

Climatic Variability and Pathways of Impact on Child Nutrition in Sub-Saharan Africa

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Abstract

Anomaly measures based on different water availability indicators at different time reference periods are constructed for the purpose of (i) shedding more light on the effects of climatic variability through the income and the disease environment pathways on child chronic undernutrition, and (ii) investigating how the estimates vary using different anomaly measures applied to the same data set. The premise of the study, also backed by some evidence, is that water availability anomalies during the growing season provide estimates of the impacts of climatic variability on child health later in life through the household income pathway, whereas rainfall and temperature anomalies in the last year reflect the composite impacts through the disease and income pathways. Droughts experienced by children in the most recent growing season since their date of birth are significantly associated with increased chronic undernutrition later in life. Measures such as the standardized precipitation evapotranspiration index and the soil water index that account for temperature and soil type suggest that the effects through the income pathway are as important as the effects of anomalies through the disease environment pathway.

JEL Codes: I15, J13, Q54, Q25, O12, O15

Keywords/topics: Child Height, Drought, Food Security, Nutrition, Rainfall, Shocks, Sub-Saharan Africa

1. Introduction

Linear height is widely accepted as a cumulative measure of parental investments in the health and nutrition of children during the critical periods of growth in early life, especially from conception to age three (Currie & Vogl, 2013). Young children in developing countries are thought to be especially vulnerable to shocks that may weaken a household's ability to secure food during times of economic distress. Growth faltering, the rapid decline in height- and weight-for-age of children in the early formative years of life, is associated with impaired cognitive development, lower school attendance rates, reduced human capital attainment, contributes to the intergenerational transmission of poverty, and a higher risk of chronic disease and health problems in adulthood (Victora, et al. 2008; Black, et al. 2013; Alderman, et al. 2006; Hoddinott, et al. 2013).¹

In Africa, specifically, the scale of undernutrition is staggering with 63.1 million children under five being too short for their age (stunted), and 12.2 million weighing too little for their height (wasted) (UNICEF, WHO, World Bank Group, 2022). The higher temperatures, and more frequent periods of drought associated with a changing climate raise the urgency for policies and programs that mitigate the adverse impacts of climatic variability on child undernutrition.² In Sub-Saharan Africa (SSA) where 95% of farmed land is rainfed and households earn a precarious living by relying on agriculture for food, the potential income effects associated with the increased frequency and intensity of rainfall anomalies are of particular concern. More frequent droughts and more variable rainfall may raise household income variability, exacerbate food insecurity and increase child undernutrition especially in the context of poorly integrated markets for food staples and lack of access to credit markets.³

Precipitation and temperature anomalies may also increase the prevalence of diarrhea.⁴ Temperature affects the growth and survival of the pathogens while precipitation facilitates the spreading of these pathogens, through water- and vector-borne diseases (such as malaria, dengue and yellow fever).⁵ Excessive rainfall and flooding in developing countries are usually linked to higher incidence of water-borne diseases such, typhoid fever, leptospirosis, and cholera (Confalonieri, et al., 2007; WHO, 2002).

Rainfall anomalies might also affect child health by changing the opportunity cost of time for parents, that affects the feeding, caregiving, and child stimulation practices. For example, a mother's ability to breastfeed depends on the competing demands for her time for agricultural work, non-agricultural work and household chores, such as water collection, all of which may depend on the weather. Recent research in developing countries documents that the opportunity cost of parental time might play an important role in the initial formation of child health. For example, Miller and Urdinola (2010) found that parents in rural Colombia cut back time-related health inputs when the cost of time is high, leading to higher infant and child mortality.⁶

The extent to which climatic variability and weather anomalies through the income, disease environment and parental care pathways, impact on different dimensions of child health has been a topic under intensive study.⁷ A recent survey by Debebe and Raju of country-specific case studies (e.g. Maccini & Yang, 2009; Rabassa, et al., 2014; Alfani, et al., 2019; Omiat & Shively, 2020) and episodes of drought (e.g., Hoddinott & Kinsey, 2001) across the world provides generally supportive evidence on the impacts of weather shocks on chronic child undernutrition (stunting) and somewhat mixed evidence that such shocks worsen acute undernutrition (wasting) among children in developing countries. Debebe and Raju (2020) provide evidence on the role of both the income and the disease environment pathways, but do not find evidence for the care practice pathway. Broadly similar findings on the effects

of rainfall and temperature on child health and nutrition emerge from studies carried out at the global or at the regional level. Cooper, et al (2019), for example, using observations of children from 53 countries across the world, find that precipitation extremes and drought, are associated with higher chronic malnutrition (lower HAZ scores). However, it is unclear how relevant these findings are for SSA countries. Using data from 18 countries exclusively in SSA, Theide and Strube (2020) find that a two standard deviation decline in precipitation is associated with 35.6 percent reduction in predicted weight.^{8/9}

Each one of the available empirical studies to date is characterized by the exclusive use of only one of the various available measures of water availability, as well as the use of different time frames for the definition of an anomaly. Cooper, et al. (2019), for example, use the standardized precipitation and evapotranspiration index (SPEI) over the 24 months before the date of the survey, whereas Theide and Strube (2020) use rainfall anomalies in the 12 months prior to the survey. Thus, it is not possible to determine whether results differ because of differences in the water availability measure used, or differences in the sample used or the time frame used for the definition of these anomalies.

This paper elaborates on the point that at the empirical level the specific hazard variable used to measure water availability is likely to conflate the effects through the income and environment pathways and that some hazard variables may be better than other others at capturing one of these effects. For example, the extent to which the amount of rainfall (in mm) affects household crop income depends on its timing in relation to the growing season, the prevailing temperature, the type of crop cultivated, and the type of soil used to grow the crop. By default, the use of cumulative rainfall (in mm) as a hazard measure is likely to reflect the combined effects of water availability through income and environment, especially if the reference period used is the last twelve months. In contrast, alternative hazard variables, measured during the growing season, such as the Standardized Precipitation and Evapotranspiration index (SPEI) that takes into account rainfall and temperature, or the Soil Water Index (SWI) that takes into account rainfall, temperature and soil characteristics, are likely to be better at capturing the effects of water availability through the income pathway relative to the disease environment pathway.

With these considerations in mind, this paper makes two main contributions to the literature on weather anomalies and child health and nutrition. First, alternative anomaly measures based on different water availability measures and different time reference periods are constructed for the purpose of (i) shedding more light on the effects of climatic shocks through the different pathways, and (ii) investigating how the results vary using different anomaly measures applied to the same data set. To our knowledge, this is the first study that investigates these issues with respect to child nutrition.¹⁰ To date, there is no clear evidence on how estimates of the impacts of weather anomalies on child nutrition may differ using the same survey on children, depending on the specific hazard measure used and/or the time frame used for the definition of an anomaly.

Second, the analysis is carried out at the regional level using a more systematic approach that is not specific to one context or event. The use of data at the regional level allows for greater variability in the anomalies experienced by children and thus a more solid basis for the construction of “damage functions” or “vulnerability functions” for the potential impacts of climate change and the design of public policies mitigating these negative effects (Auffhammer, 2018).¹¹

The issues examined are not only methodological but also useful for the design of policies in the context of climate change. Empirical evidence quantifying the extent to which rainfall anomalies impact on child

health and nutrition through the income channel and the disease environment channel can inform the allocation of scarce financial resources toward policies promoting climate-smart agricultural policies or towards strengthening access to the quantity and quality of health services for children and their mother. Evidence of significant causal effects on chronic child malnutrition of rainfall anomalies experienced in utero would suggest that the best way to protect the nutritional and health status of children may be by helping their mothers or even through pre-emptive targeting of women in their fertile years (Almond & Currie, 2011). On the other hand, the absence of any robust evidence on the negative effects of rainfall anomalies during the pre-natal period would suggest that the best way of protecting children is by increasing the quantity and quality of the resources allocated to the treatment of sick children.

The paper is structured as follows. Section 2 discusses the hazard data and the child nutrition data used. Section 3 presents the empirical specifications estimated, and the main inferences drawn from the analysis. Section 4 concludes with a discussion of the implications of the findings of this study for future research and policy.

2. Data

Hazard data

The most commonly used hazard measures are based on total rainfall accumulation, or standardized rainfall anomaly (Z-score) over the past 12 months since the date of the survey, or rainfall during the most recent rainy (monsoon) season (Rabassa, et al., 2014; Tiwari, et al., 2017, Theide & Strube, 2020; Davenport, Dorélien, & Grace, 2020; Frankenberg & Thomas, 2017). It should be noted that the primary data sources for the measure of precipitation vary a lot. Some studies use data from the University of East Anglia Climate Research Unit's Time Series (CRU TS) that are based on statistical interpolations of data on temperatures and precipitation from over 4,000 weather stations, . Other studies use the University of Delaware database on global precipitation and temperature also based on weather station data, the ERA-40 reanalyzed weather data , and the gridded satellite precipitation estimates (constructed at 0.5 degree resolution) from NASA and NOAA provided by the Climate Hazards Group InfraRed Precipitation with Station (CHIRPS) project that are based on both weather station as well as satellite data . Other studies use the Normalized Difference Vegetation Index (NDVI) (Mulmi, et al., 2016; Alfani, et al., 2019) or the Standardized Precipitation Evapotranspiration Index (SPEI) instead of rainfall (Cooper, et al., 2019).

For the analysis in this paper, a database of historic shocks based on rainfall and related measures is constructed for all SSA over the period 2000-2020. Rainfall data through the Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS) are available starting in 1981 but the 2000-2020 is used to allow comparison with other measures such as the standardized precipitation and evapotranspiration index (SPEI) or the Soil Water Index (SWI) that is available starting in 2007. The hazard data were extracted at a uniform grid resolution of 0.05° by 0.05° (about 5 km by 5 km near the equator). Data on the start and the end of the growing season (at the admin1 or state level) in each country were obtained from the UN Food and Agriculture Organization (FAO).

In addition to rainfall, we also use measures that depend on meteorological conditions, such as temperature as well as on soil characteristics. These are the standardized precipitation and evapotranspiration index (SPEI) that accounts for water loss due to evapotranspiration because of temperature, thus yielding a more accurate of water availability and agricultural stress at a location, and the soil water index (SWI) that quantifies the amount of water in the soil available for plants by considering soil properties and drainage patterns.¹²

Household Surveys

We use data from 20 countries from the harmonized versions of the DHS surveys for countries in SSA.¹³ Table 1 lists the countries and years in our sample, while Figure 1 displays the geographic distribution of the sampled clusters in the DHS surveys used in our analysis.

Merging child under nutrition measures with hazards

There is some evidence that the timing of the shock within an agricultural cycle makes a difference. Farris, Jin, Maredia and Porter find that if in utero rainfall is above average during the land preparation, planting, or during mid-season, child growth outcomes are better, but if there is higher than average

rainfall during the harvest, then child growth outcomes are worse. However, only a handful of studies use measures based explicitly on the timing of rainfall within the growing season (e.g., Skoufias & Vinha, 2013; Kudamatsu, Persson, & Stromberg, 2016; Omiat & Shively, 2020).

In this paper, the anomaly measures used are based on the amount and timing of precipitation during the first three months of the most recent completed growing season when the child was in utero.¹⁴ The growing season is usually defined as the period of the year during which rainfall distribution characteristics are suitable for crop germination, establishment, and full development. We focus on water availability during the first three months of the growing season because the start of the growing season is not likely to exhibit significant variation from year to year. In general, the empirical identification of the length of the growing season is challenging because rainfall in our sample of countries has considerable spatial variability ranging from a tropical climate to a semi-arid climate of the Sahel. Data on the start and the end of the growing season (at the admin1 or state level) in each country were obtained from the UN Food and Agriculture Organization (FAO).

The focus on the amount and timing of precipitation during the first three months of the most recent completed growing season, is likely to be better at capturing the income effect associated with better or worse growing conditions for crops, but relatively weaker at capturing the environmental or disease effects. Post-natal linear growth as measured by height-for-age (HAZ) compares the child's height (or length if measured lying down) to the height (length) distribution of healthy children of the same age and sex, such that HAZ measures the child's height in terms of standard deviations from the median height. Thus, a child whose height corresponds to the median height of healthy children of the same age and sex will have a HAZ of zero. A child taller than the "median" child will have a positive value and those shorter than the "median" child will have a negative HAZ value.

A lower value of HAZ is a more accurate reflection of the long-term effects of drought shocks experienced earlier in a child's life. The "fetal origins" hypothesis originally advanced by Barker posits that some of the long term health effects from in-utero malnutrition, are only evident later in the child's life. For this reason, we relate the incidence of a hazard at an early year in the life of the child, such as the period the child was in utero, with the HAZ of the child later in life (i.e., at the time of the survey). Based on the information available about the age of the child and their date of birth, it is possible to merge to each child surveyed in any given year the incidence of a hazard while the child is in-utero (i.e., during the growing season prior to his/her date of birth). Unlike Maccini and Yang we do not consider adult outcomes but limit our analysis to children less than 5 years of age. While there is some evidence that height at three years of age largely predetermines adult stature (Victora, et al., 2008) focusing on children less than 5 years of age reduces the likelihood that other events experienced later in life affect the nutritional status as adults.

One important consideration is the spatial scale at which the hazard measures are measured. Intuition suggests that it is preferable to relate welfare with hazards experienced at a fine geographic level and ideally directly at the household level as this reflects the impact on agricultural production and water and disease prevalence. However, it is also the case that a measure of rainfall anomaly for a larger geographic area in which a household resides may include some impacts of rainfall on agricultural prices and wages that may not be well reflected in a very localized shock measure. For example, for food availability, rainfall anomaly at the very local level such as village may not capture the true impact of the shock, since food availability may depend on the weather across a wider area. In contrast, for disease vectors the local weather conditions may be more important.

The results presented in this paper are derived by matching a household's geographic location with a spatially aggregated hazard measure within a 20 km radius.¹⁵ We chose the 20 km radius for three reasons. First, because the point location given for the DHS sampling clusters have been randomly offset by up to 10 km for rural areas. Second, this radius is meant to capture the local shock to a household as well as the impacts on prices and wages in neighboring markets. Third, it smooths out any extraordinary pattern of local precipitation or temperature.¹⁶

We use standardized anomaly measures defined as $(level - mean \text{ for local area}) / standard \text{ deviation}$ for the local area (the 20km radius), where the mean and standard deviation for the local area are calculated based on the 20 years of hazard data, or the maximum data available in the case of soil moisture.

One advantage offered by the standardization of the deviation from the local means is that it offers the opportunity to gauge the magnitude of the shock experienced across a variety of geographic contexts. This approach assumes that changes in the hazard matter not in an absolute sense, but in proportion to an area's usual variation. Thus, a 10 mm decrease in the level of rainfall does not have the same impact in wet and dry regions. As such, this assumption also considers the adaptation practices of households to their environment.

Table 2 summarizes the various hazard measures constructed using the remote sense data library of the Center for Disaster Protection (CDP). Annex B contains a more detailed description of the data sources for the hazards and the additional variables merged using other sources summarizing environmental context, whereas Annex C presents means and standard deviations of the main variable used in the analysis.

Annex D presents the simple correlation coefficients between the different standardized anomalies in the final sample of children (see Tables D.3a and D.3b) and the histograms of all the hazard measures in our sample, overlaid with the graph of normal density with the same mean and standard deviation as the sample, and four vertical lines identifying the 20th, 40th, 60th and 80th percentiles of the empirical distributions (Figure D.1).¹⁷

3. Empirical Specification and Results

Annex E contains an analytic framework relating hazards with child nutritional status. In line with that conceptual framework, the effects of shocks in the availability of water on child chronic malnutrition (or child HAZ-score) may be summarized in general by the “damage or vulnerability function” f below:

$$HAZ_{ihkt} = f(R_{k,t=IU(i)}, X_{hkt}, Z_j) + e_{ihkt} \quad (1)$$

where HAZ_{ihkt} denotes the growth faltering status of child i in household h , in locality or cluster κ , in survey period t , $R_{k,t=IU(i)}$ is the measure of the hazard at the level of the geographic cluster κ

experienced during the period the child was in-utero, i.e., $t = IU(i)$, X_{hkt} denotes household observable characteristics at the time of the survey, Z_j denotes observable variables summarizing the environment of households, and e_{ihkt} is an *error term* summarizing the influence of all other unobservable factors on HAZ.¹⁸ It is important to bear in mind that because children were in utero at different points in time, the shocks experienced are different for children of different ages in the same village. We take advantage of this feature of the data in the second half of our paper, when we examine the robustness of our inferences.

We approximate the function f with the average value of the child outcome W_{hk} conditional on specific values of the explanatory variables R_k, X_{1hk} , and Z_j , i.e., $f(r, x, z) = E(W_{hkt} | R_k = r, X_{hkt} = x, Z_j = z)$, or the Conditional Expected Function (CEF), which is typically easier to interpret and useful for deeper insights on the causal relationship between hazard and welfare (Angrist & Pischke, 2009).

We present estimates based on a nonlinear specification allowing effects to vary by different quintiles of the distribution of the hazard anomalies experienced. Specifically, we estimate the regression equation

$$W_{ihkt} = \beta_0 + \sum_{q=1}^5 \beta_{1q} R_{qkt} + \sum_{q=1}^5 \beta_{2q} T_{qkt} + \beta_5 X_{ihkt} + \gamma_1 AEZ + \gamma_2 LVZ + \gamma_3 T2UC + \mu_k + \tau_t + e_{ihkt} \quad (2)$$

where the binary variables R_{qkt} , and T_{qkt} , indicate whether the rainfall and temperature during the first 3 months of the growing season at the level of the geographic cluster κ in year t , was in the q th quintile of the standardized rainfall and temperature anomaly distributions (where $q = 1, 2, \dots, 5$). Thus, anomalies in the 1st and 2nd quintiles represent spells of rainfall shortage (drought) and low temperatures (or cold spells). Anomalies in the 3rd quintile represent relatively small negative and positive anomalies around the mean, and anomalies in the 4th and 5th quintiles represent spells of excess rainfall or very high temperatures (heat spells). In our analysis we also employ the same specification for rainfall and temperature anomalies in the twelve months prior to the child's birth, when these are included as additional regressors. Quintile-based classification of hazard measures ensures enough observations in the tails of distributions to identify impacts. Nevertheless, it is important to bear in mind that "extreme" anomalies in our sample may not be so extreme in terms of their distance in standard deviation units from the sample mean.

The variable X_{ihkt} denotes child and household observable characteristics at the time of the survey and includes: the age of the child in months, child age in months squared, binary variables identifying if the child is born in the lean season, the child is a girl, the child is the first child, the mother has more than 7 years of schooling, the house has a high-quality roof, improved and non-shared sanitation facility, and an improved water source (both binary variables defined based on WHO/UNICEF Joint Monitoring Program guidelines), the total number of household members, the number of children under five, and five binary variables for the quintile of the wealth index based on the various assets owned by the household. AEZ denotes the agroecological zone, LVZ the livelihood zone, and T2UC the time to nearest urban center, μ_k denotes country-district level fixed effects and τ_t denotes survey year effects. The country-district-level fixed effects, control for time-invariant spatial characteristics, and thus disentangle the hazard measure from many possible sources of omitted variable bias. The year effects τ_t further

neutralize any common trends and thus help ensure that the relationships of interest are identified from idiosyncratic local shocks. As such, the empirical approach is very much in line with the strong identification properties of the weather-shock approach summarized by Dell, et al. (2014). It should be noted that with country-district level fixed effects μ_k included in the specification, the coefficients γ_1 , γ_2 and γ_3 are possible to estimate only if the values of AEZ, LVZ and T2UC vary within country-districts. Otherwise, the use of the country-district dummies will absorb the effects of these environmental factors.

It is important to point out some important caveats associated with the estimates of the long-term impacts of exposure to weather anomalies in utero. In utero shocks have two potential outcomes. First, they may have a “culling effect” by increasing miscarriages, stillbirths¹⁹ or the mortality rates after birth. In addition, given negative shocks a mother may decide to abort instead of carrying to full term. Second, the shocks may have a “scarring effect” on the fetus such that the surviving child, is weaker and less healthy because of the shock. Similarly, shocks experienced in infancy may have both culling and scarring effects. Because of the culling effect, the distribution of children is different than it would have been had the shock not occurred. The degree of this mortality selection differs by shock and context.²⁰ Specifically, using a set of Sub-Saharan African countries, Davenport, et al. find that about 18% of pregnancies result in abortion or stillbirth. They also find that in some cases higher temperatures, but not rainfall, are associated with increased probability of miscarriages, abortions and stillbirths. The effect of prenatal mortality on the estimated impacts of hazards on child chronic malnutrition later in life does not account for this prenatal mortality. The effect could be that as a cohort the children that are born are stronger and more likely to thrive given that they have survived to birth effectively truncating the distribution of health of the cohort.

Non-linear specification²¹

In Tables 3a and 3b, columns (1) and (2) present estimates based on a linear specification for rainfall and temperature anomalies during the growing season (Rain_gs and Temp_gs), and in the last 12 months (Rain_p12 and Temp_p12), and columns (3) and (4) present estimates using a set of binary variables identifying the different quintiles of the distribution of the respective anomalies during the first three months of the most recent completed growing season when the child was in utero was in utero and in the twelve months prior to the date of birth (Rain_p12 and Temp_p12).

In the linear specifications, the coefficient of Rain_p12 provides an estimate of the effects of rainfall anomalies through the disease environment, controlling for any income effects associated with anomalies in cumulative rainfall during the critical months of the growing season. The linear specification in col. (2) includes as additional explanatory variables the temperature anomaly during in the growing season (Temp_gs) and the temperature anomaly during the twelve months prior to the date of birth (Temp_p12).

The estimates from the linear specification suggest that there is only a small variation in the relative sizes of the effects through the two pathways. For example, using only rainfall anomalies in the growing season and in the prior twelve months results in a larger effect of the disease environment compared to the income effect from higher rainfall in the growing season (see col. (1) in Table 3a). The estimate of the effect of higher rainfall anomalies through the disease environment increases when temperature

anomalies over the prior twelve months are added in the specification with temperature anomalies having just about the same negative effect in terms of size as rainfall anomalies (see col. (2) in Table 3a).

Table 4b confirms that the same patterns emerge when measures other than rainfall are used to summarize the effect of anomalies in the growing season. For example, when using the standardized precipitation and evapotranspiration index, an index that is better than cumulative rainfall because it measures the availability of water for crops taking into account water loss due to the temperature prevailing during the growing season (SPEI_gs), (see col. (1) in Table 3b). The growing season soil moisture anomaly (SWI_gs), which incorporates soil characteristics, continues to have a large estimate of the effect of the income channel (col. (2) in Table 3b) and is approximately the same as the effect through the disease environment summarized by the rainfall anomaly during the last 12 months.

Overall, the estimates from the linear specification in columns (1) and (2) in Table 3a and 3b reveal a remarkable robustness in the inferences drawn based on the linear and piece-wise specifications in Annex F. The estimates confirm that the effects of anomalies through the income pathway defined during the first three months of the most recent complete growing season are positive, whereas the effects of anomalies through the disease environment pathway, defined over the previous 12 months, are negative. The negative effect of temperature during the growing season observed in Tables F.1 and F.2 in Annex F, when rainfall during the growing season is not included as a regressor, disappears. Rainfall in the growing season continues to have a significant positive effect on child HAZ later in life, confirming the beneficial effects of higher crop yields on child nutrition and food security through the income pathway while rainfall and temperature anomalies over the 12-month period continue to have significant negative effects on child HAZ through the disease environment pathway.

The estimates in columns (3) and (4) of Tables 3a and 3b reveal that there are important nonlinearities associated with the intensity of the hazard experienced that are missed by the linear or even the piece-wise linear specifications. The null hypothesis that the effects of anomalies in different quintiles of the respective anomaly distribution are equal was consistently rejected and for this reason it is the specification used for the rest of the analysis in the paper.

Extreme rainfall shortages (in the bottom quintile of the rainfall z-scores) during the growing season, are significantly associated with lower HAZ scores of children in life. Rainfall anomalies that are closer to mean or above the mean do not appear to have significant effect on child HAZ later in life. Thus, it is only the exposure to conditions of extreme water scarcity or droughts during the most recent growing season that a child is in utero that impacts negatively on child health. Better than normal rainfall conditions in the growing season do not appear to be beneficial to child health later in life.

The nonlinear specification based on dummy variables identifying the quintile of the distribution of the rainfall during the last 12 months prior to birth (Rain_p12), imply that extreme rainfall shortages during the whole year have a positive effect through the disease environment that works against the negative income or crop production effects associated with extreme rainfall shortage during the growing season. This suggests that the potential negative health effects due to scarcity in the availability of clean drinking water and the hardships associated with accessing clean water during very dry years, are lower than the benefits derived from the diminished spreading of pathogens such as typhoid fever, leptospirosis, and cholera, and vector borne diseases in periods of water scarcity.²²

As is the case for the linear specification, temperature during the growing season has no effect through the income channel, while unusually low temperatures (bottom 20% of the z-score distribution) during

the twelve months prior to birth are associated with beneficial effects on child health later in life by limiting the spreading of pathogens and vector borne diseases. In contrast, unusually high temperatures (top 20% of the z-score distribution) are associated with negative effects on child health later in life though the disease environment effect.

The preceding patterns in the results are reinforced when using SPEI_gs or SWI_gs, instead of the rainfall and temperature measures during the growing season (see Table 3b). In fact the coefficients of the different quintiles of SWI_gs reveal a high negative income effect associated with unusually low values of the soil water index (bottom 20% of the z-score distribution), a smaller negative income effect associated with more mild water scarcity (20%-40% of the z-score distribution), and reversal to a positive income or crop production effect on later life child health with higher than usual water soil moisture during the growing season (60-80% of the z-score distribution; see col (4) in Table 3b).

Rainfall anomalies in the growing season, impacts through the income pathway, and heterogeneity of impacts

A fundamental premise of this paper is that rainfall anomalies during the growing season provide an estimate of the impacts of climatic variability on child health later in life through the household income pathway that are less contaminated by any impacts through the disease environment pathway.

To shed some light on this issue, we explore variability in the size of the income effect of rainfall during the growing season varies across different livelihood zones and farming systems. In fish-based farming systems, for example, where crop production is not important, anomalies in water availability during the growing season should have little or no role at all in affecting child health through the household income pathway. In contrast, in other farming systems such as the maize mixed farming system, or the agropastoral farming system, anomalies in water availability during the growing season are likely to have important effects on household income and crop production that vary in magnitude depending on the context. Maize, for example, is highly sensitive to water availability at specific growth stages, and even short dry spells at the wrong time can significantly reduce yields. Maize seeds need adequate moisture to germinate. If rains are delayed after planting, seeds may fail to germinate or result in uneven emergence. In pastoral livelihood zones, where people rely heavily on livestock, rainfall timing directly affects both pasture availability and water sources, which are essential for animal survival and productivity. If rains come late or end early, pasture is insufficient, leading to poor livestock nutrition, reduced milk and meat production, and increased animal disease and death. Root crops and tubers like cassava, potatoes, sweet potatoes, carrots, and yams, depend not just on the amount of rainfall, but also on when it falls during their growth cycle. Rainfall is important shortly after planting to ensure good germination and root establishment. And too much rain early on can cause seed rot, especially for tubers like potatoes and yams.

Table 4 presents the estimates for the nonlinear specification for the hazard measures during the growing season applied separately to the subsamples of children in households living in the following farming systems: Fish-farming, mixed-maize, agropastoral, and root crops and tubers. These estimates are obtained including the binary variables for different quintiles of rainfall and temperature measures in the 12 months prior to birth (the full set of estimates is contained in Annex G). In the areas, where fish farming is the main livelihood source, all water availability measures during the growing season (Rain_gs, Temp_gs, SPEI_gs, and SWI_gs) when a child is in utero, are not significantly associated with child health later in life. In contrast, rainfall and temperature in the 12 months prior to birth appear to

have some significant effects, primarily through the disease pathway (see Table G.1a in Annex G). Even though indirect, these estimates validate the interpretation of water availability anomalies in the growing season as measures of impacts through the income channel.

The estimates in Table 4 also reveal that the impacts of water anomalies through the income channel vary considerably across farming systems and that some anomaly measures are better suited at summarizing these income impacts in different farming systems. For example, negative rainfall anomalies (Rain_gs) appear to have no effect through the income channel in mixed-maize areas whereas positive rainfall anomalies have a negative effect. In contrast, SPEI_gs and SWI_gs reveal that negative anomalies in water availability in mixed-maize farming systems have a negative effect on child health through the income channel, a result that is more consistent with the conventional knowledge about the effect of shortages in water availability during the growing season on the yields of maize crops in SSA.

In the agropastoral and root and tuber farming systems, it appears that there is no clearly preferred measure for the impacts of anomalies through the income channel. All three hazard measures, Rain_gs, SPEI_gs, and SWI_gs seem to capture some critical dimension of water scarcity operating through the income channel in accordance with conventional knowledge.

Table 5 presents additional results on the heterogeneity of impacts of anomalies in utero between boys and girls. The literature suggests that males are biologically more vulnerable to poor conditions in utero (Almond & Mazumder, 2011; Eriksson, et al., 2010). However, the evidence on gender differences in the effect of early rainfall on adult outcomes has been mixed. Maccini and Yang (2009), for example, find that in Indonesia the effects are larger for women than for men. In contrast, Dinkelman (2017) estimates the effects of early childhood exposure to drought on later-life disabilities among South Africans confined to homelands during apartheid finds that the effects are larger for males.

The rainfall measure (Rain_gs) in Table 5 confirms that boys in utero are more vulnerable than girls to rainfall shortages in the case of drought (e.g., rainfall at the bottom quintile of the distribution) during the growing season. This result is also robust to the inclusion of temperature anomalies during the growing season (Temp_gs). However, the estimates in Table 5 suggest that this conclusion is sensitive to the hazard measure used. When SPEI_gs or SWI_gs are used in place of rainfall during the growing season, there are strong indications that girls in utero are more vulnerable to droughts.

Alderman and Headly (2018) have argued that studies of the underlying determinants of nutrition must take into consideration the different dynamics of growth faltering as summarized by HAZ. Observational analyses of linear growth indicators, such as HAZ, based on a sample of children 0-59 months old, are likely to be subject to “partial exposure bias” from the fact that children less than 24 months of age are still undergoing the process of growth faltering. Thus, an analysis of the long-term impacts of shocks experienced in utero on HAZ should focus on children 24-59 months of age, because this age group has already completed the growth faltering process. For example, if the shock is very recent, then it is likely that there has not been sufficient time for the impacts to be reflected in the HAZ of younger children, the longer-term measure of well-being.

For this reason, Table 6 presents separately the long-term effects of anomalies on younger (0-23 mo.) and older (24-59 mo.) children (the full set of estimates is also provided in Annex G). Table 6 reveals that the effect of drought anomalies as measured by the SPEI_gs and SWI_gs during the growing season is statistically significant only for older children and not for younger children. Thus, catch-up growth, or

the possibility that shocks at an early age or in utero may not have discernible scars on the nutritional status of children as they get older, does not appear to be in operation in this sample.²³ This finding also differs from Rabassa, et al. (2014) and Tiwari, et al. (2016), although their results are based on post-natal shocks in the second year of life and not when the children were in utero.

4. Concluding remarks and policy considerations

There are numerous methodological insights that emerge from our analysis. Different measures of rainfall and different time frames result in substantially different estimates depending on whether the measure used is better at capturing the effects of anomalies through the income pathway or the disease environment pathway. The usual practice in much of the literature on weather shocks and child health, relies on rainfall and temperature levels or anomalies in the twelve months prior to the date of the survey that typically reflect the effects through both pathways. The analysis in this paper demonstrates that a more concerted effort to take into account the timing of rainfall in relation to the growing season facilitates assessing the relative importance of each pathway on child health. Such an analysis can contribute to policy advice moving beyond the generic recommendation that developing countries need to strengthen their social protection systems as a means of mitigating the adverse impacts of increased climatic variability.

This study also provides the basis for developing a more standardized approach to the ex-ante estimation of the impacts of climatic shocks experienced during the pre-natal period (in utero), on child undernutrition later in life, as measured by child height for age (HAZ). Our analysis reveals that there are important nonlinearities associated with the intensity of the hazard experienced that are missed by the linear or even the piece-wise linear specifications. Extreme rainfall shortages (in the bottom quintile of the rainfall z-scores) during the growing season, are significantly associated with lower HAZ scores of children later in life. Rainfall anomalies that are closer to the mean or above the mean do not appear to have significant effect on child HAZ later in life. Thus, it is only the exposure to conditions of extreme water scarcity or droughts during the most recent growing season when a child is in utero that impacts negatively on child health. Better than normal rainfall conditions in the growing season do not appear to be beneficial to child health later in life. The nonlinear specification for rainfall during the last 12 months prior to birth reveals that controlling for the effects of droughts on child growth faltering through the income pathway, dry years overall have a positive effect on child health through the disease environment that works against the negative income or crop production effect associated with extreme rainfall shortage during the growing season. Thus, the potential negative health effects due to scarcity in the availability of clean drinking water and the hardships associated with accessing clean water during very dry years, are lower than the benefits derived from the diminished spreading of pathogens such as typhoid fever, leptospirosis, and cholera, and vector borne diseases in periods of water scarcity.

Temperature during the growing season has no effect through the income channel, while unusually low temperatures (bottom 20% of the z-score distribution) during the twelve months prior to birth are associated with beneficial effects on child health later in life by limiting the spreading of pathogens and vector borne diseases. In contrast, unusually high temperatures during the twelve months prior to birth are associated with negative effects on child health later in life through the disease environment effect.

The use of better measures of water availability for crop production are used, such as the standardized precipitation and evapotranspiration index or the soil water index, instead of rainfall, reveals even larger

negative effects of droughts on child health later in life through the income pathway that are comparable in size to the effects of the opposite sign through the disease environment summarized by temperature and rainfall during the last 12 months.

These results also yield useful insights into the type of policies and programs needed to mitigate the impacts of climatic variability. The study confirms that an emphasis in protecting pregnant women and infants in their early years has important benefits for child health and nutrition later in life. Thus, in terms of allocating the limited budget of health sectors, targeting health services towards pregnant women and infants may be more effective in the long term than the allocation of the same funds strengthening health services in the treatment of sick children. However, this does not mean there is no room for low-cost public health interventions—such as making available oral rehydration therapy—to reduce the negative health impacts of weather shocks.

In addition, the evidence that the size effect of anomalies through the income channel is as large as the disease environment effect suggests that policies and programs promoting better risk management strategies, early warning systems for droughts, access to crop insurance schemes, and actions that reduce vulnerability to droughts, pests, diseases and other climate-related risks and shocks, can contribute to improved child health and nutrition as much as programs strengthening access to the quantity and quality of health services targeted towards pregnant mothers or women in their fertile years.

Finally, the presence of significant heterogeneity in how rainfall anomalies while a child is in utero affect chronic malnutrition later in life implies that such programs cannot be “one size fits all” but rather tailored to the specific context and prevailing farming system.

Figure 1: The distribution of the sampled clusters in the DHS surveys used in the analysis

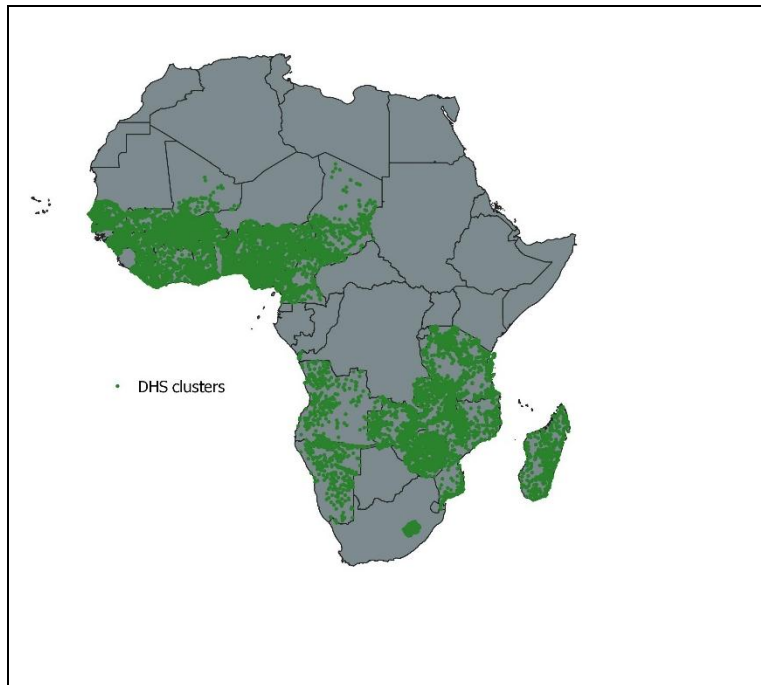


Table 1: List of harmonized DHS surveys (IPUMS) analyzed

Country	Year
Angola	2015
Benín	2001, 2011, 2017
Burkina Faso	2003, 2010
Cameroon	2004, 2011
Chad	2014
Cote d'Ivoire	2011
Ghana	2003, 2008, 2014
Guinea	2005, 2012, 2018
Lesotho	2004, 2009, 2014
Liberia	2006, 2013
Madagascar	2008
Malawi	2010, 2016
Mali	2001, 2006, 2018
Mozambique	2011
Namibia	2000, 2006, 2013
Nigeria	2003, 2008, 2013, 2018
Senegal	2005, 2010-16
Tanzania	2010, 2015
Zimbabwe	2005, 2010, 2015
Zambia	2007, 2013, 2018

Table 2: List of hazard measures used in the analysis

Source of remotely sensed data	Hazard measure
CHIRPS global rainfall data set from US Geological Survey (NASA)	Rain_gs: Cumulative rainfall anomaly (standardized) ^a during the first 3 months of the growing season prior to the child's date of birth. Rain_p12: Cumulative rainfall anomaly (standardized) ^a during the 12 months prior the child's date of birth.
ERA5-Land monthly averaged data	Temp_gs: Temperature anomaly (standardized) ^a during the first 3 months of the growing season prior to the child's date of birth. Temp_p12: Temperature anomaly (standardized) ^a during the 12 months prior the child's date of birth.
SPEI generated by the Climatic Research Unit of the University of East Anglia	SPEI_gs: Standardized Precipitation and Evapotranspiration Index at the end of the first 3 months of the growing season prior to the child's date of birth.
Soil Water Index from Copernicus Global Land Service	SWI_gs^b: Soil Water Index or soil moisture index anomaly (standardized) ^a in the first 3 months of the growing season prior to the child's date of birth. SWI_p12^b: Soil Water Index or soil moisture index anomaly (standardized) ^a in the 12 months prior to the child's date of birth
Notes: ^a Standardized anomaly for any hazard measure is defined as $[(\text{level} - \text{mean for local area}) / \text{sd for local area}]$ where the mean and standard deviation (sd) for the local area are calculated based on the 20 years of hazard data (2000-2020). Local area is defined as grid cells whose centroids are within a 20km radius from the household's location. ^b Data on SWI are available starting in 2007. This shorter timeframe results in a reduction in the sample size of children used in the regressions reported below based on SWI. CHIRPS = Climate Hazards Group InfraRed Precipitation with Station; FEWS NET = Famine Early Warning Systems Network; NASA = National Aeronautics and Space Administration.	

Table 3a: Estimates of the impacts of rainfall and temperature anomalies through the income and disease environment pathways. Dependent variable: Child HAZ

VARIABLES	(1)	(2)	(3)	(4)
Rain_gs	0.027*** [3.007]	0.026*** [2.624]		
Bottom 20% of z-scores			-0.065*** [-2.577]	-0.061** [-2.322]
20-40 % of z-scores			-0.023 [-0.986]	-0.021 [-0.914]
60-80% of z-scores			-0.028 [-1.165]	-0.025 [-1.050]
Top 20% of z-scores			0.019 [0.765]	0.021 [0.866]
Temp_gs		-0.004 [-0.355]		
Bottom 20% of z-scores				-0.017 [-0.651]
20-40 % of z-scores				-0.023 [-0.978]
60-80% of z-scores				0.033 [1.450]
Top 20% of z-scores				-0.039 [-1.507]
Rain_p12	-0.032*** [-3.573]	-0.040*** [-4.111]		
Bottom 20% of z-scores			0.082*** [3.318]	0.089*** [3.556]
20-40 % of z-scores			0.024 [1.077]	0.030 [1.304]
60-80% of z-scores			0.001 [0.035]	-0.004 [-0.176]
Top 20% of z-scores			-0.013 [-0.552]	-0.025 [-1.047]
Temp_p12		-0.037*** [-3.492]		
Bottom 20% of z-scores				0.076*** [3.073]
20-40 % of z-scores				0.032 [1.467]
60-80% of z-scores				0.009 [0.401]
Top 20% of z-scores				-0.042* [-1.713]
Constant	0.748 [0.874]	0.645 [0.754]	0.717 [0.836]	0.626 [0.722]
Observations	57,968	57,968	57,968	57,968

R-squared	0.113	0.113	0.113	0.113
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Robust t-statistics in brackets based on standard errors accounting for intra-cluster correlation

*** p<0.01, ** p<0.05, * p<0.1

Additional control variables included: Child age in months, child age in months squared, child born in lean season, child is a girl (only for the regressions by age group), child is first child, mother has more than 7 years of schooling, mother's height is more than 160 cm, the house has a high quality roof, has access to improved and non-shared sanitation facility, total number of household members, number of children under 5, time to urban center with at least 20,000 people. All regressions include country/district fixed effects, year fixed effects, agroecological zone fixed effects and livelihood farming system fixed effects.

Table 3b: Estimates of the impacts of rainfall and temperature anomalies through the income and disease environment pathways. Dependent variable: Child HAZ

VARIABLES	(1)	(2)	(3)	(4)
SPEI_gs	0.035*** [4.583]			
Bottom 20% of z-scores			-0.085*** [-3.475]	
20-40 % of z-scores			-0.100*** [-3.911]	
60-80% of z-scores			0.009 [0.351]	
Top 20% of z-scores			-0.001 [-0.047]	
SWI_gs		0.056*** [5.199]		
Bottom 20% of z-scores				-0.087*** [-3.082]
20-40 % of z-scores				-0.057** [-2.075]
60-80% of z-scores				0.055** [1.976]
Top 20% of z-scores				0.045 [1.461]
Rain_p12	-0.032*** [-3.561]	-0.053*** [-4.889]		
Bottom 20% of z-scores			0.080*** [3.287]	0.109*** [3.832]
20-40 % of z-scores			0.027 [1.205]	0.044* [1.692]
60-80% of z-scores			0.000 [0.015]	-0.010 [-0.394]
Top 20% of z-scores			-0.013 [-0.543]	-0.035 [-1.177]
Temp_p12	-0.036*** [-3.438]	0.006 [0.404]		
Bottom 20% of z-scores			0.072*** [2.923]	0.033 [1.027]
20-40 % of z-scores			0.027 [1.225]	0.024 [0.879]
60-80% of z-scores			0.011 [0.492]	0.035 [1.464]
Top 20% of z-scores			-0.052** [-2.108]	0.011 [0.376]
Constant	0.643 [0.761]	-1.165 [-1.063]	0.625 [0.741]	-1.220 [-1.113]
Observations	57,968	36,722	57,968	36,722

R-squared	0.113	0.129	0.113	0.129
Robust t-statistics in brackets based on standard errors accounting for intra-cluster correlation				
*** p<0.01, ** p<0.05, * p<0.1				

Additional control variables included: Child age in months, child age in months squared, child born in lean season, child is a girl (only for the regressions by age group), child is first child, mother has more than 7 years of schooling, mother's height is more than 160 cm, the house has a high quality roof, has access to improved and non-shared sanitation facility, total number of household members, number of children under 5, time to urban center with at least 20,000 people. All regressions include country/district fixed effects, year fixed effects, agroecological zone fixed effects and livelihood farming system fixed effects.

Table 4: Estimates of the impacts of rainfall and temperature anomalies through the income and disease environment pathways in different farming systems. Dependent variable: Child HAZ

VARIABLES	(1)	(2)	(3)
Fish-based farming systems			
Rain_gs		SPEI_gs	
Bottom 20% of z-scores	-0.059 [-0.430]	Bottom 20% of z-scores	-0.004 [-0.031]
20-40 % of z-scores	0.013 [0.130]	20-40 % of z-scores	-0.071 [-0.635]
60-80% of z-scores	-0.036 [-0.312]	60-80% of z-scores	0.070 [0.612]
Top 20% of z-scores	-0.065 [-0.459]	Top 20% of z-scores	0.090 [0.881]
Temp_gs		SWI_gs	
Bottom 20% of z-scores	-0.040 [-0.258]	Bottom 20% of z-scores	-0.024 [-0.178]
20-40 % of z-scores	0.065 [0.598]	20-40 % of z-scores	0.053 [0.459]
60-80% of z-scores	0.044 [0.441]	60-80% of z-scores	0.141 [1.351]
Top 20% of z-scores	-0.158 [-1.569]	Top 20% of z-scores	0.157 [1.258]
Observations	1,987	Observations	1,987
R-squared	0.133	R-squared	0.132
			0.156
Mixed Maize farming systems			
Rain_gs		SPEI_gs	
Bottom 20% of z-scores	-0.035 [-0.968]	Bottom 20% of z-scores	-0.036 [-1.107]
20-40 % of z-scores	-0.001 [-0.039]	20-40 % of z-scores	-0.088** [-2.561]
60-80% of z-scores	-0.071** [-2.198]	60-80% of z-scores	0.014 [0.420]
Top 20% of z-scores	-0.124*** [-3.584]	Top 20% of z-scores	0.040 [1.148]
Temp_gs		SWI_gs	
Bottom 20% of z-scores	-0.022 [-0.555]	Bottom 20% of z-scores	-0.076* [-1.925]
20-40 % of z-scores	-0.006 [-0.185]	20-40 % of z-scores	-0.045 [-1.222]
60-80% of z-scores	0.011 [0.316]	60-80% of z-scores	0.014 [0.353]
Top 20% of z-scores	-0.026 [-0.711]	Top 20% of z-scores	-0.021 [-0.492]
Observations	24,796	Observations	24,796
R-squared	0.113	R-squared	0.113
			0.107
Agropastoral farming systems			
Rain_gs		SPEI_gs	
Bottom 20% of z-scores	-0.186*** [-3.425]	Bottom 20% of z-scores	-0.196*** [-3.648]
20-40 % of z-scores	-0.050	20-40 % of z-scores	-0.114**

60-80% of z-scores	[-1.071] 0.013	60-80% of z-scores	[-2.304] 0.017	
Top 20% of z-scores	[0.284] 0.127** [2.561]	Top 20% of z-scores	[0.301] -0.025 [-0.491]	
Temp_gs		SWI_gs		
Bottom 20% of z-scores	-0.032 [-0.629]	Bottom 20% of z-scores		0.012 [0.214]
20-40 % of z-scores	-0.082* [-1.834]	20-40 % of z-scores		-0.095* [-1.708]
60-80% of z-scores	0.021 [0.458]	60-80% of z-scores		-0.002 [-0.038]
Top 20% of z-scores	-0.166*** [-2.770]	Top 20% of z-scores		0.143** [2.119]
Observations	15,752	Observations	15,752	8,825
R-squared	0.143	R-squared	0.141	0.181
Root and Tuber Crop farming systems				
Rain_gs		SPEI_gs		
Bottom 20% of z-scores	0.031 [0.425]	Bottom 20% of z-scores	-0.055 [-0.744]	
20-40 % of z-scores	-0.032 [-0.462]	20-40 % of z-scores	-0.193** [-2.224]	
60-80% of z-scores	0.071 [0.967]	60-80% of z-scores	0.071 [1.054]	
Top 20% of z-scores	0.131* [1.924]	Top 20% of z-scores	-0.050 [-0.683]	
Temp_gs		SWI_gs		
Bottom 20% of z-scores	-0.042 [-0.559]	Bottom 20% of z-scores		-0.022 [-0.261]
20-40 % of z-scores	-0.136* [-1.811]	20-40 % of z-scores		-0.157* [-1.754]
60-80% of z-scores	0.019 [0.322]	60-80% of z-scores		0.170** [1.977]
Top 20% of z-scores	-0.060 [-0.855]	Top 20% of z-scores		0.090 [1.079]
Observations	8,576	Observations	8,576	4,608
R-squared	0.108	R-squared	0.108	0.138

Robust t-statistics in brackets based on standard errors accounting for intra-cluster correlation

*** p<0.01, ** p<0.05, * p<0.1.

See Annex F for the full set of estimates. These estimates are extracted from Tables F.1a, F.1b, F.1c and F1.d that include the estimates of Rain_p12 and Temp_12.

Table 5: Estimates of the impacts of rainfall and temperature anomalies on boys and girls through the income and disease environment pathways. Dependent variable: Child HAZ

VARIABLES	Boys	Girls	Boys	Girls
Rain_gs				
Bottom 20% of z-scores	-0.082** [-2.389]	-0.047 [-1.363]	-0.073** [-2.047]	-0.045 [-1.270]
20-40 % of z-scores	-0.009 [-0.290]	-0.037 [-1.197]	-0.006 [-0.187]	-0.036 [-1.156]
60-80% of z-scores	-0.035 [-1.069]	-0.021 [-0.649]	-0.032 [-0.987]	-0.018 [-0.558]
Top 20% of z-scores	0.035 [1.023]	0.001 [0.044]	0.035 [1.018]	0.006 [0.195]
Temp_ps				
Bottom 20% of z-scores			-0.003 [-0.080]	-0.031 [-0.864]
20-40 % of z-scores			-0.034 [-1.067]	-0.013 [-0.419]
60-80% of z-scores			-0.001 [-0.027]	0.063** [2.086]
Top 20% of z-scores			-0.038 [-1.059]	-0.044 [-1.280]
Observations	28,776	29,192	28,776	29,192
R-squared	0.107	0.117	0.108	0.118
SPEI_gs				
Bottom 20% of z-scores	-0.100*** [-3.023]	-0.071** [-2.116]		
20-40 % of z-scores	-0.088*** [-2.587]	-0.116*** [-3.385]		
60-80% of z-scores	0.024 [0.741]	-0.009 [-0.281]		
Top 20% of z-scores	0.011 [0.332]	-0.018 [-0.536]		
SWI_gs				
Bottom 20% of z-scores			-0.070* [-1.809]	-0.099*** [-2.638]
20-40 % of z-scores			-0.015 [-0.390]	-0.093*** [-2.582]
60-80% of z-scores			0.064* [1.669]	0.053 [1.420]
Top 20% of z-scores			0.094** [2.245]	0.001 [0.036]
Observations	28,776	29,192	18,178	18,544
R-squared	0.108	0.118	0.123	0.138

Robust t-statistics in brackets based on standard errors accounting for intra-cluster correlation

*** p<0.01, ** p<0.05, * p<0.1.

See Annex F for the full set of estimates. The estimates above are extracted from Tables F.2a and F.2b that include the estimates of Rain_p12 and Temp_12.

Table 6: Estimates of the impacts of rainfall and temperature anomalies through the income and disease environment pathways on younger and older children. Dependent variable: Child HAZ

VARIABLES	0-23 mo	24-59 mo	0-23 mo	24-59 mo
Rain_gs				
Bottom 20% of z-scores	-0.081*	-0.068**	-0.091**	-0.040
	[-1.888]	[-2.170]	[-2.044]	[-1.217]
20-40 % of z-scores	-0.031	-0.012	-0.033	0.001
	[-0.786]	[-0.419]	[-0.848]	[0.020]
60-80% of z-scores	0.005	-0.040	0.005	-0.048
	[0.137]	[-1.363]	[0.134]	[-1.621]
Top 20% of z-scores	-0.061	0.057*	-0.052	0.039
	[-1.451]	[1.866]	[-1.251]	[1.278]
Temp_ps				
Bottom 20% of z-scores			-0.080	0.069**
			[-1.630]	[2.080]
20-40 % of z-scores			-0.073*	0.019
			[-1.825]	[0.622]
60-80% of z-scores			0.028	0.012
			[0.810]	[0.408]
Top 20% of z-scores			-0.024	-0.063*
			[-0.568]	[-1.807]
Observations	25,724	32,244	25,724	32,244
R-squared	0.124	0.075	0.124	0.076
SPEI_gs				
Bottom 20% of z-scores	-0.076	-0.079**		
	[-1.624]	[-2.543]		
20-40 % of z-scores	-0.117***	-0.052		
	[-2.761]	[-1.565]		
60-80% of z-scores	-0.002	0.044		
	[-0.065]	[1.316]		
Top 20% of z-scores	0.012	-0.016		
	[0.297]	[-0.484]		
SWI_gs				
Bottom 20% of z-scores			-0.053	-0.066*
			[-1.253]	[-1.753]
20-40 % of z-scores			-0.033	-0.040
			[-0.833]	[-1.090]
60-80% of z-scores			0.039	-0.015
			[0.915]	[-0.426]
Top 20% of z-scores			-0.004	-0.047
			[-0.076]	[-1.251]
Observations	25,724	32,244	19,128	17,594
R-squared	0.124	0.075	0.122	0.107

Robust t-statistics in brackets based on standard errors accounting for intra-cluster correlation

*** p<0.01, ** p<0.05, * p<0.1.

See Annex F for the full set of estimates. These estimates are extracted from Tables F.3a and F.3b that include the estimates of Rain_p12 and Temp_12.

References

- Alderman. H., Hoddinott J., and Kinsey B. (2006) "Long term Consequences of Early Childhood Malnutrition" *Oxford Economic Papers*, Vol. 58, No. 3 (July), pp. 450-474
- Alderman H, Headey D (2018) "The timing of growth faltering has important implications for observational analyses of the underlying determinants of nutrition outcomes." *PLoS ONE* 13 (4): e0195904. <https://doi.org/10.1371/journal.pone.0195904>
- Alfani, F., Dabalen, A., Fisker, P., Molini, V. (2019) "Vulnerability to Stunting in the West Africa Sahel", *Food Policy*, 83: 39–47.
- Almond, D., & Currie, J. (2011). "Killing me softly: The fetal origins hypothesis". *Journal of Economic Perspectives*, 25(3), 153-172. doi:10.1257/jep.25.3.153
- Almond, D., and B. Mazumder. 2011. "Health Capital and the Prenatal Environment: The Effect of Ramadan Observance during Pregnancy." *American Economic Journal: Applied Economics* 3 (4): 56–85.
- American Meteorological Society. (2013, September 19). *An Information Statement of the American Meteorological Society*. Retrieved July 3, 2021, from American Meteorological Society: <https://www.ametsoc.org/index.cfm/ams/about-ams/ams-statements/statements-of-the-ams-in-force/drought/>
- Angrist J. D., and J.S. Pischke (2009) *Mostly Harmless Econometrics* Princeton University Press
- Auffhammer, Maximilian. 2018. "Quantifying Economic Damages from Climate Change." *Journal of Economic Perspectives* 32 (4): 33–52. <https://doi.org/10.1257/jep.32.4.33>.
- Baez, J.E., Kshirsagar, V., and Skoufias, E. (2024) "Drought-Sensitive Targeting and Child Growth Faltering in Southern Africa" *World Development*, 182. <https://doi.org/10.1016/j.worlddev.2024.106702>
- Baker, R. E., & Anttila-Hughes, J. (2020). Characterizing the contribution of high temperatures to child undernourishment in Sub-Saharan Africa. *Scientific Reports*, 10, 18796. doi:10.1038/s41598-020-74942-9
- Barker, D. J. (1995). Fetal origins of coronary heart disease. *British Medical Journal*, 311, 171-177. doi:10.1136/bmj.311.6998.171
- Black R, Allen L, Bhutta Z, et al. (2008). "Maternal and child undernutrition: global and regional exposures and health consequences". *Lancet*. 2008;371:243–260.
- Black, R. E., Victora, C. G., Walker, S. P., Bhutta, Z. A., Christian, P., de Onis, M., at al. (2013). "Maternal and child undernutrition and overweight in low-income and middle-income countries". *Lancet* Aug 3;382(9890):427-451.
- Boyle, E. H., King M., Sobek, M. (2019). IPUMS-Demographic and Health Surveys: Version 7 [dataset]. Minnesota Population Center and ICF International, 2019. <https://doi.org/10.18128/D080.V7>

- Bozzoli, C., Deaton, A., & Quintana-Domeque, C. (2009). "Adult height and childhood disease." *Demography*, 46(4), 647-669.
- Brown, M. E., Grace K., Shively, G., Johnson, K., and Carroll. M. (2014). "Using satellite remote sensing and household survey data to assess human health and nutrition response to environmental change," *Population and Environment*, 36:48–72
- Carrillo, B. (2020). "Early rainfall shocks and later-life outcomes: Evidence from Colombia." *The World Bank Economic Review*, 34(1), 179-209.
- Confalonieri, U., B. Menne, R. Akhtar, K.L. Ebi, M. Hauengue, R.S. Kovats, B. Revich and A. Woodward (2007). *Human health. Climate Change 2007: Impacts, Adaptation and Vulnerability*. Contribution of Working Group II to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change, M.L. Parry, O.F. Canziani, J.P. Palutikof, P.J. van der Linden and C.E. Hanson, Eds., Cambridge University Press, Cambridge, UK, 391-431.
- Cooper, M. W., Brown, M.E., Azzarri, C., & Meinzen-Dick R. (2019)" Hunger, nutrition, and precipitation: evidence from Ghana and Bangladesh". *Population and Environment*, 41:151–208
- Cooper, M. W., Brown, M. E., Hochrainer-Stigler, S., Pflug, G., McCallum, I., Fritz, S., . Silva, J., and Zvoleff, A. (2019). "Mapping the effects of drought on child stunting". *PNAS*, 116(35), 17219-17224. doi:10.1073/pnas.1905228116
- Currie, J., & Vogl, T. (2013). "Early-life health and adult circumstance in developing countries." *Annual Reviews in Economics*, 5: 1-36. doi:10.1146/annurev-economics-081412-103704
- Davenport, F., Dorélien, A., & Grace, K. (2020). Investigating the linkages between pregnancy outcomes and climate in sub-Saharan Africa. *Population and Environment*, 41, 397-421. doi:10.1007/s11111-020-00342-w
- Davenport, F., Grace, K., Funk, C., & Shukla, S. (2017). "Child health outcomes in sub-Saharan Africa: A comparison of changes in climate and socio-economic factors." *Global Environmental Change*, 46, 72-87. doi:10.1016/j.gloenvcha.2017.04.009
- Debebe, Z. Y., & Raju, D. (2020). "Covariate shocks and child undernutrition: A review of evidence from low- and middle-income countries." *Policy Research Working Paper*, 9273. Washington, DC: The World Bank.
- Dell M., B. Jones, and B. Olken (2014) "What Do We Learn from the Weather? The New Climate–Economy Literature." *Journal of Economic Literature*, 52(3), 740–798. <http://dx.doi.org/10.1257/jel.52.3.740>
- Dinkelman, T. 2017. "Long-run Health Repercussions of Drought Shocks: Evidence from South African Homelands." *Economic Journal* 127 (604): 1906–39
- Engle, P. L., Menon, P., & Haddad, L. (1999). "Care and nutrition: Concepts and measurement." *World Development*, 27(8), 309-1337.

- Eriksson, J. G., E. Kajantie, C. Osmond, K. Thornburg, and D. J. P. Barker. 2010. "Boys Live Dangerously in the Womb." *American Journal of Human Biology* 22 (3): 330–35.
- Farris, J., Jin, S., Maredia, M. K., & Porter, M. (2018). *Assessing Heterogeneity in the Child Growth Impacts of In-Utero Rainfall Shocks in Rural Rwanda*. Washington, DC: Annual Meeting of Agricultural and Applied Economics Association. doi:10.22004/ag.econ.274230
- Fouque, F., & Reeder, J. C. (2019). "Impact of past and on-going changes on climate and weather on vector-borne diseases transmission: a look at the evidence." *Infectious Disease of Poverty*, 8(51). doi:10.1186/s40249-019-0565-1
- Frankenberg, E., and D. Thomas (2017). "Human Capital and Shocks: Evidence on Education, Health and Nutrition." Unpublished
- Galasso, E., & Wagstaff, A. (2019). The aggregate income losses from childhood stunting and the returns to a nutrition intervention aimed at reducing stunting. *Economics and Human Biology*, 34, 225-238. doi:10.1016/j.ehb.2019.01.010
- Gascoigne J.  S. Baquie  K. Vinha  E. Skoufias  E. Calcutt  V. Kshirsagar  C. Meenan  R. Hill  "The Welfare Cost of Drought in Sub-Saharan Africa". Policy Research Working Paper No. 10683, January 2024. Washington D.C.: World Bank Group
- Guerrant R, Schorling J, McAuliffe J, et al. Diarrhea as a cause and an effect of malnutrition: diarrhea prevents catch-up growth and malnutrition increases diarrhea frequency and duration. *American Journal of Tropical Medicine and Hygiene*. 1992;47:28–35.
- Hoddinott J., Alderman H., Behrman J. R., Horton S. (2013) 'The economic rationale for investing in stunting reduction', *Maternal and Child Nutrition*, 2: 69–82 doi: 10.1111/mcn.12080.
- Hoddinott, J. and B. Kinsey (2001) "Child Growth in the Time of Drought" *Oxford Bulletin of Economics and Statistics*, Vol. 63, No. 4, pp. 409-436.
- Hyland, M., & Russ, J. (2019). "Water as destiny – The long-term impacts of drought in sub-Saharan Africa." *World Development*, 115, 30-45. doi:10.1016/j.worlddev.2018.11.002
- Johnson, K. B., & Brown, M. E. (2010). Satellite remote sensing variables as environmental risk factors and their association with child nutritional status and survival in a context of climate change. Greenbelt, MD: NASA Goddard Space Flight Center.
- Kraay, A. N., Man, O., Levy, M. C., Levy, K., Ionides, E., & Eisenberg, J. N. (2020). Understanding the impact of rainfall on diarrhea: Testing the concentration-dilution hypothesis using a systematic review and meta-analysis. *Environmental Health Perspectives*, 128(1). doi:10.1289/EHP6181
- Kudamatsu, M., Persson, T., & Stromberg, D. (2012). *Weather and Infant Mortality in Africa*. Working Paper, Center for Economic Policy Research. Retrieved from <http://nobel2012.iies.su.se/Papers/Kudamatsu.pdf>

- Lapworth, D. J., MacDonlad, A. M., Kebede, S., Owor, M., Chavula, G., Fallas, H., Casey, V. (2020). Drinking water quality from rural handpump-boreholes in Africa. *Environmental Research Letters*, 15, 064020.
- Leroy, J. L., & Frongillo, E. A. (2019). Perspective: What does stunting really mean? A critical review of the evidence. *Advances in Nutrition*, 10(2), 196-204. doi:10.1093/advances/nmy101
- Maccini, S., & Yang, D. (2009). "Under the weather: Health, Schooling, and economic consequences of early-life rainfall." *American Economic Review*, 99(3), 1006-1026.
- Miller, G. and B. P. Urdinola, (2010). "Cyclicalities, Mortality, and the Value of Time: The Case of Coffee Price Fluctuations and Child Survival in Colombia." *The Journal of Political Economy*, 118(1): 113-155.
- Mulmi, P., S. A. Block, G. E. Shively, and W. A. Masters. 2016. "Climatic Conditions and Child Height: Sex-Specific Vulnerability and the Protective Effects of Sanitation and Food Markets in Nepal." *Economics and Human Biology* 23: 63–75.
- Omiat G., and G. Shively (2020) "Rainfall and Child Weight in Uganda" *Economics and Human Biology*, vo. 38. <http://dx.doi.org/10.1016/j.ehb.2020.100877>
- Rabassa, M., Skoufias, E., & Jacoby, H. (2014). "Weather and Child Health in Rural Nigeria". *Journal of African Economies*, 23(4), 464-492.
- Randell, H., Grace, K., & Bakhtsiyarava, M. (2021). "Climatic conditions and infant care: Implications for child nutrition in rural Ethiopia." *Population and Environment*. doi:10.1007/s11111-020-00373-3
- Rose, J., S. Daeschner, D. Easterling, E. Curriero, L. Lele and J. Patz (2000). "Climate and Waterborne Outbreaks." *Journal of the American Water Works Association*, 92: 87-97.
- Shi, W., & Tao, F. (2014). Vulnerability of African maize yield to climate change and variability during 1961-2010. *Food Security*, 6, 471-481.
- Shrestha, R., Di, L., Yu, G., Shao, Y., Kang, L., & Zhang, B. (2013). Detection of flood and its impact on crops using NDVI - Corn case. *2013 Second International Conference on Agro-Geoinformatics (Agro-Geoinformatics)*, (pp. 200-204). doi:10.1109/Argo-Geoinformatics.2013.6621907
- Skoufias, E & Vinha, K. (2013). The impact of climate variability on welfare in rural Mexico. *Population & Environment*. 34, 370-399.
- Stige, L. C., Stave, J., Chan, K.-S., Ciannelli, L., Pettorelli, N., Glantz, M., Herren, H.R., and Stenseth, N. C. (2006). "The effect of climate variation on agro-pastoral production in Africa". *PNAS*, 103(9), 3049-3053.
- Thai, T. Q., & Myrskylä, M. (2012, February). "Rainfall shocks, parental behaviour and breastfeeding: Evidence from rural Vietnam." MPIDR Working Paper, WP 2012-009. Retrieved from <https://www.demogr.mpg.de/papers/working/wp-2012-009.pdf>

- Thiede, B. C., & Strube, J. (2020). "Climate variability and child nutrition: Findings from sub-Saharan Africa." *Global Environmental Change*, 65, 102192. doi:10.1016/j.gloenvcha.2020.102192
- Tiwari, S., Jacoby, H. G., & Skoufias, E. (2017). "Monsoon babies: Rainfall shocks and child nutrition in Nepal." *Economic Development and Cultural Change*, 65(2), 167-188.
- UNICEF, WHO, World Bank Group Joint Malnutrition Estimates, May 2022 Edition. Available from: <https://data.unicef.org/resources/dataset/malnutrition-data/>.
- Victora, C. G., Adair, L., Fall, C., Hallal, P. C., Martorell, R., Richter, L., Sachdev, H.S., and for the Maternal and Child Undernutrition Study Group. (2008). "Maternal and child undernutrition: consequences for adult health and human capital." *Lancet*, 340-357. doi:10.1016/S0140-6736(07)61692-4
- Wani, S. P., Sreedevi, T. K., Rockström, J., & Ramakrishna, Y. S. (2009). Rainfed Agriculture - Past Trends and Future Prospects. In S. P. Wani, J. Rockström, & T. Oweis (Eds.), *Rainfed Agriculture: Unlocking the Potential* (pp. 1-35). Oxfordshire, UK: CABI International.
- World Health Organization (2002). "Health and Environment in Sustainable Development." WHO, Geneva.

ENDNOTES

¹ Recent World Bank estimates suggest that the per capita income penalty a country incurs for not having eliminated stunting when today's workers were children is around 7 percent of gross domestic product (GDP) per capita, on average. In Sub-Saharan Africa and South Asia, these figures rise to about 9–10 percent of GDP per capita (Galasso et al. 2017).

² Extreme precipitation has significant impact on child health in developed countries as well. For example, Rose et al. (2000) report that in the United States, 20 to 40% of water-borne disease outbreaks can be related to extreme precipitation events.

³ Shi and Tao (2014), for example, report that in Africa, a ten percent decrease in rainfall is associated with at least a five percent decrease in maize yields in 20 of the 32 countries studied and that in 18 countries an increase of mean temperature by one degree is associated with at least a five percent decrease in yields. Also, Stige, et al. (2006) find substantial reductions in yields for maize, sorghum, millet, rice, and groundnuts from the El Niño Southern Oscillation (ENSO) events.

⁴ In a meta-analysis of the effect of rainfall on diarrhea Kraay, et al. (2020) find that in general rainfall after a dry period is associated with increased incidence of diarrhea and some indication of lower diarrheal incidence when rainfall follows wet periods.

⁵ Lapworth et al. (2020) report that 21 percent of rural handpumps from boreholes surveyed in Africa had water with exceeding amounts of thermotolerant coliforms, which cause diarrheal disease and that the contamination increased with average annual rainfall.

⁶ In households engaged in agriculture, mothers breastfeed for a shorter period of time when there is additional rain (non-extreme) potentially as their time demands in agricultural production increase (Thai & Myrskylä, 2012; Randell, Grace, & Bakhtsiyarava, 2021). In general, the caregivers': (i) workload and time constraints; (ii) knowledge, practices, and beliefs regarding childcare; (iii) health and nutritional status; (iv) mental health, stress level, and self-confidence; (v) autonomy and control of resources; and (vi) social support received from family members and the community (Engle, Menon, & Haddad, 1999), all combine to act as intermediary factors between how child nutrition and health are affected by the climate induced changes in the household's resources and the disease environment.

⁷ We will use the terms climatic variability and weather anomalies interchangeably. Weather usually refers to the very short-term (day to day) atmospheric conditions in a specific place at a specific time, whereas climatic variability refers to natural variations in climate patterns over medium time scales (months, years, or decades). Climate change in general refers to long-term shifts in the Earth's climate system (change in the long-term mean).

⁸ Theide and Strube (2020) extract temperature and precipitation records from 1951 through 2015 for the grid cell that each DHS cluster falls to construct the standardized deviation (z-score) of precipitation in community during the 12-month period and in reference to the long-term mean and standard deviation of precipitation in that community.

⁹ A related study at the regional level in SSA is by Kudamatsu, et al. (2016), estimates the causal impacts of malarious weather and growing-season rainfall on infant mortality.

¹⁰ Copper, et al. (2019) chose the 24-month time intervals after considering alternative time windows at which SPEI values best predict child heights. But they do not consider alternative hazard measures.

¹¹ Naturally, this comes at the cost of having estimates that are not country specific.

¹² One important consideration regarding the NDVI is that it is potentially endogenous since it is likely to reflect the land use and crop production choices by households in relation to the recent or contemporary rainfall patterns. Earlier drafts of this paper (available upon request) included NDVI in the analysis for comparison with the other anomaly measures that, arguably, are exogenous.

¹³ These data sets are accessible through the IPUMS-DHS website <https://www.idhsdata.org/idhs/gis.shtml>. (Boyle, et al., 2019).

¹⁴ Annex A provides a more detailed description of how the anomaly data were matched to the date of birth of a child in the survey.

¹⁵ Specifically, for any given radius the spatial aggregation includes grid cells with at least half of the grid cell within the radius, and grid cells whose centroid is within the radius.

¹⁶ This level of spatial aggregation was chosen based on a comparison of the sensitivity of the relationship between consumption and hazard measures aggregated using different radii in the case of Malawi (see Gascoigne et al., 2024).

¹⁷ The means and standard deviations of all the variables used in the analysis are presented in Annex C.

¹⁸ The only study that is directly related to ours is Davenport, et al. (2017) which examines the effect of rainfall and temperature levels (as opposed to anomalies) during the different trimesters in-utero on child birthweight. Their investigation of the impacts on chronic malnutrition as measured by child HAZ relies on the average rainfall (during rainy seasons) and the proportion of days that are over 37.7° C during the period from the child's conception to the date of the interview.

¹⁹ Stillbirths are any fetal death after 28 weeks of gestational age.

²⁰ Bozzoli, et al. (2009) show that if the mortality rate is sufficiently high then the culling dominates scarring resulting in a taller population.

²¹ Annex F presents estimates based on a linear and piece-wise linear specification (Tables F.1, F.2, and F.3). These estimates were obtained by including only one anomaly measure at a time as an independent variable.

²² Delays in rain can mean longer treks for water, or complete lack of it, especially in arid and semi-arid areas.

²³ Leroy, et al. (2019) raise doubts about whether the Height-for-Age Z-score used as the nutrition outcome measure is the appropriate measure for catch-up growth. The standard deviation of HAZ increases with age and therefore a child could be considered to have caught up, i.e., no longer stunted or with a higher HAZ, but in fact still be on the same growth path and not actually have had faster growth relative to the median child.