Child Exposure to Climate Change: A Regional Index of Vulnerability for Better-Targeted Policies

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A Regional Index of Vulnerability for Better-Targeted Policies*

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Abstract

A growing body of evidence suggests that changes in global temperature may have drastic and long-lasting impacts on human health. Even more, these consequences may vary widely across different geographic areas. We explore the regional differences in the effects of exposure to high temperature variability – an important consequence of climate change – on a particularly vulnerable demographic group: infants. We use the case of Peru, a large and geographically diverse developing country, as a setting to showcase the potential scale of these differences. We bring together monthly, high resolution data on air temperatures with measures of physical health for children born between 1985 and 2000. We find that exposure to temperatures above the historical local mean during pregnancy negatively affects health at birth. Even more salient, the negative effects persist over time, impairing the physical growth of children. We then combine our results with forecasted temperatures to construct a regional index for child vulnerability to future temperature variability. This indicator shows that country-level measures of the potential impact of climate change may hide important heterogeneities across geography. In fact, we predict that while most regions will face a reduction of up to 0.1 standard deviations in our aggregate measure of child health by 2030, this impact could be up to three times as large in the most affected areas. Our methodology can be easily replicated in other countries to identify the most vulnerable populations. This information could improve the geographical allocation of resources and contribute to the design of more effective strategies aimed at preventing or mitigating the consequences of climate change.

Keywords: Climate Change, Temperature Variability, Vulnerability, Child Development, Health

JEL Codes: I10, I15, J13, Q54

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1. Introduction

In recent years, the discussion about the consequences of climate change on human activity has occupied a central position in the public debate. A main point of interest is its potential effect on human health. A growing body of evidence suggests that changes in the global temperature and their natural consequences may have drastic and long-lasting impacts on the world's population. Moreover, recent trends indicate that these effects are likely to magnify in the near future. This is becoming a major concern for stakeholders all over the world, who are demanding better sources of information on vulnerability to climate change in order to design effective strategies to minimize its consequences.

A particular awareness has been raised about the potential heterogeneities in the impact of climate change, which could disproportionally affect populations living in vulnerable areas. In this regard, the European Commission for Research on Climate Change indicates that "whatever the success of mitigating climate change may be, certain impacts are unavoidable and some regions will need to adapt to those impacts (…); the effects of climate change could raise serious sustainability questions" (European Research Framework Programme, 2010). With respect to human health, "[t]here is a particular need for (…) data on human exposure, sensitivities, and responses to global environmental change, such as morbidity and mortality associated with air and water quality, and vulnerabilities to extreme weather and climate events" (Committee on Strategic Advice on the U.S. Climate Change Science Program, 2009, p. 92).

Despite these emerging needs, surprisingly few studies have focused on the geographic differences in the impact of climate change on human health. A better knowledge of this topic should be highly informative for policy-makers for at least two reasons. First, certain regions are naturally more vulnerable than others due to their location and climatic conditions, and particularly because of how they are affected by the global forces of climate change. Second, specific socioeconomic differences between geographic areas are likely to influence their population's sensitivity to changing temperatures.

This paper seeks to contribute to this gap of information by determining how prenatal exposure to different levels of temperature variability – an important consequence of climate change[1]– affects birth outcomes and growth retardation before the age of five. Moreover, we explore how these effects differ across geographical areas by using our estimated impacts along with forecasted temperatures to construct a regional index of vulnerability to temperature variability. To do so, we use the case of Peru, a large and geographically diverse developing country, as a setting to showcase the potential scale of regional differences in vulnerability to climate change.[2] We combine monthly data on air temperatures at a very high resolution with measures of child physical health obtained from the Peruvian Demographic and Health Surveys for children born between 1985 and 2000. Our focus on infants is due to this group being particularly vulnerable to the consequences of climate change.[3] Both adverse neo-natal health conditions and early growth retardation have been linked to poverty and reduced well-being in adulthood (Almond and Currie, 2011; Currie, 2011).

We contribute to the literature in three different ways. First, we document that exposure to higher temperature variability (and in particular, unusually warm periods) during pregnancy not only affects birth outcomes, but also that these consequences are sizable and persist over time, impairing physical growth before the age of five. Second, our work is among the first to account for geographical heterogeneity in the impact of climate change. In this regard, our findings confirm that potential differences within a country may be of a considerable dimension. Third, we use our constructed vulnerability indices at the regional level to show the average impact of increased temperature

[1] See, for instance, Thompson et al. (2013), Thornton et al. (2014) and Wang and Dillon (2014).

[2] Our choice of setting is particularly relevant, since Peru's territory comprises a wide range of geographical features and micro-climates (i.e., it covers coastal regions, highlands and a portion of the Amazonian jungle). Furthermore, the Andean region has been predicted to be among the regions most affected by climate change in the future (Brooks and Adger 2003; Kreft et al. 2014). On the other hand, by focusing on a highly heterogeneous developing country, we also highlight the importance of socioeconomic differences in the population in determining their vulnerability to changing temperatures.

[3] A recent report from the World Health Organization (WHO) posits that "health and other impacts [of climate change] may fall disproportionately on women, children, people with disabilities, and elderly people" (WHO, 2014).

variability on a selection of child health outcomes. This showcases how a simple methodology may provide valuable information that can be used by stakeholders to predict the areas that have the largest health burdens due to climate change in the next decades.

Contrary to the extensive literature about the effects of higher temperature levels over human health, there is little comparable evidence on increased temperature variability. The medical literature has distinguished at least five channels through which fetal health can be affected by temperature levels: (i) diseases which are related to changes in the temperature levels per se (i.e., respiratory diseases); (ii) exposure to extreme temperatures; (iii) transmission of infectious diseases that are caused by increased biological vectors; (iv) maternal mental illnesses; and (v) food insecurity resulting from negative agricultural shocks induced by higher temperatures (WHO 2003; McMichael et al. 2007; NIEHS 2010). Considering that climate shocks become more unpredictable and larger in magnitude when temperature variability is high, these effects are also likely to prevail or even magnify under such conditions. In this regard, a recent study by Molina and Saldarriaga (2017) found that exposure to a one standard deviation relative to the municipality's long-term temperature mean during pregnancy increases the probability a child is born with low weight by more than 10 percent.

Our results confirm this hypothesis and extend previous findings on the impacts of temperature variability on child physical health. Specifically, we show that exposure to a one standard deviation above the long-term local temperature mean during pregnancy reduces child's height for age by a -0.09 of a standard deviation and body mass index by -0.15 kg/m2 at age of 5, even after controlling for birth weight. We also provide evidence that these impacts of increased temperature variability may be highly heterogeneous across the different regions of a country, a feature that national averages are not able to capture. In fact, we predict that while most regions will face a reduction of up to 0.1 standard deviations in our aggregate measure of child health by 2030, this impact could be as high as 0.3 standard deviations in the capital and in some Amazonian regions.

From a policy standpoint, our findings show that exploring the geographical differences in the effects of temperature variability allows for a better identification of vulnerable areas in terms of the health burden due to climate change in the near future. Geographical targeting has been employed for many years in anti-poverty programs, particularly in developing countries where information and resources are limited (for a short review, see Bigman and Fofack, 2000). We argue that the regional vulnerability indices that we develop could be used in a similar fashion to address the consequences of climate change. In this regard, our proposed methodology can be easily replicated in countries with availability of public data on measures of child health, as is the case of Peru, by combining this information with publicly available remote sensing data and temperature forecasts. These new inputs could help stakeholders make better decisions regarding the allocation of resources across their territory and contribute to the design of more effective medium- and long-term strategies aimed at preventing or mitigating climate change-induced health problems in vulnerable populations.

The paper proceeds as follows. In section 2, we describe how temperature variability has evolved in different regions of Peru during the last decades. In section 3, we explain our sources of information and the empirical approach used to uncover the effects of temperature variability on child health. In section 4 we introduce the methodology to show child vulnerability to temperature variability across regions. In section 5 we present our main results and the vulnerability analysis. The policy implications of our results are included in section 6. In section 7, conclusions are presented.

2. Climate Change in Peru: Trends and Child Exposure

In this section, we describe the trends in average temperatures and temperature variability in Peru over the period 1950-2010. We also present evidence of an increased exposure to unusually hot temperatures among newborns born between 1980 and 2010.

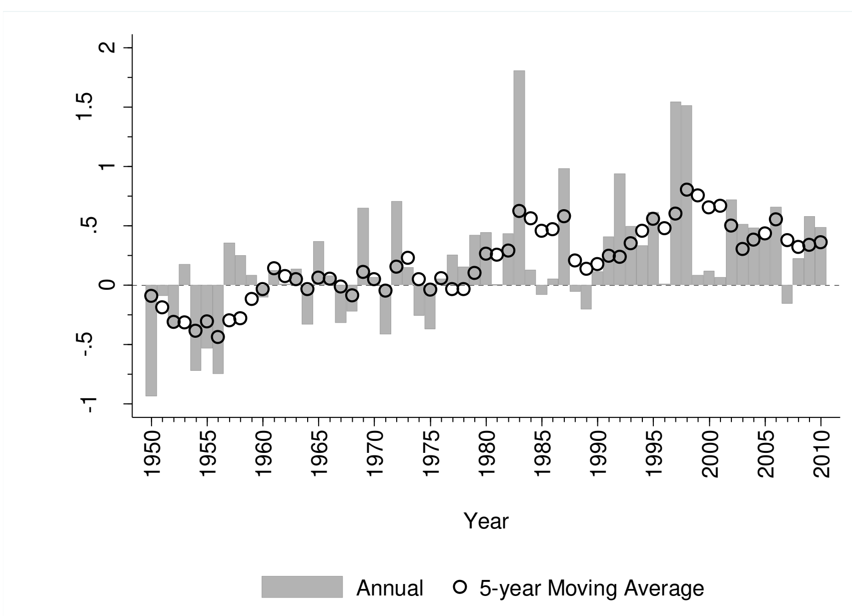
2.1. Trends in Average Temperatures and Temperature Variability: 1950-2010

Peru is considered the third most vulnerable country to climate change (Brooks and Adger, 2003). The country's average temperature is expected to rise by more than 5°C by the end of the century unless current prevention policies are considerably improved (World Health Organization, 2015). Furthermore, a human development report by the UN Development Programme (UNDP) pointed out that climate change could undo Peru's recent advances in poverty reduction through different channels, ranging from natural disasters to health-related consequences of temperature changes (UNDP, 2013).

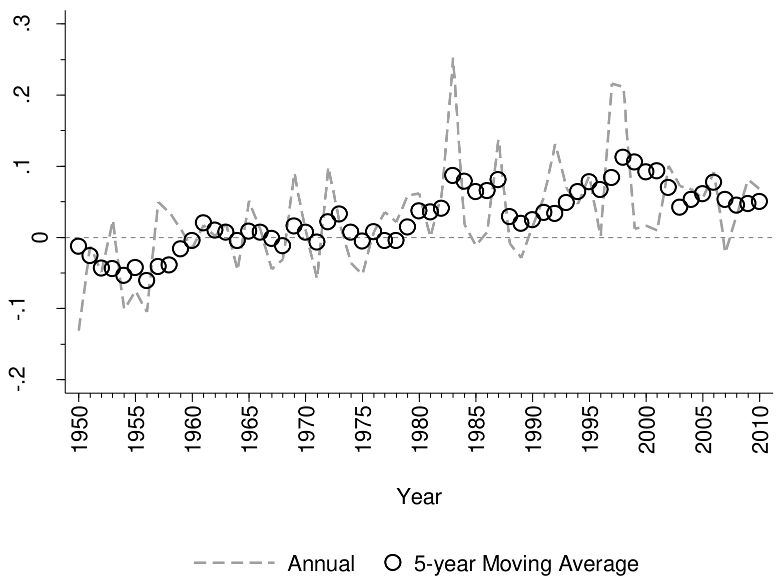
A review of weather information between 1950 and 2010 provides crucial facts on how climate change has affected Peru. First, there has been an increase in the average temperature in the country, which we estimate to be around 0.75°C (see Panel A of Figure 1). Second, as Panel B of Figure 1 portraits, temperature variability (measured in standard deviations relative to the 1950-2010 average) has also increased, causing an intensification of extreme weather events. Specifically, the share of years with positive temperature variability has increased towards the end of the period, which suggests that temperatures have been reaching record highs over the last decades.

Figure 1: Temperature Anomalies and Temperature Variability over Time

A. Temperature Anomalies over Time



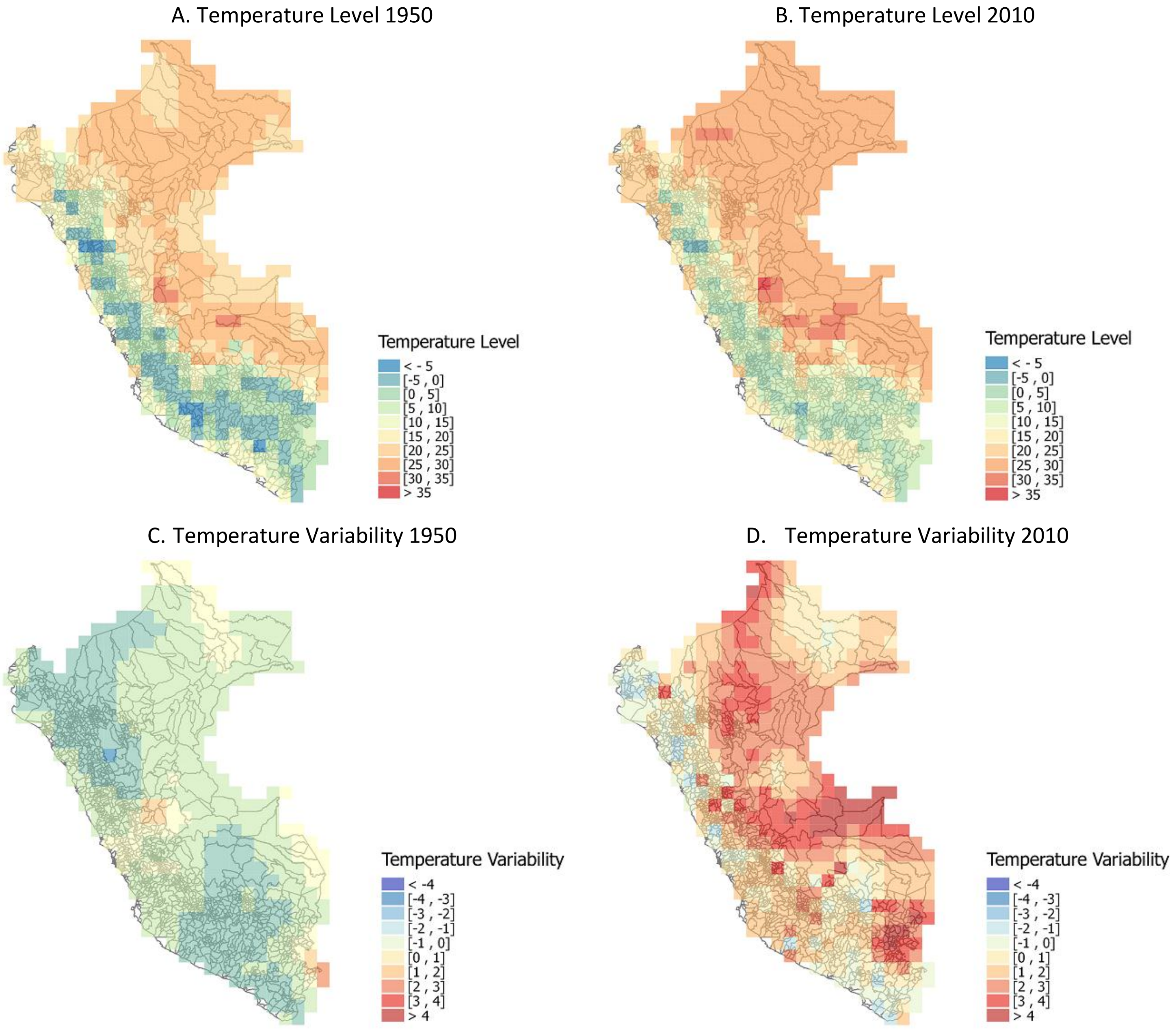
B. Temperature Variability over Time



Notes: The figure shows the temperature anomalies (Panel A) and the temperature variability (Panel B) in Peru over the period 1950-2010. Temperature anomaly is defined as the average deviation (in degree Celsius) relative to the historical (1951-1980) temperature mean. Temperature variability is defined as the number as standard deviations relative to the historical (1951-1980) temperature mean.
Source: Authors' own calculations using geo-referenced information from the *Terrestrial Air Temperature: 1900-2010 Gridded Monthly Time Series Version 3.01* (Matsuura and Willmott 2009).

However, this information hides important differences across the country's territory. Figure 2 compares how these climatic phenomena vary across the Peruvian territory between the years 1950 and 2010. Panel A and B suggest an important geographical heterogeneity in the increase of the temperature, with changes in the average temperature between 1950 and 2000 range from 0°C in some coastal regions to more than 3°C in certain municipalities in the Andean region. More interestingly, there is also evidence of significant regional differences regarding temperature variability (see Panel C and D of Figure 2). While most municipalities in the Amazon region have become more likely to experience extremely high temperatures (in the range between 2 and 3 standard deviation above the long-term local temperature mean), there are certain municipalities in the Andean region that are still vulnerable to unusually cold weathers (up to 2 standard deviations below the long-term local temperature mean). Also, several municipalities have experienced in 2010 extremely high temperature variability (more than 3 standard deviations relative to the historical local temperature mean), something very difficult to find sixty years before. These figures indicate that the consequences of climate change differ significantly across regions, with some communities being severely affected.

Figure 2: Temperature Levels and Temperature Variability in 1950 and 2010



Notes: The figure shows the temperature level in each node covering the peruvian territory in year 1950 (Panel A) and year 2010 (Panel B) and the temperature variability in each node covering the peruvian territory in year 1950 (Panel C) and year 2010 (Panel D). The temperature level is expressed in degree Celsius. The temperature variability is expressed in standard deviations relative to the 1951-1980 node-specific mean.

Source: Authors' own calculations using geo-referenced information from the *Terrestrial Air Temperature: 1900-2010 Gridded Monthly Time Series Version 3.01* (Matsuura and Willmott 2009).

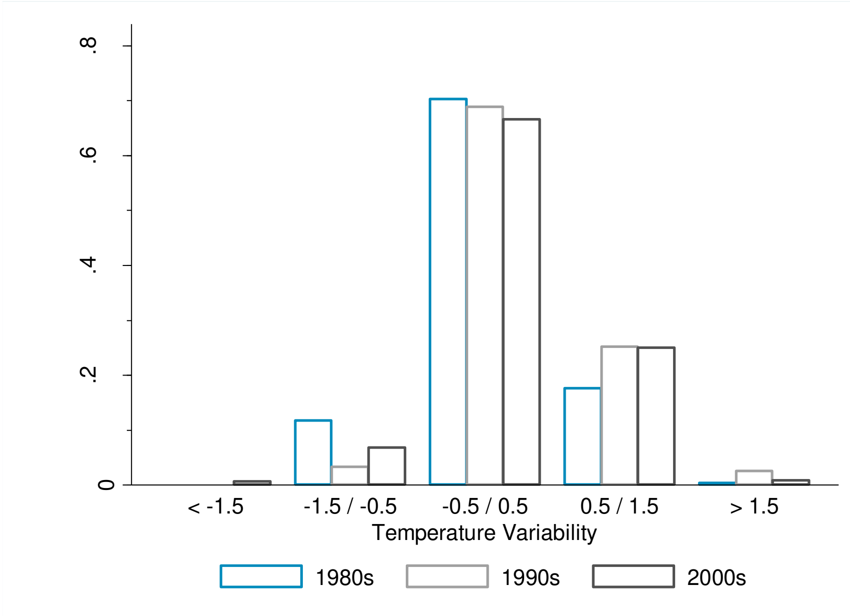
2.2. Child Exposure to Climate Change

The evidence regarding recent changes in average temperature and temperature variability implies important challenges for Peru's population, with children being among the most vulnerable groups. Figure 3 presents the distribution of births by temperature variability level during pregnancy. First, Panel A displays the in-utero exposure to temperature variability for different cohorts in our sample, showing that the fraction of births born in relatively low levels of variability (between -0.5 and 0.5 standard deviations from the average) has decreased over the last decades.

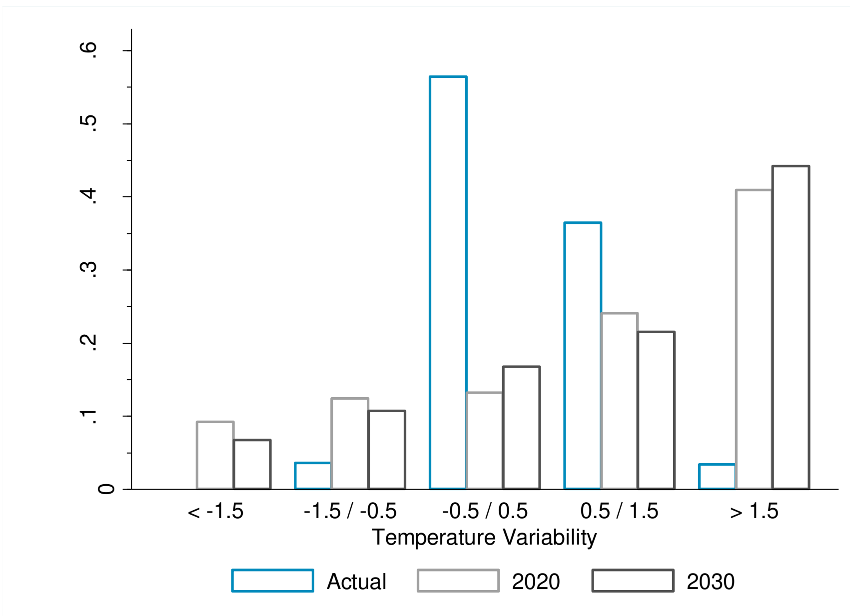
Second, Panel B presents the distribution of births by the predicted temperature variability level for a child been born in the same month and municipality during the period 2020-2040. While almost 70% of children nowadays are born after periods of relatively low temperature variability, our estimates indicate that this number will decrease to less than 20% over the next two decades. Furthermore, the share of children born after unusually hot periods (more than 1.5 standard deviations above average) might rise from 2% to more than 40% during the same period. The consequences of these estimates of future temperatures are alarming: almost 4 out of 10 children will be born in areas with high temperature variability in Peru by 2030.

Figure 3: In-utero Exposure to Temperature Variability: Actual and Forecasted

A. Exposure to Temperature Variability: Cohort Level



B. Exposure to Temperature Variability: Actual and Forecasted



Notes: The figure shows the in-utero exposure to different temperature variability levels for every cohort in our sample (Panel A) and also the observed and forecasted distribution of births according to different temperature variability levels (Panel B). To construct the forecasted exposure to temperature variability, we assume the same geographical and seasonal distribution of births as that observed in year 2010.

Source: Authors' own calculations based on the *Terrestrial Air Temperature: 1900-2010 Gridded Monthly Time Series Version 3.01* (Matsuura and Willmott 2009) and on the NCAR CCSM2-A3 model.

3. Empirical Methodology

This section describes the data used for empirical purposes as well as the regression framework we follow for estimating the effect of temperature variability on physical health early in life.

3.1. Data

We bring together information about historical and forecasted (future) temperatures and information about health outcomes observed at birth and before age 5 from Peruvian children born between 1986 and 2010. In our empirical methodology, we use historical data on temperatures and data on health outcomes early in life to estimate the effect of temperature variability – defined as the fluctuations over the long-term local temperature mean – on measures of child health. We then use this estimates to make inferences about the areas which will be more affected by temperature variability between 2020 and 2040.

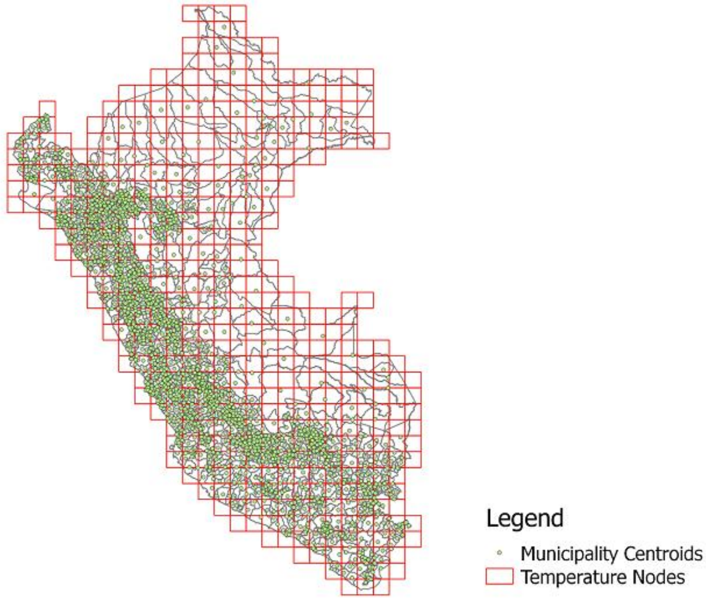
Historical Temperatures. Information about historical temperatures is gathered from the *Terrestrial Air Temperatures: 1900-2010 Gridded Monthly Time Series Version 3.01* (Matsuura and Willmott 2009). This dataset provided geo-referenced (gridded) information of the air temperature on a monthly basis from 1900 to 2010 at a resolution of 0.5 x 0.5 degrees (each degree corresponds to approximately 56 kilometers at the equator).

Monthly average temperatures for each temperature node were interpolated using information from 20 nearby weather stations. In Panel A of Figure 4, we plot the distribution of the nodes as well as the municipality centroids on the geographic coordinate system, where the horizontal axis represents the longitude and the vertical axis represents the latitude of each point. For each municipality, we assign its corresponding monthly temperature based on the closest node to the municipality's centroid.[4]

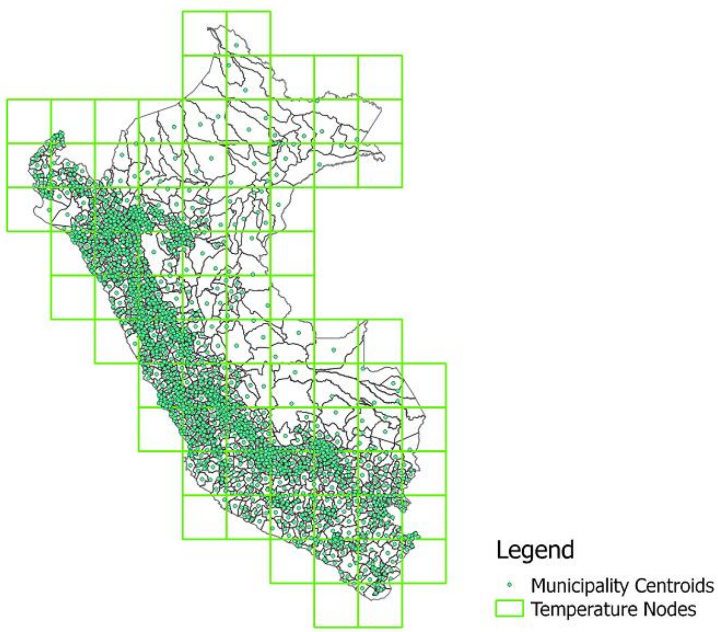
[4] Alternatively, we interpolated municipality monthly temperatures based on a weighted average of the temperatures of all nodes entirely covering the municipality boundary, where we used the inverse of the distance between the node's centroid and the municipality's centroid as the weights. Our results remain unchanged when using this alternative interpolation method.

Figure 4: Distribution of Temperature Nodes

A. Historical Temperature Nodes



B. Forecasted Temperature Nodes



Notes: The figure shows the historical (Panel A) and forecasted (Panel B) temperature nodes enclosing the Peruvian territory. Historical temperature nodes are at a resolution of 0.5 x 0.5 degrees and forecasted temperature nodes are at a resolution of 1.4 x 1.4 degrees. Each degree corresponds to approximately 56km. at the equator.

Source: Authors' own calculations using geo-referenced information from the *Terrestrial Air Temperature: 1900-2010 Gridded Monthly Time Series Version 3.01* (Matsuura and Willmott 2009) and from the NCAR CCSM2-A3 model.

The resulting dataset is at the municipality-by-month-by-year level, covering the entire Peruvian territory over the period 1950-2010. Following the standard literature, we define temperature variability as the fluctuations in the air temperature from each municipality's historical average (Scherrer et al. 2005). The indicator we use to define temperature variability is constructed based on each child's municipality of birth/residence and date of birth and is calculated using the following formula:

$$SD_{mt} = \left[\frac{1}{9}\sum_{\tau=t-8}^{t}(temp_{m\tau} - \overline{temp}_m)\right]/\sigma_m ,$$

for a child born in municipality m at date (year-month) t. The variable $temp_{m\tau}$ is the average monthly temperature in the corresponding municipality for the τ-th month before the child's month of birth, $\overline{temp}_m$ is the municipality's historical temperature mean for the period 1950-2010, and σ_m is the standard deviation of the municipality's temperature observed in this time period. Put it simply, SD_{mt} indicates the number of standard deviations, on average, during the nine months before the child's date of birth with respect to the municipality's historical temperature mean.

Forecasted Temperatures. We extract information about forecasted temperatures from the CCSM3-A2 (Community Climate System Model) model. Forecasted temperatures from this model were used for elaboration of the Assessment Report 4 from the Intergovernmental Panel on Climate Change (IPCC). The CCSM3-A2 is constructed by the US National Center for Atmospheric Research (NCAR) of National Science Foundation.[5]

The dataset from the CCSM3-A2 provides monthly gridded forecasted temperatures over the period 2020-2040 at a resolution of 1.4 x 1.4 degrees. Panel B of Figure 3 depicts the distribution of the CCSM3-A2 temperature nodes along the Peruvian territory. Forecasted municipality-level monthly temperatures over the period 2020-2040 are interpolated based on the closest node to the municipality.

[5] Information about future temperatures from the CCSM3-A2 has been previously used by Deschênes et al. (2009).

Child Physical Health. Measures of child physical health are obtained from the Peruvian Demographic and Health Survey (DHS) from the period 1992-2013. The DHS provides detailed information about birth weight and actual weight and height of children ages 0-59 months. Thus, we observe measures of child physical health since the date of birth for children born between 1986 and 2010.

We restrict our sample to only include children whose mothers report having lived in the municipality for at least two years before the child's date of birth. This restriction ensures that we are correctly assigning each child with its corresponding average temperature while *in utero*, given that the mother has been living in the municipality since before the date of conception.

Because twinning is usually related with a lower birth weight and growth retardation (Kramer 1987), we drop from the sample children born from multiple births; namely duplets, triplets, etc. We also exclude children whose birth weight was observed to be below 500 grams or above 6,500 grams, as the medical literature points out that these values are considered to be out of the normal range for birth weight (Doubilet et al. 1997). Finally, we exclude all the children whose mothers were younger than 15 or older than 45 years, so that we ensure that all the children were born during the childbearing age of their mothers and the health condition at birth is not affected by the mother's age.

Important for empirical purposes, the DHS also provides detailed information about maternal background. This information is used to control for socio-economic characteristics of the family by the time of the child's birth. Specifically, we construct indicators for the mother's year of birth, indicators for the mother's age at her first birth, indicators for the mother's age at the child's year of birth, indicators for mother's schooling, indicators for the child's year of birth, indicators for the child's birth order, an indicator for the child's sex, an indicator for living in rural areas and node-specific linear time trend. These characteristics would serve as control variables in all our regressions.

3.2. Outcomes and Descriptive Statistics

Based on the information provided by the DHS, we construct three outcome variables measuring child physical health: birth weight (measured in grams), a standardized score (z-score) for height for age and the child's body mass index. These three indicators are intended to capture physical health and growth retardation since very early stages of life.

Birth weight is intended to measure fetal health. In recent years, a number of studies have been conducted using birth weight as their principal outcome variable.[6] Although being regarded as an imperfect measure of health at birth, "many studies have shown that birth weight can be affected by a variety of subtle and less subtle shocks during the fetal period (…) [and] is the most widely measure available and most studied measure of fetal health (…)" (Almond and Currie 2011).

Height for age, on the other hand, is intended to capture growth retardation. The World Health Organization (WHO) released in year 2006 a new growth standard statistical distribution for children aged 0-59 months. These standards were constructed based on what the WHO believes is an optimal environment for growth of children and the distribution shows how infants and young children grow under these circumstances. In short, the z-score for height for age indicates the number of standard deviations the child is relative to the average (optimal) height for her or his age.[7][8]

Lastly, the body mass index (BMI) is intended to quantify the amount of mass (muscle, fat and bone) in an individual. As such, the BMI is often used for determining underweight or obesity among

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[6] See Almond and Currie (2011) and Currie (2011) for a review of studies on birth weight and fetal health.

[7] The height for age is also used for determining stunting condition of children under age 5. According to the WHO, a child is consider as stunted if her corresponding height for age is below -2 standard deviations.

[8] According to the DHS protocols, for children younger than 60 months of age, height and weight are measured to the nearest 0.1 cm. All survey team members receive standardized training on how to weight and measure children, and instructions are based on the United Nations manual on how to obtain anthropometric measures of children. All records are entered onto a standardized paper form or into an automated computer system in the field. After the records are computerized at the country level, they are transferred to Macro International Incorporated, an Opinion Research Corporation company (ORC Macro), for inclusion in the DHS database.

individuals. This indicator is calculated by dividing the body weight (measured in kilograms) over the square of the body height (measured in meters).[9]

In Table 1 we present summary statistics for the three outcome variables. The final dataset comprises information about fetal health (birth weight) for 56,418 children born between 1986 and 2010.Yet, we observe information about height for age and body mass index for 38,487 children. This is due to the fact that parental consent was required for children to be measured and weighted. Our results, however, remain unchanged when restricting the sample to include only children for whom we observe complete of information about the three outcome variables.

Table 1: Summary Statistics

	N	Mean	Standard Deviation	Min.	Max.
	Panel A: Continuous-type Outcomes				
Birth weight (in grams)	56,418	3233.74	591.54	500.00	6000.00
Height for age (z-score)	38,487	-1.02	1.21	-5.98	5.99
Body Mass Index (kg./m.^{2})	38,487	16.94	1.72	9.69	28.94
	Panel B: Binary-type Outcomes				
Low birth weight	56,418	0.078	0.268	0	1
Stunting	38,487	0.197	0.398	0	1
Normal range for BMI	38,487	0.538	0.499	0	1

3.3. Regression Framework

Our objective is to estimate the effect of temperature variability on measures of physical health before age 5. With information for child i born in municipality m in date (month and year) t, we perform linear regressions of the form:

[9] We follow closely the definitions and charts provided by the US Center for Disease Control (CDC) to construct the body mass index of each child in our sample. Although the CDC makes it clear that body mass index should be only calculated since age of 2, we follow the line of previous empirical studies examining the effect of health at birth and child physical health (Saldarriaga 2015) to construct the body mass index for children ages 0-23 months. The charts for physical health (nutritional status) can be found in the following links (for girls and boys, respectively):
https://www.cdc.gov/growthcharts/data/set1clinical/cj41l024.pdf
https://www.cdc.gov/growthcharts/data/set1clinical/cj41l023.pdf

$$y_{imt} = \beta_0 + \beta_1 SD_{mt} + X'_{imt}\gamma + \phi\, Trend_{ny} + \mu_{rt} I_{rt} + \mu_y I_y + \varepsilon_{imt}, \qquad (1)$$

where y_{imt} is the indicator for child physical health, SD_{mt} is the indicator for temperature variability during the nine months before the child's birth, X_{imt} is a vector of child and maternal characteristics, I_y are year-of-birth fixed effects and $Trend_{ny}$ is a *node*-specific linear time trend. The term ε_{imyt} is an error term capturing all other omitted factors.

We include region-by-month-of-birth fixed effects, $\mathrm{I_{rt}}$, in the regressions to account for all observed and unobserved factors equally affecting a given region in a particular time of the year. By including region-by-month-of-birth fixed effects, we also ensure that the region's seasonal mean temperature is kept constant. Thus, we capture the effects of changes in the variance while keeping the (long-term) average temperature within the region and month of the year unchanged.

However, given our objective of constructing a regional index for exposure to temperature variability, we need its effect on child physical health to vary across geography. Thus, in our regressions, we allow for the effect of temperature variability (β_1) to differ across different regions. We therefore modify our model as follows:

$$y_{imt} = \beta_0 + \sum_r \beta_1^r \cdot (SD_{mt} \times I_r) + X'_{imt}\gamma + \phi\, Trend_{ny} + \mu_{rt} I_{rt} + \mu_y I_y + \varepsilon_{imt}\ , \qquad (2)$$

where I_r is a vector of region-specific fixed effects. All remaining terms are the same as in Equation (1). Estimates of β_1^r from equation (2) capture the effect of temperature variability during the prenatal period on measures of child physical health that are specific to each region. If these estimates are negative and statistically significant, then this implies that temperature variability impairs child physical health. In all specifications, we cluster standard errors at the node level.

We present the results from an alternate regression specification in Appendix C. In this alternate specification, we divide the temperature variability shocks according to each trimester of pregnancy. Put differently, we calculate the temperature variability for each trimester of pregnancy and explore heterogeneous effects according to the pregnancy period. These explorations will allow us understanding whether there are critical periods during pregnancy in which climate shocks may affect differently the physical development of children.[10]

4. Exposure to Temperature Variability Regional Index

Our objective is (i) to estimate a measure of the average exposure at the municipal level for each health outcome and (ii) to construct a child vulnerability index that ranks municipalities according to the vulnerability to climate change faced by children living there. Using estimates of β^{r} from equation (1) and the municipality-level temperature forecasts, we estimate the future measure of physical health of child i had he born in municipality m at (future) time t, $\widehat{y_{\imath m t}}$, as:

$$\widehat{y_{\imath m t}} = \widehat{\beta^{r}} \cdot SD_{mt}^{f} , \tag{3}$$

where $\widehat{\beta_1^{r}}$ is the resulting estimate from equation (2) and SD_{my}^{f} is the forecasted average temperature variability for the municipality m in year-month t. Equation (3) also accounts for child i's other characteristics to estimate the future measure of physical health. Temperature forecasts are obtained from the CCSM3-A2.

Next, we use $\widehat{y_{\imath m t}}$ and the observed (actual) measure for physical health y_{imt} to calculate the expected change (in standard deviations) in child physical health in region r, Δ_r, as:

$$\Delta_r = [\textstyle\sum_{i,r}(\widehat{y_{\imath m t}} - y_{imt})/n_r]/\sigma_r^{y} , \tag{4}$$

where n_r is the number of observations (i.e., children) in region r and σ_r^{y} is the standard deviation of the indicator for child physical health in our sample. We construct Δ_r for every measure of child physical health we have (i.e., birth weight, height for age and BMI).

[10] Unfortunately, the DHS does not provide information about the time of conception. Thus, to construct the indicators for trimester of pregnancy, we count backwards from the date of birth. Each trimester of pregnancy is constructed as follows: 1st. trimester is defined as months 8-6 before birth; 2nd. trimester is defined as months 5-3 before birth; 3rd. trimester is defined as months 2-0 before birth.

Finally, we combine these partial measures of exposure to construct an index that reflects the level of overall vulnerability to climate change experienced by children in each municipality. This child vulnerability index is calculated as the arithmetic mean of the partial measures for each health outcome:

$$g_r = (\Delta_r^{BW} + \Delta_r^{HA} + \Delta_r^{BMI})/3\,, \tag{5}$$

where g_r can take any real value. By using a simple mean to construct the index, we are not imposing specific weights for each child health outcome.

We expect that this child vulnerability index showing the geographical differences of the impact of climate change on children´s health will help policymakers to prioritize specific interventions to improve the supply of health for newborns and infants in areas most affected by climate change. Being able to contrast the current index with the expected future one will allow policymakers to take progressive actions in advance. The simplicity in the construction of the index seeks to facilitate its replicability elsewhere.

5. Results

In this section, we present the main results of the effects of temperature variability on birth weight and physical health early in life. We begin the discussion by presenting the general results of different levels of temperature variability on birth weight, height for age and BMI. Next, we discuss heterogeneity by region. We close the section by discussing the regional-specific effects of temperature variability on measures of child physical health in future decades.

5.1. How Does Temperature Variability Affect Child Physical Health?

The linear effects of temperature variability on measures of child physical health are summarized in Table 2. Our results indicate that a temperate one standard deviation relative to the long-term local temperature mean reduces birth weight by almost 22 grams, reduces height for age by 0.09 standard deviations and reduces BMI by 0.15 kg/m2.

Table 2: Effect of Temperature Variability on Child Physical Health

	(1)	(2)	(3)
Dependent Variable:	Birth Weight	Height for age	BMI
Temperature Variability	-21.980	-0.088	-0.151
	(10.912)**	(0.028)***	(0.055)***
	[10.894]**	[0.027]***	[0.061]**
N	56,418	38,487	38,487
Clusters (municipality)	1,288	1,190	1,190
Clusters (node)	295	292	292

Notes: ***, ** and * denote statistical significance at $p < 0.01$, $p < 0.05$ and $p < 0.10$ levels respectively. The table shows estimates of the effect of temperature variability during the nine months before the child's birth (pregnancy period) on birth weight (column 1), the z-score of height for age (column 2) and body mass index (column 3). Clustered standard errors at the municipality and node levels are presented in parentheses and brackets respectively. Additional controls include: indicators for the mother's year of birth (1950-1955; 1956-1960; 1961-1965; 1966-1970; 1971-1975; 1976-1980; 1981-1985; 1986-1990; 1991-1995; base: born before 1949), indicators for the mother's age at her first birth (15-19; 20-29; 30-39; 40 or older; base younger than 15), indicators for the mother's age at the child's year of birth (20-29; 30-39; 40-45; base: 15-19), indicators for mother's schooling (incomplete primary; complete primary; some high school; high school diploma; some tertiary education; base: no education), indicators for the child's year of birth (1991-1995; 1996-2000; 2001-2005; 2006 or later; base: 1986-1990), indicators for the child's birth order (2; 3; 4; 5 or more; base: firstborn child), an indicator for the child's sex, an indicator for living in rural areas, a node-specific linear time trend and municipality-by-month fixed effects. Additional details of each specification are described within the table. The data used for the regressions come from the Peruvian DHS over the period 1992-2013 and from the *Terrestrial Air Temperatures: 1900-2010 Gridded Monthly Time Series Version 3.01* (Matsuura and Willmott 2009).

Additonally, in Appendix C we present estimates of the effect of temperature variability on child physical health by trimester of pregnancy. The results suggest that birth weight and BMI are affected more by an increase in temperature variability during the first trimester of pregnancy. By contrast, height for age – a measure of growth retardation – is more affected by temperature variability during the first trimester of pregnancy. These results indicate that there are heterogeneous impacts of temperature variability on measures of child health and, moreover, these impacts may differ when considering indicators of nutrition (such as birth weight and BMI) and indicators of physical growth (such as height for age) which is consistent with previous empirical evidence (Currie and Rossin-Slater 2013).

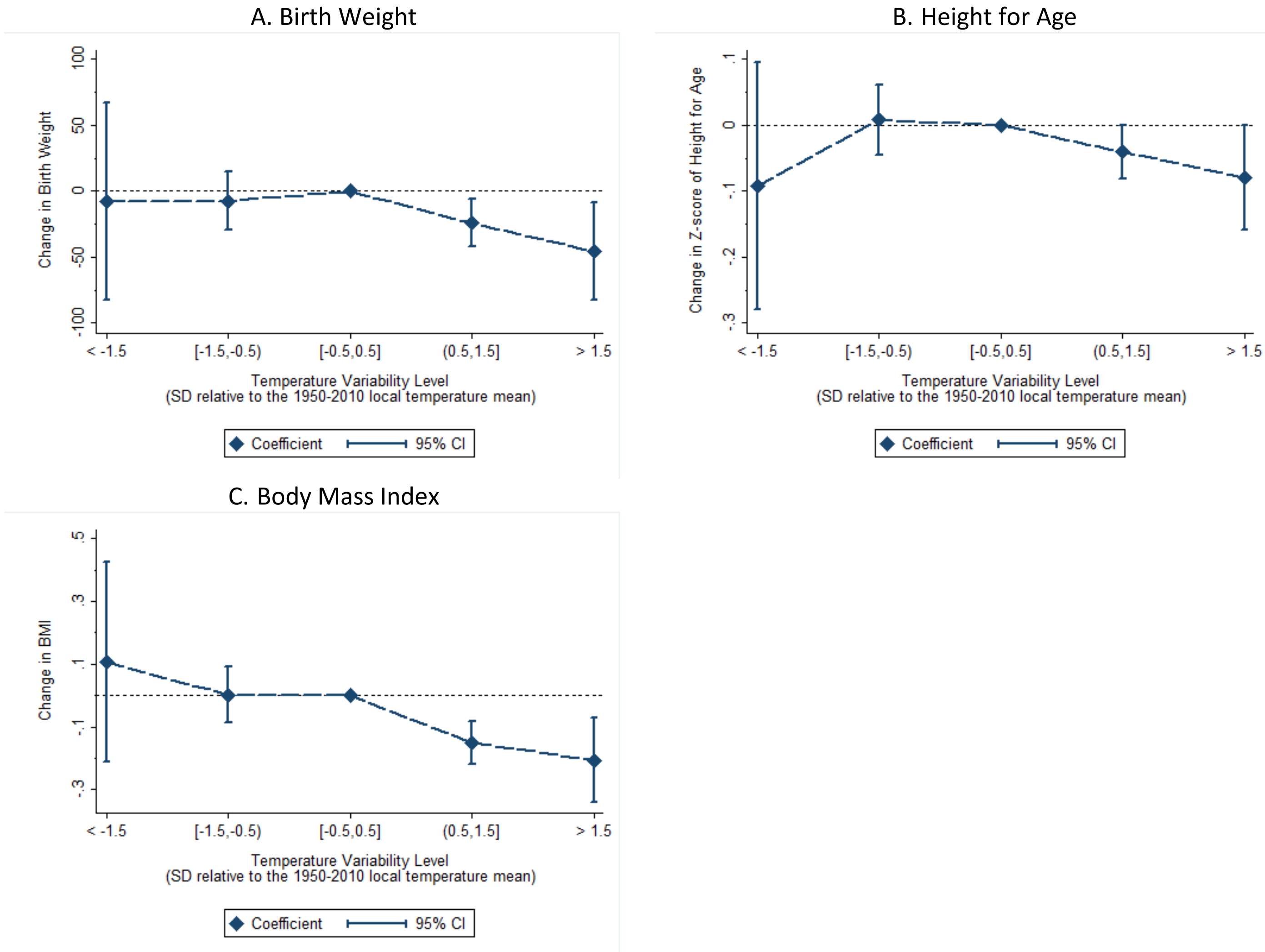
Since our model assumes a lineal relationship between temperature variability and our measures of health outcomes, we also test an alternative specification that employs indicators based on the number of standard deviations from the municipality's historical mean. These indicators are constructed according to the following categories: < -1.5s; [-1.5s, -0.5s); [-0.5s, 0.5s]; (0.5s, 1.5s]; > 1.5s. This way we allow for a more flexible specification exploiting all the available variations in the data and at the same time we deal with potential non-linearities in the effect of temperature variability on birth outcomes.

In Figure 5, we plot the effects of different levels of temperature variability on our measures of child health birth weight (Panel A), the z-score of height for age (Panel B) and BMI (Panel C). Interestingly, we find that temperature variability impairs child physical health only when temperature variability is higher than 0.5 standard deviations relative to the normal local temperature range. We do not find any statistically significant effect of cold weathers on any of the three measures of child physical health.[11]

We estimate a 24 grams decrease in birth weight when temperature variability lies between 0.5 to 1.5 SD from the local long-term temperature mean. Above these levels, we find a sizable reduction of 45 grams. We also estimate a 0.04 SD decrease in height for age in the 0.5-1.5 temperature variability level with a stronger negative effect of 0.09 SD in height for age when the temperature variability is observed to be above 1.5 SD. Finally, we find that BMI is reduced by 0.15 kg/m^2 and by 0.18 kg/m^2 when temperature variability is between 0.5-1.5 SD or above 1.5 SD, respectively, from the local long-term temperature mean.

[11] In Appendix Figure B1, we present the results for the binary outcome variables including low birth weight, stunting condition, and normal range of BMI. The results are consistent with our findings for the continuous-type outcomes.

Figure 5: Effect of Temperature Variability on Birth Weight, Height for Age and BMI, By Temperature Variability Level



Notes: The figure shows the estimated effects of different temperature variability levels on birth weight (Panel A), height for age (Panel B) and Body Mass Index (Panel C). Each point estimate should be interpreted relative to the temperature variability bin [-0.5 , 0.5], which we consider the normal temperature variability range.

Source: Own calculations based on the Peruvian Demographic and Health Surveys over the period 1992-2013 and the *Terrestrial Air Temperature: 1900-2010 Gridded Monthly Time Series Version 3.01* (Matsuura and Willmott 2009).

5.2. How Do These Effects Vary Across Geography?

Thus far, we have discussed the effects of temperature variability on child physical health, with our findings indicating a negative effect of temperature variability on measures of child physical health. Yet, a more comprehensive analysis would discuss how these effects vary across different regions. We address this inquiry by presenting regional-specific effects of temperature variability on measures of child health.

Motivated by geo-political divisions, we group the country into five different regions: Lima and Callao (the Peruvian capital and its metropolitan area), the northern regions, the southern regions, the Amazonas, and the Middle regions. A more detailed explanation about this division can be found in Appendix A.

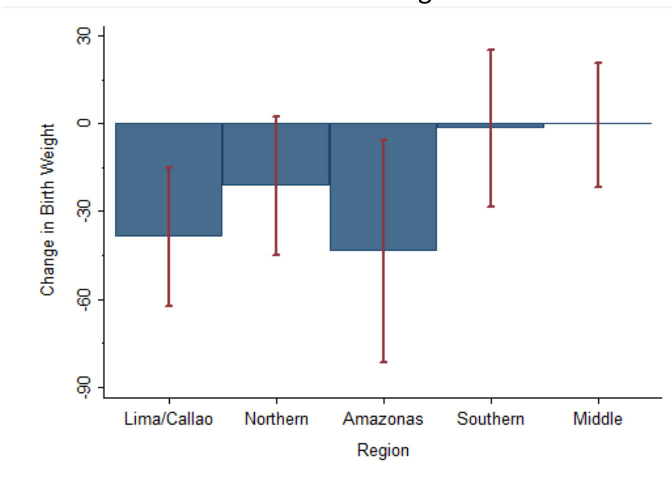
Figure 6 plots estimates of β^{r}, along with its associated 95% confidence intervals, from equation (1) in section 3. In Panel A, the dependent variable is birth weight. We find that temperature variability negatively affects birth weight only in Lima and Callao, the Northern regions, and the Amazonas. We do not find statistically significant effects of temperature variability on birth weight for the Southern and Middle regions.[12] By contrast, temperature variability affects height for age before age 5 in all regions, as Panel B indicates. Lastly, in Panel C, we plot estimates from the equation of temperature variability on BMI. We find that the BMI is only affected by temperature variability in Lima and Callao and the northern regions.[13]

[12] Typically, cold weathers characterize these regions since they are closer to the Andean mountain range. Thus, it is not surprising that increases in temperatures above its normal range have no effect on health at birth.

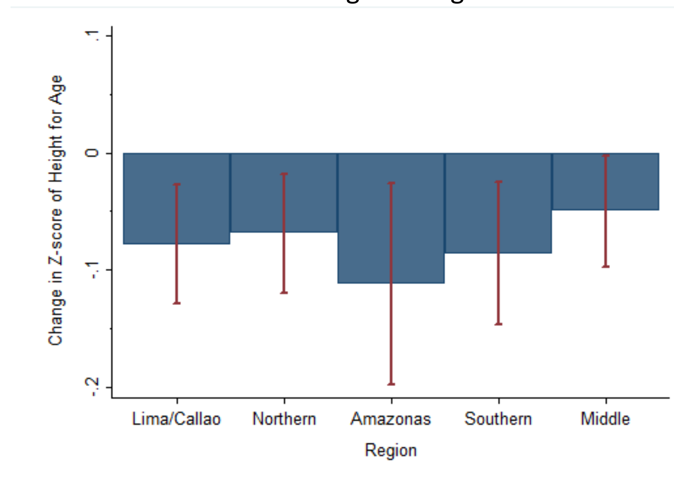
[13] In Appendix Figure B2 we present estimates of β_1^{r} when the dependent variables are in binary form. Panel A presents estimates for low birth weight, Panel B for stunting condition and Panel C for the normal range of BMI. The results are similar to what we found when using the continuous-type dependent variables.

Figure 6: Regional-specific Effects of Temperature Variability on Birth Weight, Height for Age and BMI

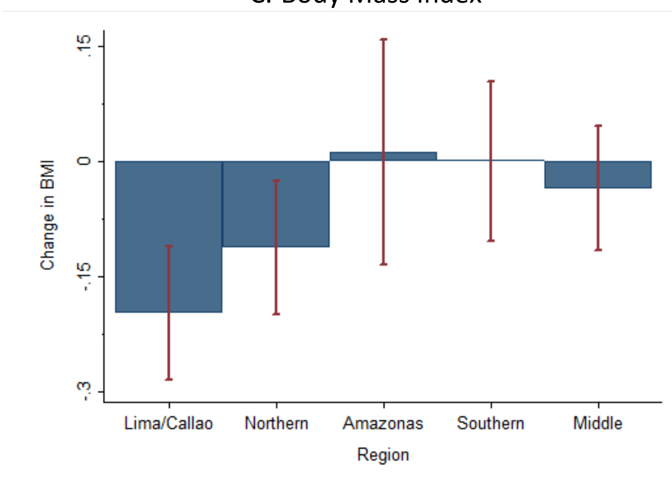
A. Birth Weight



B. Height for Age



C. Body Mass Index



Notes: The figure shows estimates of β_1^r, along with their 95% confidence intervals, from equation (1) in section 3. Each graph shows the regional-specific effects of temperature variability on birth weight (Panel A), height for age (Panel B) and Body Mass Index (Panel C).

Source: Own calculations based on the Peruvian Demographic and Health Surveys over the period 1992-2013 and the *Terrestrial Air Temperature: 1900-2010 Gridded Monthly Time Series Version 3.01* (Matsuura and Willmott 2009).

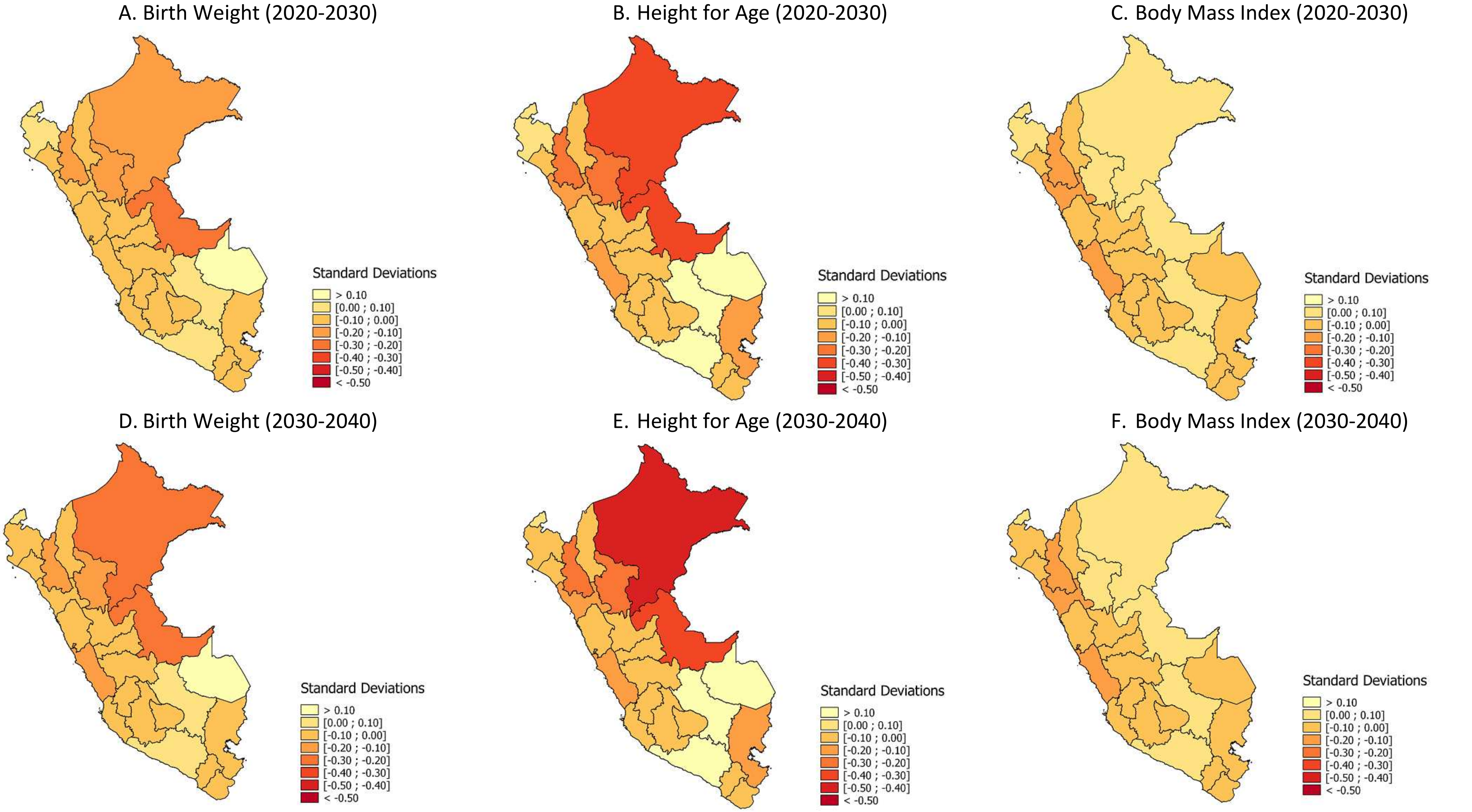
5.3. A Regional Measure of Future Exposure to Temperature Variability

We combine estimates of β^r from equation (1) and weather forecasts from the CCSM3-A2 model to predict how child physical health is expected to vary in future decades. To that extent, we assume that the geographical and seasonal distribution of births will remain the same as that from year 2010.[14] Further, we assume that children in the sample we use to make predictions will be born in years 2025 and 2035 and will preserve their month of birth.

Figure 7 depicts estimates of Δ_r for each of the three measures of child physical health in the decades of 2020 (Panels A through C) and 2030 (Panels D through F). We find expected significant changes in birth weight and height for age, especially in the Amazonian regions of Loreto and Ucayali. By the decade of 2030, our results indicate a decrease of between -0.2 and -0.3 in birth weight in these regions. Regarding height for age, the predicted reduction in Loreto is between -0.3 and -0.4, while in the case of Ucayali it could be as high as -0.5 standard deviations.

[14] We have also tested the sensitivity of the results and assume that the geographical and seasonal distribution of births is the same as that from the period 2000-2010. The results remain unchanged under this alternative specification.

Figure 7: Expected Change in Measures of Child Physical Health (decades of 2020 and 2030)



<u>Notes</u>: The figure shows the estimated expected impacts (in standard deviations relative to the 2010 mean) of temperature variability on measures of child physical health in the decades of 2020 (Panels A through C) and 2030 (Panels D through F).

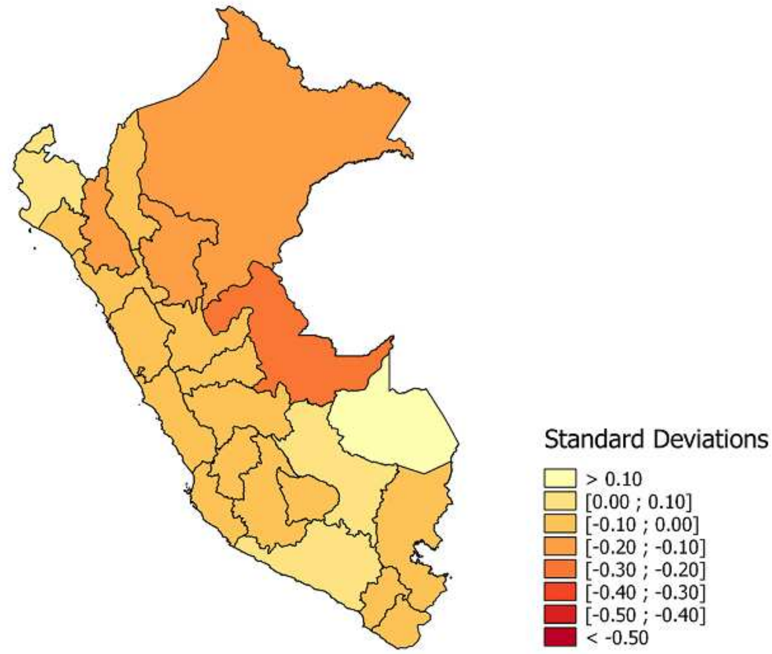
Source: Source: Own calculations based on the Peruvian Demographic and Health Surveys over the period 1992-2013, the *Terrestrial Air Temperature: 1900-2010 Gridded Monthly Time Series Version 3.01* (Matsuura and Willmott 2009) and the NCAAR CCSM3-A2 model.

Figure 8 depicts estimates of g_r for the decades of 2020 (Panel A) and 2030 (Panel B). In general, the results provide evidence that the impacts of increased temperature variability will be highly heterogeneous across the different regions of a country. In the decade of 2020, it is expected that children in the Amazonian region of Ucayali will suffer most from temperature variability. Specifically, these children will experience a drop of between -0.2 and -0.3 standard deviations in the aggregate indicator for child physical health relative to children born in year 2010.

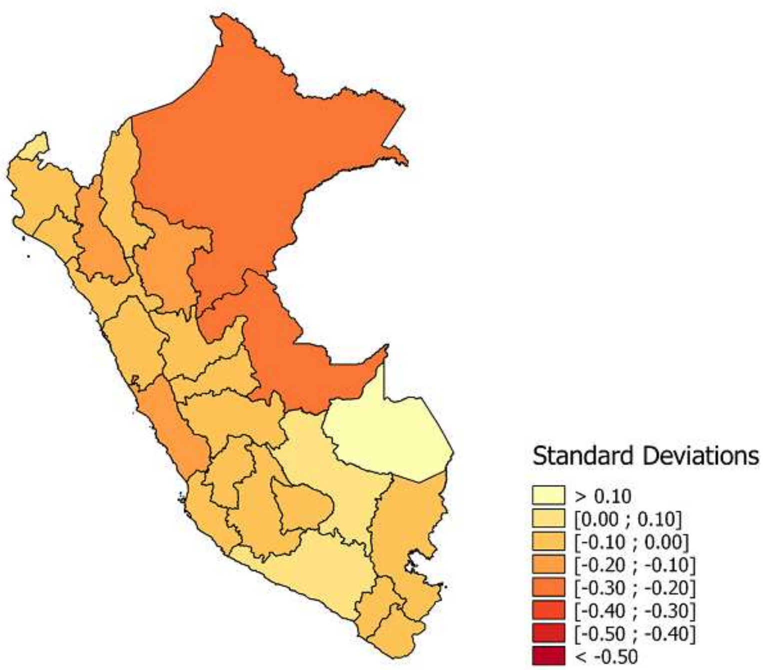
Yet, it is expected that children born in the decade of 2030 will suffer more from an increased temperature variability experienced during pregnancy. More regions are expected to experience sizeable losses in term of child health during this period. Specifically, our results reveal that while most areas in the country will experience reductions of up to -0.1 standard deviations in the aggregate index of child health, the Amazonian regions of Loreto and Ucayali are likely to bear the largest health burdens in the country, with a predicted drop of up to -0.3 standard deviations relative to children born in 2010. The capital and some areas in the Northern highlands are also expected to experience sizeable losses in terms of child health: for these regions, the corresponding drop in the aggregate index is expected to be between -0.1 and -0.2 standard deviations.

Figure 8: Expected Change in the Aggregate Indicator for Child Physical Health (decades of 2020 and 2030)

A. Decade 2020-2030



B. Decade 2030-2040



Notes: The figure shows the estimated expected impacts (in standard deviations relative to the 2010 mean) of temperature variability on the aggregate indicator for child physical health in the decades of 2020 (Panel A) and 2030 (Panels B).

Source: Source: Own calculations based on the Peruvian Demographic and Health Surveys over the period 1992-2013, the *Terrestrial Air Temperature: 1900-2010 Gridded Monthly Time Series Version 3.01* (Matsuura and Willmott 2009) and the NCAAR CCSM3-A2 model.

6. Policy Implications

The results presented in the previous section have several important implications, especially for policies tackling the health-related consequences of climate change. In this section, we discuss these implications and also address the usefulness of our study in generating knowledge that can be used for the design public policies aimed at reducing the impacts of climate change on human health.

First, the study of the effects of climate change requires examining a comprehensive set of measures related to different aspects of health. In our study, we have analyzed three different indicators – all of them related to child physical health. As we have demonstrated, increased temperature variability during pregnancy impacts physical health since very early stages of life. Moreover, these impacts are long-lasting, affecting growth retardation along the first years of life. Preventing these consequences of climate change should be particularly relevant for stakeholders, since several studies have linked early health deficiencies with later outcomes such as human capital accumulation and other aspects of general well-being. Thus, public policies aimed at attenuating the impacts of climate change need to take in consideration the different dimensions through which it may impact human health.

Second, our results show the importance of examining how climate change will affect health outcomes of vulnerable populations differently across geography. Oftentimes, academics are only interested in the average impacts that climate change may generate on human health. Yet, as we have shown, the average impacts hide important differences across regions and children from some regions might be more affected than the average child in the country. We argue that the regional vulnerability indices that we develop should be helpful in designing better-targeted policies. Geographical targeting has been employed for many years in anti-poverty programs, particularly in developing countries where reliable administrative data at the individual level is absent (for a short review, see Bigman and Fofack, 2000). Many studies document the potential efficiency gains from targeting smaller administrative units in transfer programs (Henninger and Snel, 2002; Elbers et al., 2007). We believe that disaggregated information on vulnerability to climate change could be used in a similar fashion by stakeholders to design cost-effective strategies to prevent or mitigate its consequences.

It is also important to note that due to the availability of remote sensing data, our methodology to assess the effects of climate variability on human health can easily be replicated in other countries where similar household survey data is publicly available. Considering the potential benefits of generating geographically disaggregated information on vulnerability to climate change, it is important that governments and public institutions responsible for gathering such information include policies aimed at making these data available for public use. This would allow local researchers to elaborate more and better studies about the health implications of climate change.

7. Conclusion

In recent years there has been a growing interest on measuring the effects of climate change on human health. Many have been the efforts in analyzing how rising temperatures and other consequences of climate change can impair the health status of individuals, especially among the most vulnerable ones. Yet, these studies are interested in estimating average health impacts and oftentimes overlook the geographic differences in the impacts of climate change on health.

In this study, we aimed at estimating the effects of temperature variability – a consequence of climate change – on measures of child physical health. Even more, our study also analyzes the heterogeneous impacts of temperature variability on child physical health based on geography, and estimates an index of regional exposure to climate change for children of ages 0 to 5 years. We bring together geo-referenced information on historical and future temperatures with data on measures of physical health of children born in Peru. Our sample comprises information of children born between

1985 and 2010, providing a richness of data to analyze the effects of temperature variability on indicators such as birth weight, height for age and Body Mass Index.

Our results indicate that a temperate one standard deviation from the municipality historical temperature mean reduces birth weight by 22 grams, reduces height for age by 0.9 standard deviations and reduces BMI by 0.15 units. These effects are also found to differ across geography, being the Amazonian regions of Loreto and Ucayali the ones more affected by temperature variability and where future generations are expected to carry the burdens of climate change-induced diseases. In fact, our regional index of vulnerability to temperature variability reveals that the impact in these areas could be up to three times larger than in most regions of the country.

Our study has several policy implications. First, we document the importance of evaluating a range of indicators when assessing the impacts of climate change on human health. Second, we provide evidence about the large geographic differences these effects. Using our results and forecasted temperatures, we develop a simple methodology to construct an index of child vulnerability to temperature variability at the regional level that can be easily replicated in other developing countries. We believe that this information should help stakeholders in the design of better-targeted and more effective medium- and long-term strategies aimed at preventing or mitigating the consequences of climate change.

Needless to say, more studies are required in order to understand the potential mechanisms through which climate change affects human health, especially among the most vulnerable populations. This is important for the design of public policies as it may allow health stakeholders to elaborate mitigation plans addressing specific elements that are important for the production of human health. Fortunately, recent innovations regarding the availability of remote sensing data have made these studies possible. In this regard, public institutions in charge of gathering and processing climate and health-related data need to work together to make this information available for researchers in order to improve the scope of public policies aimed at fighting climate change-induced diseases.

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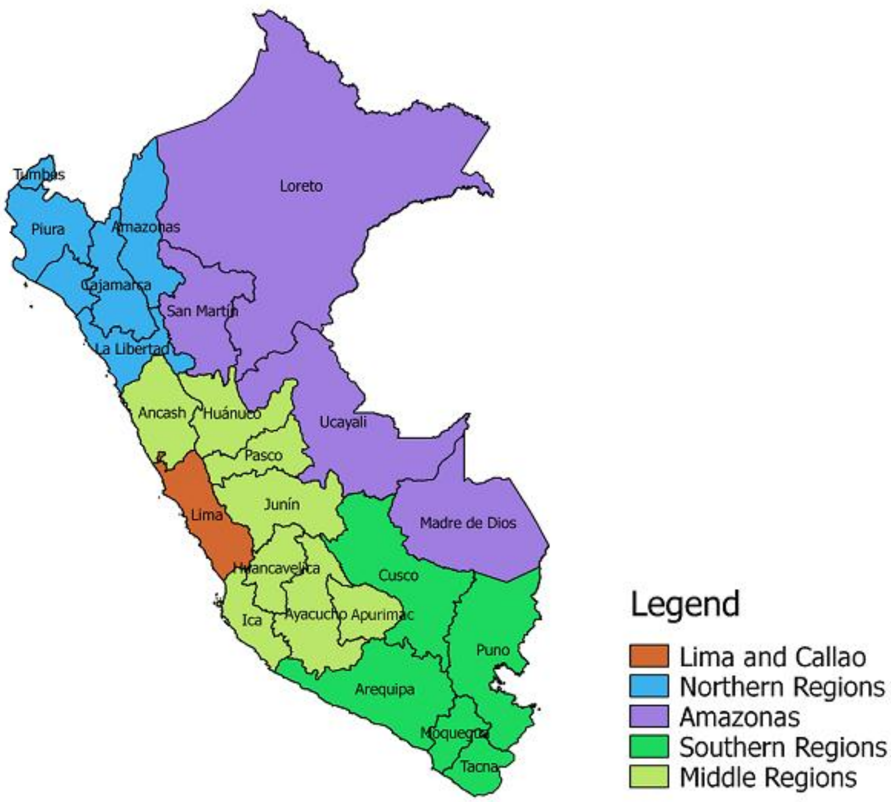
Appendix A: Grouping Regions

The analysis of regional-specific effects of temperature variability on indicators for child physical health requires that we estimate different effects for every region in the Peruvian territory. Peru is composed of 24 regions. This would require us estimating 24 different effects of temperature variability on child physical health; a tasks which is computationally demanding.

Instead, we group this 24 regions into 5 different regions following the geo-political division of the so-called macro-regions in Peru. This division is based on the Peruvian *Presidencia del Consejo de Ministros* criterion for defining macro-regions in Peru. Appendix Figure A1 depicts the Peruvian map along with the five macro-regions considered in the analysis.

Appendix Figure A1: Regional Division of the Peruvian Territory



<u>Notes</u>: The figure shows the division of the Peruvian territory according to five macro regions. This division has been performed based on the Peruvian *Presidencia del Consejo de Ministros* (PCM) criterion for defining macro-regions in Peru.

Appendix B: Results for Binary-type Indicators

In section 5 of the main text, we presented the results based on the continuous-type outcome variables. In this appendix, we complement the analysis by presenting the results when the dependent variables in the regressions are of binary-type (dichotomous variables). We begin by explaining how we construct the indicators. Next, we show the overall results of temperature variability on measures for child physical health. Finally, we present the regional-specific impacts of temperature variability on our binary-type measures of child physical health.

B.1 Binary-type Measures of Child Physical Health

To construct the binary-type measures of child physical health we follow the definitions from the World Health Organization (WHO) and the Center for Disease Control (CDC) on child nutritional condition. Specifically, we construct three indicators based on birth weight, height for age and the body mass index: low birth weight, stunting condition and normal range of body mass index.

Low birth weight. We use information about birth weight to construct an indicator for low birth weight. Low birth weight is defined by the WHO as birth weight being less than 2,500 grams. A low birth weight infant can be born too small, too early or both. Compared to normal weight infants, low birth weight infants are more likely to develop health problems both in the short- and long-run. Moreover, low birth weight infants are in serious risk of death within the first year of life.

Stunting. Height for age levels determine stunting condition or stunted growth. An infant is said to be stunted if its z-score of height for age is below -2 standard deviations relative to the norm for her age and sex. Stunting is a reduced growth rate in human development and is often associated with undernutrition.

Normal Range for BMI. To calculate the normal range for BMI, we follow the definition from the CDC, indicating that a BMI above the 5th. percentile and below the 85th. lies within the normal range for body mass index. In our data, these figures correspond to values of BMI between 14.5 and 18.5.

B.2 Estimated Impacts of Temperature Variability

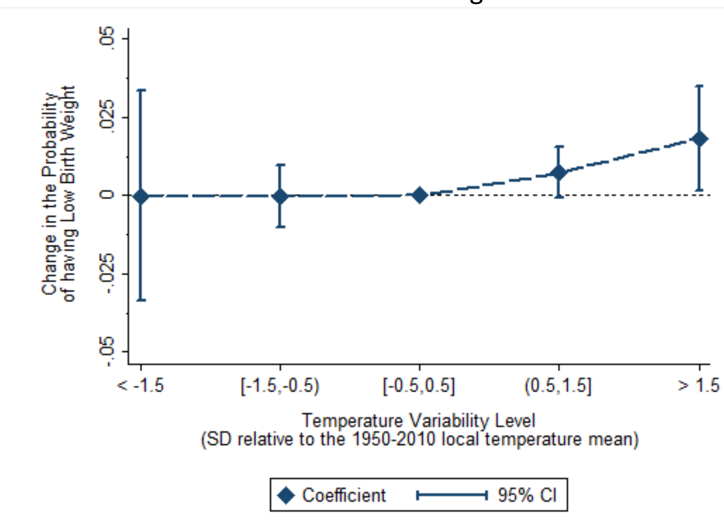
Appendix Figure B1 depicts the effects of different temperature variability levels on low birth weight (Panel A), stunting condition (Panel B) and the normal range for BMI (Panel C). Consistent with the results presented in section 5 of the main text, we find that child physical health is only affected with positive distributional changes in temperature variability. For temperature variability levels below the local long-term temperature mean, we do not find statistically significant effects on any of the three measures of child physical health.

B.3 Regional-specific Estimated Impacts of Temperature Variability

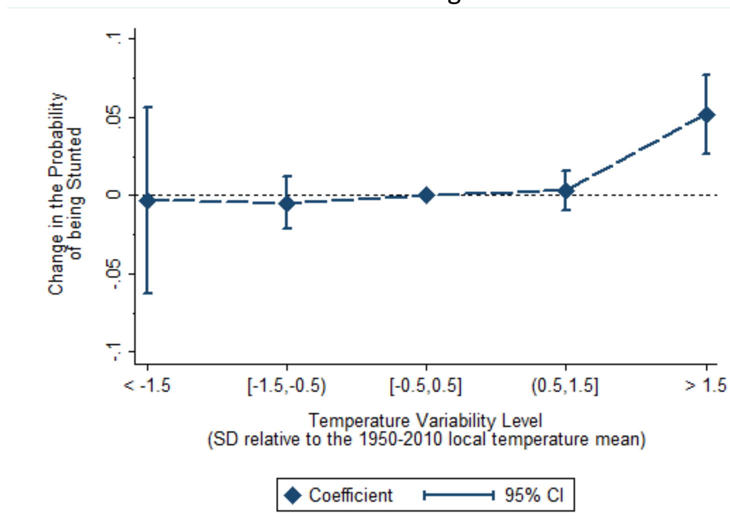
The regional-specific effects of temperature variability on binary-type indicators for child physical health are depicted in Appendix Figure B2. Relative to the estimates based on continuous-type dependent variables, the results based on binary-type outcomes are less precise. Yet, the direction of the impacts are consistent with the results discussed in section 5 of the main text.

Appendix Figure B1: Effect of Temperature Variability on LBW, Stunting and Normal Range for BMI

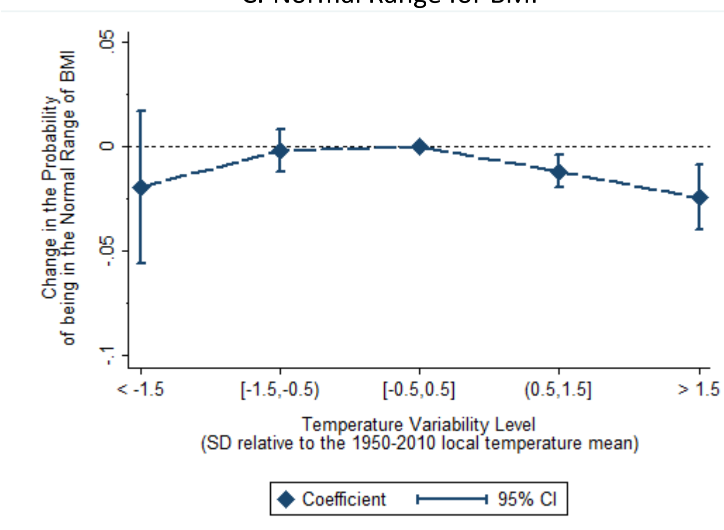
A. Low Birth Weight



B. Stunting



C. Normal Range for BMI

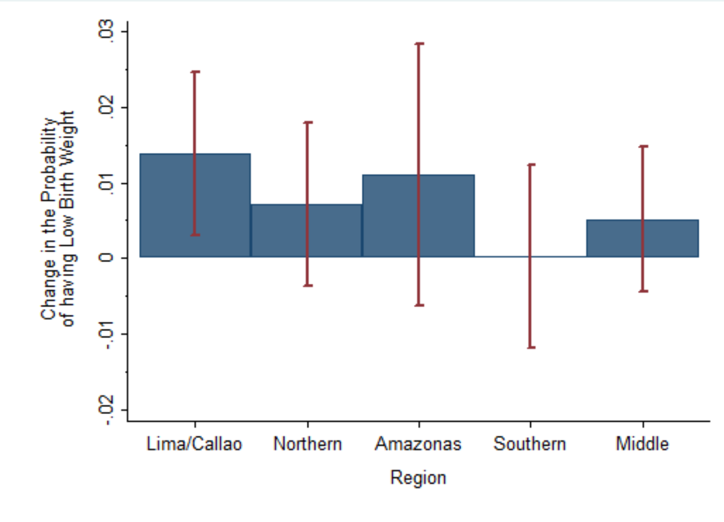


Notes: The figure shows the estimated effects of different temperature variability levels on low birth weight (Panel A), stunting condition (Panel B) and normal range for Body Mass Index (Panel C). Each point estimate should be interpreted relative to the temperature variability bin [-0.5 , 0.5], which we consider the normal temperature variability range.

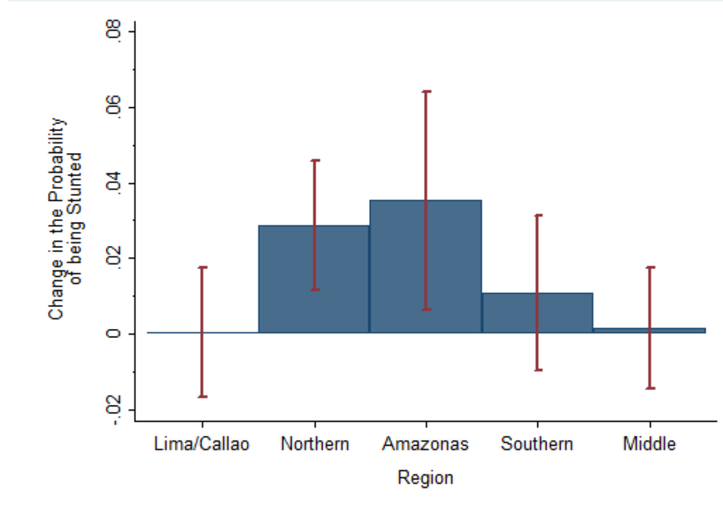
Source: Own calculations based on the Peruvian Demographic and Health Surveys over the period 1992-2013 and the *Terrestrial Air Temperature: 1900-2010 Gridded Monthly Time Series Version 3.01* (Matsuura and Willmott 2009).

Appendix Figure B2: Regional-specific Effects of Temperature Variability on LBW, Stunting and Normal Range for BMI

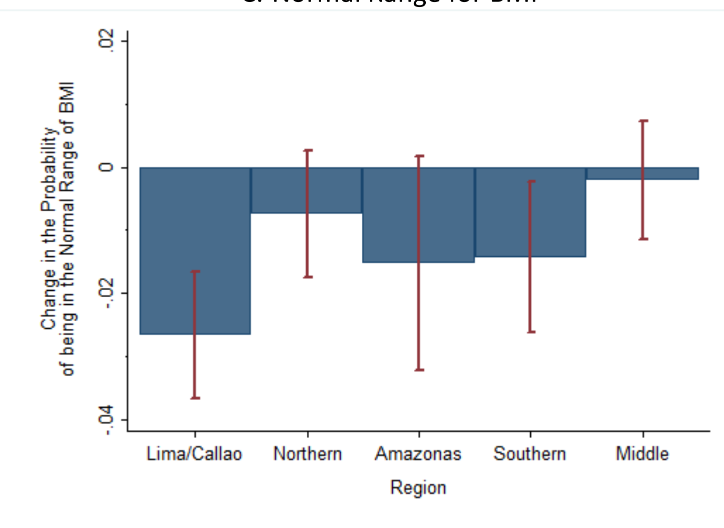
A. Low Birth Weight



B. Stunting



C. Normal Range for BMI



Notes: The figure shows estimates of β_1^r, along with their 95% confidence intervals, from equation (1) in section 3 of the main text. Each graph shows the regional-specific effects of temperature variability on low birth weight (Panel A), stunting condition (Panel B) and normal range for Body Mass Index (Panel C).

Source: Own calculations based on the Peruvian Demographic and Health Surveys over the period 1992-2013 and the *Terrestrial Air Temperature: 1900-2010 Gridded Monthly Time Series Version 3.01* (Matsuura and Willmott 2009).

Appendix C: Heterogeneous Effects by Trimester of Pregnancy

Our principal regression specification from equation (1) in the main text examines the effect of temperature variability during the whole pregnancy period on child physical health. In this Appendix we explore how temperature variability in different stages of pregnancy can affect physical development of children. Each trimester of pregnancy are constructed as follows: 1st. trimester is defined as months 8-6 before birth; 2nd. trimester is defined as months 5-3 before birth; 3rd. trimester is defined as months 2-0 before birth.

Once we construct the temperature variability observed in each trimester of pregnancy, we perform linear regressions of the form:

$$y_{imt} = \beta_0 + \beta_1^{TRIM1} \cdot SD_{imt}^{TRIM1} + \beta_1^{TRIM2} \cdot SD_{imt}^{TRIM2} + \beta_1^{TRIM3} \cdot SD_{imt}^{TRIM3} \qquad \text{(C.1)}$$
$$+ X'_{imt}\gamma + \phi\, Trend_{ny} + \mu_{rt} I_{rt} + \mu_y I_y + \varepsilon_{imt}\ ,$$

where $\mathrm{SD}_{\mathrm{imt}}^{\mathrm{TRIM1}}$, $\mathrm{SD}_{\mathrm{imt}}^{\mathrm{TRIM2}}$ and $\mathrm{SD}_{\mathrm{imt}}^{\mathrm{TRIM3}}$ are the temperature variabilities observed in the first, second and third trimester of pregnancies respectively and all the other variables are defined the same as in equation (1) in section 3.3 of the main text.

Equation (C.1) allows for identifying heterogeneous impacts of temperature variability on child physical health according to different stages in pregnancy. This exploration follows from previous empirical evidence showing heterogeneous effects of shocks observed in-utero according to the gestational period when the shock was realized (see for example Quintana-Domeque and Ródenas-Serrano forthcoming). The results from this alternate specification are presented in Appendix Table C.1.

Appendix Table C.1: Temperature Variability on Child Physical Health (By Trimester of Pregnancy)

Dependent Variable:	(1) Birth Weight	(2) Height for age	(3) BMI
Temperature Variability	-19.957	-0.041	-0.083
(1st. Trimester)	(10.715)**	(0.030)	(0.042)*
	[9.474]**	[0.031]	[0.045]*
Temperature Variability	-4.827	0.035	-0.008
(2nd. Trimester)	(12.858)	(0.033)	(0.061)
	[12.165]	[0.034]	[0.063]
Temperature Variability	1.967	-0.091	-0.067
(3rd. Trimester)	(10.295)	(0.028)***	(0.049)
	[9.553]	[0.027]***	[0.050]
N	56,418	38,487	38,487
Clusters (municipality)	1,288	1,190	1,190
Clusters (node)	295	292	292

Notes: ***, ** and * denote statistical significance at $p < 0.01$, $p < 0.05$ and $p < 0.10$ levels respectively. The table shows estimates of the effect of temperature variability on each trimester of pregnancy on birth weight (column 1), the z-score of height for age (column 2) and body mass index (column 3). Clustered standard errors at the municipality and node levels are presented in parentheses and brackets respectively. See the notes on Table 1 in the main text for information about the control variables included in the regressions. Additional details of each specification are described within the table. The data used for the regressions come from the Peruvian DHS over the period 1992-2013 and from the Terrestrial Air Temperatures: 1900-2010 Gridded Monthly Time Series Version 3.01 (Matsuura and Willmott 2009).