	0.089
	(0.032)	(0.058)	(0.064)	(0.146)	(0.029)	(0.072)
Observations	72,696	72,668	72,696	72,668	72,696	72,668
Mortality Rate	1.34		3.28		1.97	
SD Mortality Rate	1.89		7.27		3.34	
Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes
Municipality $\times$ Month FE	No	No	No	No	No	No
Municipality $\times$ Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Year $\times$ Month FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: ***p-value < 0.001, **p-value < 0.01, *p-value < 0.05. Standard errors clustered at the municipality level reported in parenthesis. All regressions are weighted by population.

Table A.7: Cumulative Dynamic Effect 5 Months by Age Group All Sample

	Monthly Mortality Rate per 100,000							
	(0-4)	(5-9)	(10-19)	(20-29)	(30-39)	(60-69)	(70-79)	(80+)
Base: $\in$ [23C,25C) [73F,77F)								
Temperature < 17	0.068	0.012	0.105**	0.024	0.077	0.207	1.806***	9.522***
	(0.140)	(0.022)	(0.045)	(0.054)	(0.050)	(0.250)	(0.540)	(1.954)
Temperature $\in$ [17,19)	-0.095	-0.025*	0.040	-0.024	0.038	0.068	0.823**	5.517***
	(0.108)	(0.013)	(0.024)	(0.042)	(0.042)	(0.195)	(0.410)	(1.471)
Temperature $\in$ [19,21)	-0.079	-0.027**	0.022	-0.006	0.026	0.051	0.259	3.104**
	(0.089)	(0.011)	(0.020)	(0.038)	(0.035)	(0.167)	(0.313)	(1.271)
Temperature $\in$ [21,23)	-0.116*	-0.008	0.014	0.042	0.053	0.058	-0.021	1.445
	(0.065)	(0.010)	(0.018)	(0.031)	(0.032)	(0.152)	(0.246)	(1.071)
Temperature $\in$ [25,27)	0.097*	0.028**	-0.002	0.059*	0.111***	0.269*	0.108	1.224
	(0.051)	(0.012)	(0.016)	(0.033)	(0.032)	(0.162)	(0.361)	(0.954)
Temperature ≥ 27	0.345**	0.029**	-0.016	0.052	0.132***	0.563***	0.778	4.901**
	(0.122)	(0.012)	(0.017)	(0.041)	(0.039)	(0.169)	(0.538)	(1.706)
25th Precipitation Pctile	-0.314	-0.202**	-0.217	0.044	-0.045	0.086	-4.154	2.158
	(0.485)	(0.101)	(0.183)	(0.332)	(0.274)	(1.067)	(2.664)	(6.913)
75th Precipitation Pctile	-0.175	0.137	0.011	0.994***	0.318	1.157	-0.347	9.776
	(0.458)	(0.094)	(0.140)	(0.245)	(0.246)	(1.012)	(1.845)	(6.150)
Observations	304,536	304,536	304,536	304,536	304,536	304,536	304,416	304,368
Mean Mortality Rate	26.05	2.47	8.20	16.96	17.45	105.12	249.45	778.89
SD Mortality Rate	27.95	7.24	13.05	21.76	20.09	79.58	169.87	520.39
Municipality × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year × Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: ***p-value < 0.001, **p-value < 0.01, *p-value < 0.05. Standard errors clustered at the municipality level reported in parenthesis. All regressions are weighted by population. Each column is a separate regression and the header indicate the number of lags included in the model. Ages 40-59 not reported.

Table A.8: All Cause By Age-Group % Effect Mountain Municipalities

Age-Group	Contemporaneous		Dynamic 5 Months		Mean Mortality Rate
	< 17	≥ 25	< 17	≥ 25	
0-4	0.92**	0.91***	0.39	1.34***	27.2
5-9	-0.86**	1.13**	1.32	3.87***	2.66
10-19	-0.17	0.81**	1.26**	0.99**	9.3
20-29	-0.41**	0.46**	0.24	1.13**	18.33
30-39	0.11	0.50**	0.72**	1.25***	18.44
40-49	0.12	-0.03	0.45	0.14	24.22
50-59	0.02	0.03	0.23	0.24	47.79
60-69	0.40**	0.12	0.31	0.92**	111.57
70-79	0.63***	0.20*	0.79***	0.58	265.22
80+	0.76***	0.35**	1.22***	0.83**	819.47

Notes: Estimates in each row comes from separate regressions by age group with municipality, municipality-by-year and month-by-year fixed effects. The columns labeled Contemporaneous refer to estimates from the model with no lags and 4 lags to the dynamic cumulative effect with an exposure window of 5 months. The entries under each temperature bin are calculated by taking point estimates and dividing them by average monthly mortality rates for each age group. ***p-value < 0.001, **p-value < 0.01, *p-value < 0.05 from point estimates in each regression. Standard errors (not reported) clusted at the municipality level.

Table A.9: All Cause By Age-Group % Effect Sea-Level Municipalities

Age-Group	Contemporaneous		Dynamic 5 Months		Dynamic 9 Months		Mean Mortality Rate
	< 23	≥ 27	< 23	≥ 27	< 23	≥ 27	
0-4	0.00	0.04	-0.57**	1.23**	-0.53	1.37	23.09
5-9	-0.05	0.57	0.00	1.34	-0.67	1.96	1.94
10-19	-0.14	-0.12	1.00	0.08	1.64	0.52	5.00
20-29	0.10	0.37	0.73	0.64	1.12	-0.11	12.56
30-39	-0.05	0.46**	0.05	0.75*	0.79	1.40	14.01
40-49	-0.32	0.34*	-0.29	0.66**	0.53	1.24**	18.34
50-59	-0.06	0.29**	-0.67*	0.14	-1.14	1.44**	34.57
60-69	0.02	0.17	-0.17	0.61**	0.60	0.97*	79.07
70-79	-0.04	0.09	-0.19	0.17	-0.01	0.91*	186.11
80+	0.17	0.09	0.06	0.35	0.05	1.01	622.37

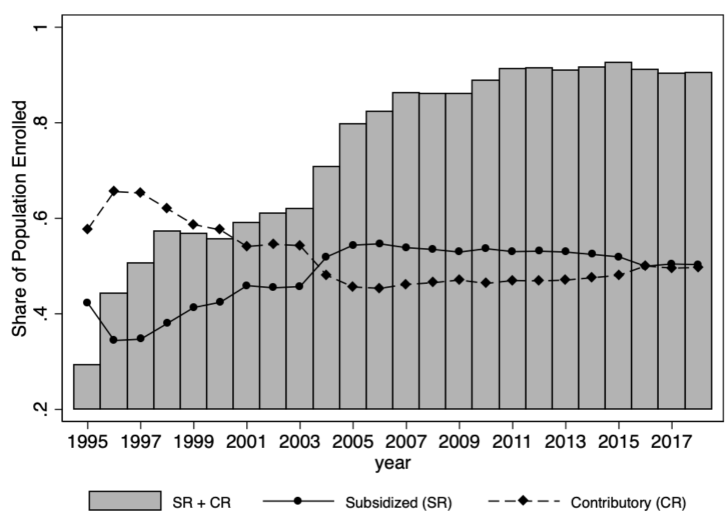
Notes: Estimates in each row comes from separate regressions by age group with municipality, municipality-by-year and month-by-year fixed effects. The columns labeled Contemporaneous refer to estimates from the model with no lags, 4 Lags to the dynamic cumulative effect with an exposure window of 5 months, and 8 Lags to the dynamic cumulative effect with an exposure window of 9 months . The entries under each temperature bin are calculated by taking point estimates and dividing them by average monthly mortality rates for each age group. ***p-value < 0.001, **p-value < 0.01, *p-value < 0.05 from point estimates in each regression. Standard errors (not reported) clusted at the municipality level.

Appendix B

Appendix for Chapter 3

B.1 Appendix Figures and Tables

Figure B.1: Health System Coverage: Overall and By Regime



Notes: Share of the population covered by either contributory or subsidized regime per year depited in bars. Share of population covered in subsidized regime represented by the solid line, and share in the contributory regime by the dashed line.)

Table B.1: Hospitalization by Type of Disease

	Hospitalization Rate per 100,000						
	Infectious	Circulatory	Respiratory	Genitourinary	Pregnancy	External	NC
Base: $\in$ **[23C,25C) [73F,77F)**							
Temperature < 17	-2.323***	-1.140*	-3.045**	-1.248*	-6.495**	-2.798***	-2.777
	(0.654)	(0.659)	(1.023)	(0.687)	(2.084)	(0.801)	(2.474)
Temperature $\in$ [17,19)	-1.661***	-0.514	-1.998**	-0.676	-5.004***	-1.822**	-2.086
	(0.484)	(0.493)	(0.710)	(0.517)	(1.482)	(0.594)	(1.851)
Temperature $\in$ [19,21)	-1.065***	-0.517	-1.435**	-0.326	-3.220**	-1.174**	-1.242
	(0.305)	(0.324)	(0.476)	(0.347)	(0.978)	(0.388)	(1.192)
Temperature $\in$ [21,23)	-0.431**	-0.356*	-0.534*	-0.185	-1.293**	-0.509**	-0.296
	(0.183)	(0.198)	(0.301)	(0.226)	(0.631)	(0.231)	(0.606)
Temperature $\in$ [25,27)	0.586**	0.774***	1.008***	0.703***	1.560***	1.047***	1.169
	(0.192)	(0.203)	(0.259)	(0.212)	(0.463)	(0.264)	(0.834)
Temperature ≥ 27	1.748***	2.378**	3.247***	2.041***	3.392***	2.602**	5.126
	(0.496)	(0.739)	(0.616)	(0.496)	(0.940)	(0.792)	(4.087)
Observations	7,320	7,905	7,918	7,846	8,116	8,083	7,648
Mean Rate	165.83	269.44	368.14	274.12	462.66	304.63	233.03
Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Department × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: ***p-value < 0.001, **p-value < 0.01, *p-value < 0.05. Each column reports point estimates for temperature variables on variations of the baseline specification described in equation (3.1). All regressions control for precipitation and weighted by population. Standard errors clustered at the municipality level reported in parenthesis.

Table B.2: Emergencies by Type of Disease

	Emergencies Rate per 100,000						
	Infectious	Circulatory	Respiratory	Osteomuscular	Pregnancy	External	NC
Base: $\in$ [23C,25C) [73F,77F)							
Temperature < 17	2.811	0.326	8.706	7.063*	0.162	-5.592	-7.872
	(5.818)	(1.968)	(9.787)	(3.898)	(1.889)	(4.867)	(6.868)
Temperature $\in$ [17,19)	2.156	1.205	9.989	6.119**	0.696	-0.836	-5.589
	(4.307)	(1.445)	(6.826)	(2.683)	(1.131)	(4.024)	(5.895)
Temperature $\in$ [19,21)	2.394	1.355	7.809*	4.783**	0.750	1.011	-1.688
	(3.045)	(0.977)	(4.576)	(1.864)	(0.764)	(2.868)	(4.017)
Temperature $\in$ [21,23)	1.298	0.519	3.902	2.366**	0.274	1.258	0.513
	(1.702)	(0.579)	(2.535)	(1.088)	(0.446)	(1.731)	(2.399)
Temperature $\in$ [25,27)	2.630	0.370	2.035	-0.499	1.069**	2.336	6.643
	(1.774)	(0.592)	(2.343)	(0.829)	(0.516)	(2.062)	(4.340)
Temperature ≥ 27	3.196	0.524	2.828	-2.128	1.496	3.015	5.557
	(3.037)	(1.180)	(4.599)	(1.761)	(1.043)	(3.660)	(4.874)
Observations	7,725	7,968	7,931	7,307	7,778	8,124	7,954
Mean Rate	1119.37	535.35	1565.34	623.80	461.45	1212.65	1128.59
Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Department $\times$ Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: ***p-value < 0.001, **p-value < 0.01, *p-value < 0.05. Each column reports point estimates for temperature variables on variations of the baseline specification described in equation (3.1). All regressions control for precipitation and weighted by population. Standard errors clustered at the municipality level reported in parenthesis.

Table B.3: Consultation by Type of Disease

	Consultation Rate per 100,000								
	Infec	Endo	Mental	Circ	Resp	Digest	Osteo	Genito	Preg
Base: $\in$ **[23C,25C) [73F,77F)**									
Temperature < 17	35.018	46.354*	15.610	34.344	15.113	118.658	47.451	37.419	-8.324
	(26.501)	(27.049)	(17.868)	(49.574)	(35.288)	(94.069)	(34.308)	(30.697)	(5.748)
Temperature $\in$ [17,19)	20.513	33.130**	12.806	18.460	6.055	65.052	29.464	32.361	-3.700
	(18.602)	(16.679)	(11.907)	(35.405)	(22.977)	(61.938)	(22.296)	(20.278)	(3.917)
Temperature $\in$ [19,21)	18.111	27.736**	15.414**	27.296	7.408	62.310	29.886**	33.213**	-1.953
	(11.948)	(10.782)	(7.210)	(23.245)	(14.751)	(37.864)	(14.073)	(13.668)	(2.779)
Temperature $\in$ [21,23)	16.018**	9.299	7.808*	-2.992	6.641	39.821*	21.377**	17.942**	-1.344
	(6.668)	(6.691)	(4.245)	(14.894)	(8.765)	(21.451)	(8.588)	(8.627)	(1.795)
Temperature $\in$ [25,27)	2.162	-10.502**	-8.528**	-5.438	-0.301	-15.480	-11.524**	-6.530	2.268**
	(5.480)	(3.811)	(3.209)	(9.198)	(8.219)	(15.811)	(5.552)	(5.902)	(0.929)
Temperature ≥ 27	-2.592	-10.264	-19.219**	23.422	5.195	-26.594	-27.401**	-19.760*	2.107
	(10.347)	(10.960)	(6.810)	(24.929)	(16.920)	(39.191)	(12.572)	(11.936)	(2.463)
Observations	8,351	8,331	8,269	8,353	8,352	8,370	8,348	8,354	8,265
Mean Rate	9446.60	9925.84	4218.72	19875.20	14720.26	30524.58	14176.04	12860.07	1784.42
Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Department $\times$ Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Linear Municip. Trend	No	No	No	No	No	No	No	No	No

Notes: ***p-value < 0.001, **p-value < 0.01, *p-value < 0.05. Each column reports point estimates for temperature variables on variations of the baseline specification described in equation (3.1). All regressions control for precipitation and weighted by population. Standard errors clustered at the municipality level reported in parenthesis.

Table B.4: Procedures by Type of Disease

	Procedures Rate per 100,000				
	Infectious	Circulatory	Respiratory	Digestive	NC
Base: $\in$ [23C,25C) [73F,77F)					
Temperature < 17	0.799	-86.079*	-15.415	274.467**	82.336*
	(11.240)	(45.567)	(22.439)	(121.421)	(46.558)
Temperature $\in$ [17,19)	-0.356	-38.521	-5.309	213.727**	49.096
	(7.698)	(31.683)	(15.596)	(85.699)	(33.796)
Temperature $\in$ [19,21)	1.067	-54.325**	-4.158	163.793**	16.046
	(5.302)	(21.713)	(12.134)	(56.406)	(21.057)
Temperature $\in$ [21,23)	1.876	-53.426***	-15.076	88.020**	-20.726
	(3.612)	(14.377)	(9.221)	(31.204)	(12.737)
Temperature $\in$ [25,27)	-1.555	17.043	-4.764	-86.243**	5.396
	(2.883)	(13.298)	(6.341)	(29.265)	(14.577)
Temperature $\geq$ 27	8.050	98.535***	8.513	-113.898	68.917**
	(6.002)	(29.498)	(11.709)	(77.979)	(25.174)
Observations	7,851	8,196	8,062	8,323	8,236
Mean Rate	3299.35	12429.98	5753.13	20538.97	10977.06
Municipality FE	Yes	Yes	Yes	Yes	Yes
Department × Year FE	Yes	Yes	Yes	Yes	Yes

Notes: ***p-value < 0.001, **p-value < 0.01, *p-value < 0.05. Each column reports point estimates for temperature variables on variations of the baseline specification described in equation (3.1). All regressions control for precipitation and weighted by population. Standard errors clustered at the municipality level reported in parenthesis.

Table B.5: Share

	Share			
	Consultation	Procedures	Emergencies	Hospitalization
Intestinal	34.27	28.82	62.51	47.45
Tuberculosis	0.95	4.15	0.21	1.59
Zoonotic	0.11	0.25	0.10	0.35
Other Bacterial	1.60	12.78	1.42	9.66
Sexual Transmission	1.94	2.73	0.36	1.55
Spirochaetal	0.61	1.18	0.81	1.60
Other Chlamydiae	0.01	0.01	0.00	0.02
Rickettsioses	0.03	0.05	0.07	0.14
Viral Infections	0.18	0.42	0.14	0.40
Arthropod-borne	2.70	6.01	6.18	13.80
Viral Infec. Skin	7.45	4.28	5.16	4.04
Viral Hepatitis	0.34	1.51	0.28	0.66
HIV	7.06	14.00	0.43	9.38
Other Viral	10.94	9.47	19.32	5.53
Mycoses	11.89	4.99	0.91	0.75
Protozoal	0.68	1.30	0.66	1.55
Helminthiases	16.57	6.20	1.01	0.57
Pediculosis	1.78	0.52	0.29	0.34
Sequelae of infectious	0.17	0.25	0.02	0.13
Other 1	0.73	0.96	0.10	0.48
Other 2	0.01	0.12	0.00	0.01
Total Cases (Millions)	34.8	12.0	4.1	0.6

Notes: ***p-value < 0.001, **p-value < 0.01, *p-value < 0.05. Each column reports point estimates for temperature variables on variations of the baseline specification described in equation (3.1). All regressions control for precipitation and weighted by population. Standard errors clustered at the municipality level reported in parenthesis.

Table B.6: Hospitalization by Infectious Diseases

	Hospitalization Rate per 100,000						
	Intestinal	Bacteria	Arthropod	Skin	Other Viral	Protozoal	Helminthiases
Base: ∈ [23C,25C) [73F,77F)							
Temperature < 17	-1.038**	-0.154**	-0.811***	-0.275***	-0.270	-0.271	-0.171*
	(0.504)	(0.062)	(0.212)	(0.078)	(0.170)	(0.194)	(0.101)
Temperature ∈ [17,19)	-0.627*	-0.085*	-0.593***	-0.172**	-0.191	-0.415**	-0.075
	(0.376)	(0.045)	(0.136)	(0.053)	(0.119)	(0.189)	(0.054)
Temperature ∈ [19,21)	-0.418*	-0.045	-0.382***	-0.089**	-0.125	-0.315**	-0.037
	(0.238)	(0.030)	(0.090)	(0.035)	(0.078)	(0.136)	(0.038)
Temperature ∈ [21,23)	-0.130	-0.020	-0.159**	-0.004	-0.071	-0.216**	-0.018
	(0.142)	(0.017)	(0.065)	(0.023)	(0.054)	(0.097)	(0.032)
Temperature ∈ [25,27)	0.271**	0.063***	0.092**	0.082***	0.072	0.096*	0.023*
	(0.137)	(0.015)	(0.046)	(0.020)	(0.049)	(0.051)	(0.013)
Temperature ≥ 27	1.059**	0.170***	0.238**	0.186***	-0.010	0.162	0.046
	(0.422)	(0.036)	(0.095)	(0.042)	(0.101)	(0.101)	(0.029)
Observations	6,214	4,734	4,058	1,890	1,785	1,541	828
Mean Rate	81.28	17.55	26.11	8.90	12.53	3.53	1.41
Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Department × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: ***p-value < 0.001, **p-value < 0.01, *p-value < 0.05. Each column reports point estimates for temperature variables on variations of the baseline specification described in equation (3.1). All regressions control for precipitation and weighted by population. Standard errors clustered at the municipality level reported in parenthesis.

Table B.7: Emergencies by Type of Disease

	Hospitalization Rate per 100,000						
	Intestinal	Bacteria	Arthropod	Skin	Other Viral	Protozoal	Helminthiases
Base: $\in$ [23C,25C) [73F,77F)							
Temperature < 17	4.259	-0.127	-0.759	0.260	-0.300	-3.122*	0.590
	(3.982)	(0.128)	(1.149)	(0.492)	(1.796)	(1.687)	(0.453)
Temperature $\in$ [17,19)	4.579	-0.053	-1.037	0.417	-0.130	-3.467*	0.390*
	(2.855)	(0.094)	(0.858)	(0.337)	(1.341)	(1.953)	(0.218)
Temperature $\in$ [19,21)	3.822*	-0.017	-0.495	0.257	0.301	-2.607*	0.258*
	(1.962)	(0.057)	(0.622)	(0.226)	(0.964)	(1.501)	(0.145)
Temperature $\in$ [21,23)	1.753	-0.023	-0.155	0.101	0.637	-1.790	0.114
	(1.066)	(0.033)	(0.353)	(0.130)	(0.574)	(1.214)	(0.103)
Temperature $\in$ [25,27)	0.375	-0.017	0.183	0.021	1.618*	1.032	-0.088
	(1.029)	(0.024)	(0.208)	(0.102)	(0.854)	(0.844)	(0.058)
Temperature ≥ 27	0.425	0.035	0.881*	0.031	1.448*	1.790	-0.160
	(1.997)	(0.054)	(0.493)	(0.219)	(0.845)	(1.516)	(0.112)
Observations	7,377	3,599	4,167	3,822	4,833	1,619	2,526
Mean Rate	705.93	18.85	79.90	68.38	241.13	9.86	14.46
Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Department $\times$ Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: ***p-value $<$ 0.001, **p-value $<$ 0.01, *p-value $<$ 0.05. Each column reports point estimates for temperature variables on variations of the baseline specification described in equation (3.1). All regressions control for precipitation and weighted by population. Standard errors clustered at the municipality level reported in parenthesis.

Table B.8: Consultation by Type of Disease

	Hospitalization Rate per 100,000						
	Intestinal	Bacteria	Arthropod	Skin	Other Viral	Protozoal	Helminthiases
Base: $\in$ [23C,25C) [73F,77F)							
Temperature < 17	6.986	-0.177	-1.332	3.751**	-3.579	-1.827	22.382*
	(9.939)	(0.773)	(2.916)	(1.809)	(4.450)	(1.267)	(11.993)
Temperature $\in$ [17,19)	6.293	-0.013	-3.398	2.378**	-4.856	-1.605*	18.230**
	(6.728)	(0.623)	(2.175)	(1.064)	(3.280)	(0.935)	(8.472)
Temperature $\in$ [19,21)	6.643	0.067	-2.335	1.893**	-2.580	-1.211*	11.740**
	(4.192)	(0.444)	(1.502)	(0.669)	(2.544)	(0.668)	(5.395)
Temperature $\in$ [21,23)	6.575**	-0.101	-1.163	0.976**	0.803	-0.920*	6.393**
	(2.436)	(0.223)	(0.782)	(0.411)	(1.255)	(0.513)	(2.937)
Temperature $\in$ [25,27)	-2.633	0.012	1.269**	-0.315	6.544***	0.518	-2.165
	(1.884)	(0.193)	(0.612)	(0.304)	(1.771)	(0.362)	(2.304)
Temperature ≥ 27	-5.590	0.173	3.984**	-0.501	8.208***	0.616	-6.874
	(3.974)	(0.404)	(1.473)	(0.610)	(2.316)	(0.626)	(4.348)
Observations	8,292	7,028	6,226	7,951	7,715	6,025	8,171
Mean Rate	3246.27	155.44	269.76	711.14	1051.32	67.12	1559.63
Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Department $\times$ Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: ***p-value $<$ 0.001, **p-value $<$ 0.01, *p-value $<$ 0.05. Each column reports point estimates for temperature variables on variations of the baseline specification described in equation (3.1). All regressions control for precipitation and weighted by population. Standard errors clustered at the municipality level reported in parenthesis.

Table B.9: Procedures by Type of Disease

	Hospitalization Rate per 100,000							
	Intestinal	Bacteria	Arthropod	Skin	HIV	Other Viral	Protozoal	Helminthiases
Base: $\in$ [23C,25C) [73F,77F)								
Temperature < 17	6.943	11.237**	-11.704***	-1.424	-7.531*	-0.942	-2.873**	2.375
	(4.565)	(4.055)	(3.033)	(0.955)	(4.448)	(2.702)	(1.023)	(3.344)
Temperature $\in$ [17,19)	5.084	6.953**	-7.504***	-1.006	-5.397	-0.444	-1.430**	2.827
	(3.104)	(2.847)	(1.885)	(0.687)	(3.321)	(1.905)	(0.606)	(2.055)
Temperature $\in$ [19,21)	3.739	4.406**	-4.256***	-0.565	-2.529	0.069	-1.080**	1.514
	(2.277)	(2.002)	(1.140)	(0.432)	(1.842)	(1.437)	(0.416)	(1.424)
Temperature $\in$ [21,23)	1.662	2.921	-1.564*	-0.447*	0.619	0.091	-0.526*	0.876
	(1.530)	(1.814)	(0.813)	(0.235)	(0.783)	(0.791)	(0.273)	(0.898)
Temperature $\in$ [25,27)	-1.754	0.101	1.569**	0.074	-1.011	1.423**	0.026	-0.481
	(1.342)	(1.013)	(0.480)	(0.151)	(0.666)	(0.721)	(0.334)	(0.688)
Temperature ≥ 27	2.406	1.051	3.828***	0.380	-1.835	3.124*	0.181	-1.553
	(1.975)	(2.203)	(1.007)	(0.567)	(1.513)	(1.789)	(0.584)	(1.689)
Observations	6,792	4,849	3,951	4,572	3,686	4,352	3,111	4,775
Mean Rate	980.85	464.34	230.08	158.82	538.14	355.45	51.62	225.67
Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Department $\times$ Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: ***p-value < 0.001, **p-value < 0.01, *p-value < 0.05. Each column reports point estimates for temperature variables on variations of the baseline specification described in equation (3.1). All regressions control for precipitation and weighted by population. Standard errors clustered at the municipality level reported in parenthesis.

Table B.10: Share Pregnancy

	Share			
	Consultation	Procedures	Emergencies	Hospitalization
Abortive	11.38	10.90	12.65	8.13
Hypertensive	6.77	12.30	5.01	6.83
Other Maternal Dis.	31.01	15.61	29.94	10.65
Fetus and amniotic cavity	26.78	22.94	23.04	26.13
Complications of Labor	5.52	5.33	5.58	8.31
Delivery	12.72	30.23	21.25	37.86
Complications	4.06	1.67	2.11	1.54
Other 2	1.77	1.01	0.42	0.55
Total Cases (Millions)	6.6	9.0	1.7	1.7

Notes:

Table B.11: Hospitalization by Pregnancy and Child Birth

	Hospitalization Rate per 100,000					
	Abortive	Hypertensive	Maternal Dis	Fetus	Complications Labor	Delivery
Base: $\in$ [23C,25C) [73F,77F)						
Temperature < 17	-0.452**	-0.304**	-1.347**	-1.957**	-0.455	-2.143**
	(0.172)	(0.146)	(0.543)	(0.906)	(0.392)	(0.851)
Temperature $\in$ [17,19)	-0.345**	-0.219**	-0.751**	-1.554**	-0.171	-1.911**
	(0.132)	(0.098)	(0.328)	(0.703)	(0.222)	(0.636)
Temperature $\in$ [19,21)	-0.180**	-0.135**	-0.513**	-1.161**	-0.047	-1.088**
	(0.088)	(0.064)	(0.216)	(0.491)	(0.142)	(0.424)
Temperature $\in$ [21,23)	-0.032	-0.053	-0.225*	-0.508*	0.032	-0.444
	(0.059)	(0.042)	(0.129)	(0.299)	(0.084)	(0.285)
Temperature $\in$ [25,27)	0.162**	0.097**	0.285***	0.679***	-0.170	0.452*
	(0.068)	(0.031)	(0.078)	(0.202)	(0.105)	(0.274)
Temperature ≥ 27	0.200*	0.255***	0.781***	1.461***	0.032	0.564
	(0.110)	(0.066)	(0.201)	(0.398)	(0.197)	(0.486)
Observations	6,301	5,659	6,494	7,111	6,372	7,677
Mean Rate	39.21	33.62	51.66	123.53	39.94	176.85
Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes
Department $\times$ Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: ***p-value < 0.001, **p-value < 0.01, *p-value < 0.05. Each column reports point estimates for temperature variables on variations of the baseline specification described in equation (3.1). All regressions control for precipitation and weighted by population. Standard errors clustered at the municipality level reported in parenthesis.

Table B.12: Emergencies by Pregnancy and Child Birth

	Hospitalization Rate per 100,000					
	Abortive	Hypertensive	Maternal Dis	Fetus	Complications Labor	Delivery
Base: ∈ [23C,25C) [73F,77F)						
Temperature < 17	-0.150	0.119	-0.049	-0.009	0.327	-0.050
	(0.278)	(0.116)	(0.707)	(0.475)	(0.297)	(0.805)
Temperature ∈ [17,19)	-0.125	0.094	0.158	0.285	0.216	0.185
	(0.173)	(0.078)	(0.454)	(0.310)	(0.214)	(0.429)
Temperature ∈ [19,21)	0.009	0.082	0.202	0.055	0.197	0.310
	(0.117)	(0.051)	(0.313)	(0.209)	(0.148)	(0.273)
Temperature ∈ [21,23)	0.010	0.060*	0.093	-0.034	0.157	0.093
	(0.071)	(0.032)	(0.186)	(0.131)	(0.101)	(0.170)
Temperature ∈ [25,27)	0.202*	0.065*	0.319**	0.517***	-0.066	0.034
	(0.104)	(0.036)	(0.155)	(0.131)	(0.136)	(0.196)
Temperature ≥ 27	0.225	0.074	0.626*	0.928**	-0.169	-0.201
	(0.177)	(0.072)	(0.363)	(0.298)	(0.185)	(0.407)
Observations	5,848	4,503	6,583	6,397	5,199	6,358
Mean Rate	61.35	25.88	143.03	110.34	27.76	102.22
Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes
Department × Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: ***p-value < 0.001, **p-value < 0.01, *p-value < 0.05. Each column reports point estimates for temperature variables on variations of the baseline specification described in equation (3.1). All regressions control for precipitation and weighted by population. Standard errors clustered at the municipality level reported in parenthesis.

Table B.13: Consultation by Pregnancy and Child Birth

	Hospitalization Rate per 100,000					
	Abortive	Hypertensive	Maternal Dis	Fetus	Complications Labor	Delivery
Base: $\in$ [23C,25C) [73F,77F)						
Temperature < 17	-2.173*	-0.469	-2.894	-2.411	0.045	-0.322
	(1.222)	(0.471)	(2.119)	(2.483)	(0.636)	(1.379)
Temperature $\in$ [17,19)	-1.423	-0.102	-0.729	-1.568	0.324	-0.016
	(0.901)	(0.321)	(1.359)	(1.722)	(0.430)	(1.079)
Temperature $\in$ [19,21)	-1.050*	-0.004	-0.529	-1.102	0.296	0.673
	(0.612)	(0.215)	(0.926)	(1.149)	(0.295)	(0.911)
Temperature $\in$ [21,23)	-0.524	-0.038	-0.110	-0.792	0.124	0.094
	(0.344)	(0.141)	(0.576)	(0.674)	(0.191)	(0.609)
Temperature $\in$ [25,27)	0.349	0.101	0.330	0.527	-0.171	0.998***
	(0.234)	(0.085)	(0.351)	(0.557)	(0.227)	(0.269)
Temperature ≥ 27	0.994	0.172	1.143	0.454	-0.533	-0.518
	(0.976)	(0.211)	(0.778)	(1.071)	(0.344)	(0.705)
Observations	7,544	6,821	7,948	7,879	7,320	7,762
Mean Rate	204.73	124.14	559.21	480.90	99.32	227.06
Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes
Department $\times$ Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: ***p-value < 0.001, **p-value < 0.01, *p-value < 0.05. Each column reports point estimates for temperature variables on variations of the baseline specification described in equation (3.1). All regressions control for precipitation and weighted by population. Standard errors clustered at the municipality level reported in parenthesis.

Table B.14: Procedures by Pregnancy and Child Birth

	Hospitalization Rate per 100,000					
	Abortive	Hypertensive	Maternal Dis	Fetus	Complications Labor	Delivery
Base: ∈ [23C,25C) [73F,77F)						
Temperature < 17	-3.774**	-3.750**	-4.169**	-3.655	-0.585	2.631
	(1.354)	(1.515)	(2.105)	(2.355)	(0.885)	(3.845)
Temperature $\in$ [17,19)	-2.263**	-1.894*	-1.663	-2.063	0.391	3.468
	(0.964)	(0.985)	(1.442)	(1.521)	(0.642)	(2.961)
Temperature $\in$ [19,21)	-1.264**	-0.414	-0.501	-0.454	0.423	3.017
	(0.637)	(0.683)	(0.943)	(0.992)	(0.447)	(1.981)
Temperature $\in$ [21,23)	-0.180	-0.470	-0.305	-0.342	0.219	2.387**
	(0.366)	(0.467)	(0.530)	(0.636)	(0.284)	(1.216)
Temperature $\in$ [25,27)	0.399	0.682*	0.105	-0.325	-0.749**	0.516
	(0.433)	(0.360)	(0.423)	(0.588)	(0.306)	(1.472)
Temperature ≥ 27	0.036	2.078**	2.001*	1.199	0.215	-3.661
	(0.787)	(0.784)	(1.064)	(1.279)	(0.516)	(2.467)
Observations	7,170	5,250	6,201	6,924	6,193	7,989
Mean Rate	270.18	325.85	404.57	575.24	135.31	737.62
Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes
Department × Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: ***p-value < 0.001, **p-value < 0.01, *p-value < 0.05. Each column reports point estimates for temperature variables on variations of the baseline specification described in equation (3.1). All regressions control for precipitation and weighted by population. Standard errors clustered at the municipality level reported in parenthesis.

Appendix C

Appendix for Chapter 4

C.1 Appendix Figures and Tables

Table C.1: Weight-for-Age z-score 12 to 60 months

	Age Group 12 to 60 Months					
	(Contemp)	(2m)	(5m)	(6m)	(8m)	(9m)
Base Temperature: $\in$ [15,20)						
Temperature $<$ 15	-0.005	-0.005	-0.020**	-0.020**	-0.027**	-0.039**
	(0.004)	(0.004)	(0.008)	(0.008)	(0.010)	(0.013)
Temperature $\in$ [20,25)	-0.001	-0.003*	-0.000	0.003	0.003	-0.002
	(0.001)	(0.001)	(0.002)	(0.003)	(0.004)	(0.005)
Temperature $\in$ [25,30)	-0.004**	-0.006**	-0.003	0.001	0.004	-0.000
	(0.001)	(0.002)	(0.003)	(0.004)	(0.006)	(0.007)
Temperature $\in$ [30,35)	-0.007***	-0.008***	-0.010**	-0.007	-0.005	-0.011
	(0.002)	(0.002)	(0.004)	(0.006)	(0.009)	(0.010)
Temperature $\geq$ 35	-0.009**	-0.006	-0.002	-0.003	-0.002	-0.005
	(0.003)	(0.005)	(0.009)	(0.013)	(0.016)	(0.019)
Total Month Precipitation	-0.000**	-0.000**	0.000	-0.000	-0.001	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
Precipitation Squared	0.000*	0.000**	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Female	0.075***	0.075***	0.078***	0.078***	0.077***	0.076***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Age	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	257,679	256,947	245,897	238,419	225,302	220,165
Mean	-1.140					
SD	1.23					
Adm2 FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Country × year	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The first column (Contemp) fits the contemporaneous relationship between temperature and WAZ. Each column adds lags of temperature in equation 4.3.3. Columns 2m, 5m, 6m, 8m, and 9m include 1, 4, 5, 7 and 8 lags respectively. Stars correspond to significance of the cumulative dynamic effect. Standard errors clustered at administrative/sub-national (adm2) level.

Table C.2: Weight-for-Age z-score (12 - 36 Months)

	Age Group 12 to 36 Months					
	(Contemp)	(2m)	(5m)	(6m)	(8m)	(9m)
Base Temperature: $\in$ [15,20)						
Temperature $<$ 15	-0.001	-0.001	-0.016	-0.011	-0.015	-0.025
	(0.005)	(0.005)	(0.011)	(0.011)	(0.014)	(0.017)
Temperature $\in$ [20,25)	-0.001	-0.002	0.005	0.006*	0.002	-0.006
	(0.002)	(0.002)	(0.003)	(0.004)	(0.005)	(0.006)
Temperature $\in$ [25,30)	-0.005**	-0.006**	0.001	0.003	0.003	-0.007
	(0.002)	(0.002)	(0.004)	(0.005)	(0.008)	(0.009)
Temperature $\in$ [30,35)	-0.008***	-0.009**	-0.009*	-0.007	-0.010	-0.028**
	(0.002)	(0.003)	(0.005)	(0.007)	(0.010)	(0.012)
Temperature $\geq$ 35	-0.009**	-0.007	-0.001	-0.001	-0.013	-0.034
	(0.004)	(0.005)	(0.011)	(0.016)	(0.019)	(0.021)
Total Month Precipitation	-0.000**	-0.000**	0.000	0.000	-0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
Precipitation Squared	0.000	0.000**	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Female	0.145***	0.145***	0.147***	0.146***	0.145***	0.145***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Age	-0.004***	-0.004***	-0.004***	-0.004***	-0.004***	-0.004***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	145,275	144,853	138,835	134,678	126,891	123,511
Mean	-1.150					
SD	1.3					
Adm2 FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Country $\times$ year	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The first column (Contemp) fits the contemporaneous relationship between temperature and WAZ. Each column adds lags of temperature in equation 4.3.3. Columns 2m, 5m, 6m, 8m, and 9m include 1, 4, 5, 7 and 8 lags respectively. Stars correspond to significance of the cumulative dynamic effect. Standard errors clustered at administrative/sub-national (adm2) level.

Table C.3: Weight-for-Age z-score (36 - 60 Months)

	Age Group 36 to 60 Months					
	(Contemp)	(2m)	(5m)	(6m)	(8m)	(9m)
Base Temperature: $\in$ [15,20)						
Temperature < 15	-0.009**	-0.009*	-0.025**	-0.031**	-0.044***	-0.057***
	(0.005)	(0.005)	(0.009)	(0.010)	(0.012)	(0.013)
Temperature $\in$ [20,25)	-0.002*	-0.004**	-0.006**	0.000	0.005	0.005
	(0.001)	(0.002)	(0.003)	(0.004)	(0.005)	(0.005)
Temperature $\in$ [25,30)	-0.003*	-0.005**	-0.008*	-0.001	0.009	0.011
	(0.002)	(0.002)	(0.004)	(0.005)	(0.007)	(0.008)
Temperature $\in$ [30,35)	-0.006**	-0.008**	-0.013**	-0.006	0.004	0.013
	(0.002)	(0.003)	(0.006)	(0.007)	(0.011)	(0.012)
Temperature $\geq$ 35	-0.009	-0.003	0.002	-0.000	0.029	0.050*
	(0.006)	(0.009)	(0.013)	(0.016)	(0.024)	(0.027)
Total Month Precipitation	-0.000	-0.000	-0.000	-0.001	-0.001	-0.001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
Precipitation Squared	0.000*	0.000**	0.000*	0.000*	0.000*	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Female	-0.018**	-0.018**	-0.014**	-0.014**	-0.013*	-0.013*
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Age	-0.007***	-0.006***	-0.006***	-0.006***	-0.007***	-0.007***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	112,383	112,073	107,041	103,722	98,394	96,637
Mean	-1.140					
SD	1.14					
Adm2 FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Country × year	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The first column (Contemp) fits the contemporaneous relationship between temperature and WAZ. Each column adds lags of temperature in equation 4.3.3. Columns 2m, 5m, 6m, 8m, and 9m include 1, 4, 5, 7 and 8 lags respectively. Stars correspond to significance of the cumulative dynamic effect. Standard errors clustered at administrative/sub-national (adm2) level.

Table C.4: Weight-for-Age z-score Gender (12 to 60 Months)

	Age Group 12 to 60 Months					
	(Contemp)	(2m)	(5m)	(6m)	(7m)	(8m)
Base Temperature: $\in$ [15,20)						
Temperature $<$ 15 Male	-0.005	-0.005	-0.018**	-0.020**	-0.030**	-0.027**
	(0.004)	(0.004)	(0.009)	(0.009)	(0.010)	(0.011)
Temperature $\in$ [20,25) Male	-0.002*	-0.003**	-0.001	0.003	0.004	0.002
	(0.001)	(0.001)	(0.002)	(0.003)	(0.003)	(0.004)
Temperature $\in$ [25,30) Male	-0.005**	-0.006***	-0.003	0.001	0.004	0.004
	(0.002)	(0.002)	(0.003)	(0.004)	(0.005)	(0.006)
Temperature $\in$ [30,35) Male	-0.007***	-0.010***	-0.011**	-0.008	-0.005	-0.006
	(0.002)	(0.002)	(0.005)	(0.006)	(0.007)	(0.009)
Temperature $\geq$ 35 Male	-0.007**	-0.002	0.005	0.005	0.007	0.010
	(0.004)	(0.005)	(0.010)	(0.014)	(0.016)	(0.016)
Temperature $<$ 15 $\times$ Female	-0.000	0.000	-0.005	-0.001	0.001	-0.002
	(0.005)	(0.005)	(0.006)	(0.006)	(0.006)	(0.006)
Temperature $\in$ [20,25) $\times$ Female	0.002**	0.002**	0.001	0.002*	0.002*	0.002*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Temperature $\in$ [25,30) $\times$ Female	0.001*	0.001	0.000	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Temperature $\in$ [30,35) $\times$ Female	0.002	0.003**	0.002	0.003**	0.003	0.003
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
Temperature $\geq$ 35 $\times$ Female	-0.005	-0.010**	-0.014*	-0.016*	-0.018*	-0.023**
	(0.004)	(0.004)	(0.008)	(0.009)	(0.010)	(0.011)
Observations	257,679	256,947	245,897	238,419	231,155	225,302
Mean	-1.140					
SD	1.23					
Adm2 FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Adm0 $\times$ year	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The first column (Contemp) fits the contemporaneous relationship between temperature and WAZ. Each column adds lags of temperature in equation 4.3.3. Columns 2m, 5m, 6m, 7m, and 8m include 1, 4, 5, 6 and 7 lags respectively. Stars correspond to significance of the cumulative dynamic effect. Standard errors clustered at administrative/sub-national (adm2) level.

Table C.5: Weight-for-Age z-score Gender (12 to 36 Months)

	Age Group 12 to 36 Months					
	(Contemp)	(2m)	(5m)	(6m)	(7m)	(8m)
Base Temperature: $\in$ [15,20)						
Temperature $<$ 15 Male	-0.001	-0.002	-0.015	-0.012	-0.018	-0.014
	(0.006)	(0.006)	(0.013)	(0.014)	(0.015)	(0.016)
Temperature $\in$ [20,25) Male	-0.002	-0.003	0.003	0.004	0.003	-0.001
	(0.002)	(0.002)	(0.003)	(0.004)	(0.005)	(0.005)
Temperature $\in$ [25,30) Male	-0.006**	-0.007**	0.000	0.001	0.005	0.001
	(0.002)	(0.002)	(0.004)	(0.005)	(0.007)	(0.008)
Temperature $\in$ [30,35) Male	-0.009***	-0.011***	-0.012**	-0.011	-0.009	-0.015
	(0.002)	(0.003)	(0.006)	(0.007)	(0.009)	(0.010)
Temperature $\geq$ 35 Male	-0.005	-0.001	0.012	0.010	0.008	0.006
	(0.004)	(0.005)	(0.012)	(0.017)	(0.020)	(0.020)
Temperature $<$ 15 $\times$ Female	-0.002	-0.001	-0.007	-0.003	-0.001	-0.005
	(0.008)	(0.008)	(0.010)	(0.010)	(0.008)	(0.009)
Temperature $\in$ [20,25) $\times$ Female	0.001	0.002	0.001	0.002	0.002	0.002
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
Temperature $\in$ [25,30) $\times$ Female	0.001	0.001	-0.000	0.000	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
Temperature $\in$ [30,35) $\times$ Female	0.001	0.003	0.003	0.003	0.003	0.004
	(0.001)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)
Temperature $\geq$ 35 $\times$ Female	-0.007	-0.012**	-0.020**	-0.017	-0.024*	-0.033**
	(0.004)	(0.005)	(0.009)	(0.013)	(0.014)	(0.014)
Observations	139,760	139,355	133,586	129,598	125,509	122,073
Mean	-1.150					
SD	1.31					
Adm2 FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Adm0 $\times$ year	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The first column (Contemp) fits the contemporaneous relationship between temperature and WAZ. Each column adds lags of temperature in equation 4.3.3. Columns 2m, 5m, 6m, 7m, and 8m include 1, 4, 5, 6 and 7 lags respectively. Stars correspond to significance of the cumulative dynamic effect. Standard errors clustered at administrative/sub-national (adm2) level. Controls for precipitation, age and gender.

Table C.6: Weight-for-Age z-score Gender (36 to 60 Months)

	Age Group 36 to 60 Months					
	(Contemp)	(2m)	(5m)	(6m)	(7m)	(8m)
Base Temperature: $\in$ [15,20)						
Temperature $<$ 15 Male	-0.010**	-0.010**	-0.023**	-0.031**	-0.047***	-0.044***
	(0.005)	(0.005)	(0.009)	(0.011)	(0.012)	(0.013)
Temperature $\in$ [20,25) Male	-0.003**	-0.005**	-0.007**	-0.001	0.002	0.004
	(0.002)	(0.002)	(0.003)	(0.004)	(0.004)	(0.005)
Temperature $\in$ [25,30) Male	-0.004**	-0.006**	-0.008**	-0.001	0.002	0.008
	(0.002)	(0.002)	(0.004)	(0.005)	(0.007)	(0.007)
Temperature $\in$ [30,35) Male	-0.007**	-0.010***	-0.014**	-0.007	-0.002	0.003
	(0.002)	(0.003)	(0.006)	(0.007)	(0.009)	(0.011)
Temperature $\geq$ 35 Male	-0.011*	-0.000	0.004	0.006	0.015	0.032
	(0.006)	(0.009)	(0.014)	(0.017)	(0.023)	(0.026)
Temperature $<$ 15 $\times$ Female	0.002	0.002	-0.002	-0.001	0.002	-0.001
	(0.005)	(0.006)	(0.007)	(0.007)	(0.007)	(0.007)
Temperature $\in$ [20,25) $\times$ Female	0.002*	0.002**	0.002	0.002	0.003*	0.003
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
Temperature $\in$ [25,30) $\times$ Female	0.002*	0.002*	0.001	0.002	0.002	0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Temperature $\in$ [30,35) $\times$ Female	0.002	0.003**	0.002	0.003	0.003	0.003
	(0.001)	(0.001)	(0.002)	(0.002)	(0.003)	(0.003)
Temperature $\geq$ 35 $\times$ Female	0.006	-0.005	-0.005	-0.012	-0.003	-0.002
	(0.006)	(0.008)	(0.013)	(0.016)	(0.018)	(0.019)
Observations	112,383	112,073	107,041	103,722	100,702	98,394
Mean	-1.140					
SD	1.14					
Adm2 FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Adm0 $\times$ year	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The first column (Contemp) fits the contemporaneous relationship between temperature and WAZ. Each column adds lags of temperature in equation 4.3.3. Columns 2m, 5m, 6m, 7m, and 8m include 1, 4, 5, 6 and 7 lags respectively. Stars correspond to significance of the cumulative dynamic effect. Standard errors clustered at administrative/sub-national (adm2) level. Controls for precipitation, age and gender.

Table C.7: Weight-for-Height z-score Gender (12 to 36 Months)

	Age Group 12 to 36 Months					
	(Contemp)	(2m)	(5m)	(6m)	(7m)	(8m)
Base Temperature: $\in$ [15,20)						
Temperature $<$ 15 Male	0.002	0.003	-0.002	0.001	-0.009	0.001
	(0.006)	(0.006)	(0.014)	(0.014)	(0.015)	(0.015)
Temperature $\in$ [20,25) Male	-0.003*	-0.004*	-0.001	-0.002	0.001	0.003
	(0.002)	(0.002)	(0.003)	(0.004)	(0.005)	(0.006)
Temperature $\in$ [25,30) Male	-0.008***	-0.010***	-0.005	-0.007	-0.002	0.004
	(0.002)	(0.003)	(0.004)	(0.006)	(0.007)	(0.008)
Temperature $\in$ [30,35) Male	-0.009***	-0.012***	-0.023***	-0.025***	-0.016*	-0.008
	(0.002)	(0.003)	(0.006)	(0.008)	(0.009)	(0.011)
Temperature $\geq$ 35 Male	-0.009**	-0.007	0.015	0.005	0.001	0.001
	(0.004)	(0.006)	(0.014)	(0.020)	(0.023)	(0.025)
Temperature $<$ 15 $\times$ Female	-0.001	0.001	-0.003	0.001	0.003	0.001
	(0.008)	(0.007)	(0.009)	(0.009)	(0.009)	(0.009)
Temperature $\in$ [20,25) $\times$ Female	0.002*	0.003*	0.003	0.003*	0.002	0.002
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
Temperature $\in$ [25,30) $\times$ Female	0.002*	0.002*	0.002	0.002	0.002	0.002
	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)	(0.002)
Temperature $\in$ [30,35) $\times$ Female	0.004**	0.006**	0.008**	0.009***	0.008**	0.007**
	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)
Temperature $\geq$ 35 $\times$ Female	-0.003	-0.010*	-0.017*	-0.019	-0.025*	-0.026
	(0.005)	(0.005)	(0.010)	(0.013)	(0.015)	(0.016)
Observations	139,677	139,272	133,503	129,515	125,426	121,990
Mean	-0.300					
SD	1.4					
Adm2 FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Adm0 $\times$ year	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The first column (Contemp) fits the contemporaneous relationship between temperature and WHZ. Each column adds lags of temperature in equation 4.3.3. Columns 2m, 5m, 6m, 7m, and 8m include 1, 4, 5, 6 and 7 lags respectively. Stars correspond to significance of the cumulative dynamic effect. Standard errors clustered at administrative/sub-national (adm2) level. Controls for precipitation, age and gender.

Table C.8: Weight-for-Height z-score Gender (36 to 60 Months)

	Age Group 36 to 60 Months					
	(Contemp)	(2m)	(5m)	(6m)	(7m)	(8m)
Base Temperature: $\in$ [15,20)						
Temperature $<$ 15 Male	-0.006	-0.006	-0.009	-0.009	-0.013	-0.016
	(0.006)	(0.006)	(0.010)	(0.011)	(0.012)	(0.012)
Temperature $\in$ [20,25) Male	-0.003**	-0.004**	-0.011**	-0.009**	-0.005	0.004
	(0.002)	(0.002)	(0.003)	(0.004)	(0.005)	(0.006)
Temperature $\in$ [25,30) Male	-0.007**	-0.009***	-0.016**	-0.017**	-0.010	0.005
	(0.002)	(0.002)	(0.005)	(0.006)	(0.008)	(0.008)
Temperature $\in$ [30,35) Male	-0.008**	-0.011***	-0.028***	-0.033***	-0.027**	-0.008
	(0.003)	(0.003)	(0.007)	(0.009)	(0.011)	(0.012)
Temperature $\geq$ 35 Male	-0.012*	-0.019**	-0.022	-0.011	-0.002	0.013
	(0.007)	(0.010)	(0.020)	(0.025)	(0.032)	(0.035)
Temperature $<$ 15 $\times$ Female	-0.003	-0.003	-0.009	-0.008	-0.005	-0.009
	(0.006)	(0.006)	(0.008)	(0.009)	(0.009)	(0.009)
Temperature $\in$ [20,25) $\times$ Female	-0.001	-0.001	-0.001	-0.000	-0.000	-0.001
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
Temperature $\in$ [25,30) $\times$ Female	0.001	0.001	0.001	0.001	0.002	0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Temperature $\in$ [30,35) $\times$ Female	0.004**	0.004**	0.005*	0.007**	0.006*	0.007**
	(0.001)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)
Temperature $\geq$ 35 $\times$ Female	-0.000	-0.005	-0.004	-0.025*	-0.013	-0.012
	(0.008)	(0.011)	(0.014)	(0.015)	(0.017)	(0.019)
Observations	112,347	112,037	107,005	103,686	100,666	98,358
Mean	-0.110					
SD	1.26					
Adm2 FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Adm0 $\times$ year	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The first column (Contemp) fits the contemporaneous relationship between temperature and WHZ. Each column adds lags of temperature in equation 4.3.3. Columns 2m, 5m, 6m, 7m, and 8m include 1, 4, 5, 6 and 7 lags respectively. Stars correspond to significance of the cumulative dynamic effect. Standard errors clustered at administrative/sub-national (adm2) level. Controls for precipitation, age and gender.

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