Adverse Early Life Shocks and Impacts on Short-Term and Long-Term Outcomes: Evidence from Rural Malawi

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Abstract

This paper examines the impact of exposure to rainfall shocks at early life on children's anthropometric health measures and other welfare outcomes. We use repeated cross-section household data on Malawi and exogenous variation in precipitation across space to identify the impact of rainfall deviation and disaggregated extreme shocks on health and productivity outcomes. Our main estimate for the impact of disaggregated extreme shocks on children's anthropometric health reveals that drought shocks lead to an average decrease of 15 percent, 17 percent and 43 percent in age-standardised weight z-scores for shocks experienced in-utero, in the first and second years of life respectively. Correspondingly, the impact of drought shocks on age-standardised height z-scores are 14 percent, 15 percent and 27 percent. There is only a short-lived effect from wet shocks. On long-term outcomes, we find that females exposed to in-utero drought shocks are more frequently hospitalised and less likely to be productive, with no apparent effects on males. We provide suggestive evidence for the gender-driven resource allocation within households as the origin for the persistent effect that we find for females.

Keywords: Critical period programming, drought, child growth, welfare, Malawi

JEL Classification Codes: I12, J22, J24, J46

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1. Introduction

A large portion of the empirical evidence in favour of persistent impacts of early life shocks on long-term socioeconomic outcomes focus on nutrition as an important transmission mechanism (Alderman *et al.* 2006; Yamauchi 2008; Alderman *et al.* 2009; Maluccio *et al.* 2009; Neelsen and Stratmann 2011; Ampaabeng and Tan 2013; Dercon and Porter 2014 and Bertoni 2015). Most of the literature focuses on health and education outcomes as the mainstream human capital outcomes. Commonly used health variables include height, weight, frequency of sickness, health expenditure and chronic illness of individuals in the data (Maccini and Yang 2009; Dercon and Porter 2014). Additional outcome variables, such as cognitive development, labour market proficiency, life achievements and satisfaction levels, are equally used for broader understanding of the impact of early life shocks. The consensus for childhood welfare outcomes for children between the ages of 0 to 60 months are anthropometric health measures captured by standardised Z-scores in weight-for-height (WHZ), weight-for-age (WAZ) and height-for-age (HAZ) (Hidrobo 2014; Rabassa *et al.* 2014; Thai and Falaris 2014). In a low-income setting, many authors use variability in weather patterns to capture the vulnerability of agricultural dependent households – usually smallholder farmers – for an understanding of food security dynamics in these households. These include Hoddinott and Kinsey (2001), Maccini and Yang (2009), and Thai and Falaris (2014).

Recent studies extend the analysis by studying other unconventional outcomes to provide evidence on mental health and death. Adhvaryu *et al.* (2014)[1] study the origins of adult mental health using early life income variations originating from exogenous cocoa price fluctuation in Ghana. Using variation in cocoa prices around the time of birth, the paper shows that a rise in the price of cocoa for cohorts born around the same time significantly decreases the likelihood of severe mental distress in adulthood (by around half of the average prevalent rate). Comfort (2016) finds that exposure to early life adverse shock increases the likelihood of maternal mortality for women. She examined this hypothesis in 14 African countries by relating rainfall when a woman was in-utero with her maternal survival in adulthood. Her results indicate that sufficient levels of rainfall, representing better in-utero conditions, decrease the probability of maternal death by 1.1 percentage points, a 58% decrease from a mean of 1.9%. Better rainfall while in-utero also reduces the probability of anemia during pregnancy, a risk factor for postpartum hemorrhage. Although the rapidly expanding body of literature regarding the welfare impact of exposure to early life shocks consistently reveals the adverse impact of negative shocks, an important strand of this literature studies the impact of intervention programmes on the devastating effect of these shocks on welfare (Maluccio *et al.* 2009; Yamano *et al.* 2005; Hidrobo 2014). None of the existing literature has considered the interaction effects of exposure to early life shocks and gender resource allocation.[2]

[1] This literature is closely related to a growing body of work that has established critical period programming through evidence from early life famine and natural disaster on adulthood mental health in the field of medicine (Huang *et al.* 2013a; Maclean *et al.* 2016; Xu *et al.* 2016).

[2] This argument is valid within the context of a large body of literature that reveals discriminatory intra-household resource allocation for boys (Masterson 2012; Zimmermann 2012; Azam and Kingdon 2013) and girls (Himaz 2010).

This paper estimates the impact of rainfall shocks at the developmental stages of life on short-term children's anthropometric health measures and long-term welfare outcomes, paying particular attention to welfare outcomes important to rural livelihood in Malawi.[3] The contribution of this paper is in the use of disaggregated extreme rainfall shock measures to capture the symmetric or asymmetric impact of rainfall shocks – namely drought and wet shocks – on welfare outcomes. This approach will provide an in-depth understanding to the prevailing mechanisms at work when studying the impact of rainfall shocks in the sub-Saharan African region. We also use multiple shock exposure around the time of birth of individuals, covering three separate agricultural seasons from in-utero to the second year to examine the comprehensive impact of shocks around birth on welfare outcomes.[4] Lastly, we contribute to the understanding of some additional pathways of early life rainfall shocks on children's anthropometric health measures.

Our baseline results for rainfall deviation specifications regarding child anthropometric health measures indicate that negative (positive) rainfall shocks in early life – in-utero period inclusive – decrease (increase) WAZ and HAZ. We focus on a disaggregated extreme shock econometric specification for the interpretation of results. An incidence of drought shock leads to a decrease of 15%, 17% and 43% in WAZ for shock exposure at the in-utero stage, in the first and second years respectively. Correspondingly, the impacts of drought shock on HAZ are 14%, 15% and 27%. The impact of wet shocks on both variables deteriorates across early life reference periods. Additional results from various alternative indicators, such as underweightness or moderate and severe stunting, corroborate our standardised score results. We also find that the impact of drought shocks at the in-utero stage persists for hospitalisation and hours of informal labour outcomes. More importantly, we find that this evidence pertains to women only, while no substantial evidence is reported for men. In the paper, we provide evidence suggesting that the use of nutritional intervention programmes reveal that the gender-specific asymmetric results could potentially be linked to intra-household resource allocation between males and females in Malawian households.

The remainder of the paper is organised as follows: Section 2 provides a country background, while section 3 describes the household data and summarises the main variables. Section 4 describes the construction of the rainfall deviation and the disaggregated extreme rainfall shock measures. Section 5 unveils the conceptual framework and empirical strategy for evaluating the impact of rainfall shock on infant and other welfare measures. Section 6 presents the main results for children, highlights potential pathways, presents overall welfare results and examines the role of access to intervention nutrition programmes. Section 7 discusses the findings and provides the concluding remarks.

[3] While health and labour market outcomes have been extensively investigated in the literature, as highlighted above, this study pays particular attention to the elements of health and labour market outcomes that directly determines the livelihood of rural households in a developing country framework.

[4] The closest literature in this regard is Thai and Falaris (2014) on Vietnam. A distinguishing feature of our paper is the emphasis placed on disaggregated extreme rainfall shock specification in our analytical framework and the consideration of more salient welfare outcomes to reflect livelihood and sustenance of individuals in the rural areas of the sub-Saharan African region. Also this study takes on a broader perspective to investigate the intra-household dynamics of gender-based differential welfare outcomes of early life shocks in Malawian individuals.

2. Country Background

The context for our study is Malawi, a sub-Saharan African country located on the south-eastern part of the continent. This country shares borders with Zambia, Mozambique and Tanzania. The total area of the country is 118,484 km² by land mass, and it had a population of approximately 17 million people in 2014 (World Bank, 2014). According to World Bank statistics Malawi was rated among the world's poorest countries in 2014. The country is predominantly made up of rural communities, which play host to smallholder farmers. There is a seasonal rainfall pattern across the various Malawi regions, with the rainy season continuing from November to April in the following year. Most crop cultivation takes place during this season, while the rainfall pattern for the dry season, between May and October, is unreliable for crop cultivation.

Malawi's agricultural sector contributes about 29 percent to the country's GDP and accounts for around 85 percent of the export revenue of the economy. Small holder farmers rely mostly on seasonal rainfall for their crop cultivation and other agricultural activities. As a result, weather patterns have a profound effect on agricultural harvests and Malawi's GDP. Furthermore, the Malawian diet is overwhelmingly dominated by maize consumption, which relies on the seasonal precipitation of agricultural seasons. Not only are rural livelihoods affected by the severe weather pattern on the agricultural sector, nonfarm rural and poor urban sectors are equally vulnerable given the strong production and price linkages between the agricultural sector and the rest of the economy in Malawi.

The landlocked African country suffers from frequent droughts and floods. Flooding leads to destruction, which, in effect, damages infrastructure and housing – occasionally leading to displacement of population – and droughts to severe crop failure and, hence, malnutrition. However, more attention is usually paid to their effect on agricultural production and national food security issues in this context. Malawi has been hit by a series of devastating droughts over its history. The adverse weather shocks that have had substantial impacts on agricultural practice and food security in Malawi include droughts in 1999, 2002, 2009 and 2012-2013. Whenever a drought affects agricultural yields, the national food security of the country is threatened due to low crop production and storage. Children often suffer disproportionately from drought events, and a nutritional pathway of critical programming hypothesis (for children developmental stages) has been widely established in the literature.

3. Data and Summary Statistics

We used three rounds of Malawian household survey data collected by the World Bank, which are made up of the Malawi Integrated Household Survey (IHS) and Malawi Living Standard Measurement Study-Integrated Survey on Agriculture (LSMS-ISA), hereinafter called the Malawi Household Surveys (MHS) in this paper. The first wave is from 2004 to 2005, while the last waves, between 2010 and 2011, and 2013, are for a panel of observations. The number of observations matched with rainfall data from the household survey for the surveys are 11,280, 3,246 and 4,000 households, comprising 49,066, 15,582 and 20,076 individuals

respectively. We pooled the different household survey rounds for repeated cross-section data to investigate the impact of weather variation around the time of birth on children's short-term anthropometric health status and other welfare outcomes. We estimated the impact of weather shocks on the health status of children using observations between six and 59 months in the data. We used children born before the first round of the survey and in between the surveys. We made use of an important component of the MHS, which documents the locality of the births of the individuals interviewed. We constructed rainfall shocks for individuals around their period of birth by place of birth to examine the impact of childhood agricultural weather shocks on welfare outcomes. The assumption here is that individuals' place of birth is the place of early life shock exposure.

To measure local rainfall shocks, we relied on rainfall data from terrestrial precipitation: the 1900 to 2010 gridded monthly time series from the University of Delaware's (UDel) Center for Climatic Research (version 3.01). The dataset provides estimates of monthly precipitation on a 0.5° by 0.5° grid covering terrestrial areas across the globe for the period 1900 to 2010.[5] Rainfall estimates are based on the climatologically-aided interpolation of available weather station information. The data have been compiled and made available by Matsuura and Willmott (2012). We used the GPS information provided for each local community in the MHS by matching each community to the four closest weather stations in order to obtain rainfall data for the years spanning 1900 to 2010. We weighed the four closest weather stations by the distance to GPS supplied in the MHS in obtaining the rainfall data.

3.1 Children's Anthropometric, Health and Labour Market Outcomes

This paper uses anthropometric measures for children between the ages of six and 59 months in the MHS. These data consist of the height[6] and weight of each observed child in this category. The combination of the anthropometric data with the age of children in months was used for calculating the nutritional anthropometric outcomes in line with standard child growth trajectory measures of the World Health Organization (WHO). Stata code for the WHO children growth trajectories by nutritional health standard was used for constructing the WAZ and HAZ scores for child health outcomes (Leroy 2011). Using anthropometry measures and the monthly ages of children over the three rounds, in addition to community weather shocks around the periods of births, we were able to identify the community level average effect of weather shocks on the nutritional health status of children born within a community using community-fixed effects and year dummies.

We also examine hospitalisation rates in addition to health expenditure and the likelihood of chronic ailment as indicators of health wellbeing. Similarly, we focus our attention on hours committed to various labour activities within the previous week as a determinant of individual level labour productivity in the repeated cross-sectional MHS data.

[5] The University of Delaware (UDel) rainfall data repository is well cited in the economics literature and is commonly used for empirical studies. Recent papers that have used the UDel rainfall data for the purpose of empirical investigation include Chaurey (2015), Rocha and Soares (2015), and Foureaux Koppensteiner and Manacorda (2016).

[6] Note that height or length indicates standing or lying measurement positions in the data. This helps in the construction of the child nutritional health measures, which are HAZ and WAZ scores.

The likelihood of hospitalisation captures the health wellbeing of all the observations in the data, while labour market activities are restricted to individuals above five years of age. We investigate the effect of early life shocks on health and labour market variables by the respondents' gender.

3.2 Summary Statistics

Our analysis focuses on rural Malawi. The summary statistics in Table 1 Section A can be compared to the international reference group, which has an expected mean z-score of 0 for all normalised growth indices. In general, z-scores that are two standard deviations below the reference are associated with growth retardation in the case of WAZ and HAZ,[7] referring to underweight and stunting respectively. The standardised distribution of WAZ and HAZ for children between six and 59 months of age in our sample is displayed in figures 1 and 2 below. Each distribution is highly skewed to the left, implying that growth retardation is prevalent among children of this category in rural Malawi. Section A further provides the summary statistics for WAZ and HAZ in focused observations of 6,422 and 6,695 children by gender and age in months. An average child in our sample is 0.6 standard deviations underweight and 1.6 standard deviations shorter than the international reference mean of 0. Using relative indices, approximately 9% and 39% of children are underweight and stunted respectively. Boys are more likely to suffer from growth retardation than girls, with a stunting ratio of 42% to 36%. This gender-specific pattern is consistent with the observed pattern of growth gradients for boys and girls in Nigeria (Rabassa *et al.* 2014). By age group, stunting is more prevalent among children in their third and fourth years, with 49% and 43% respectively exhibiting stunting. This is followed by 39% and 38% stunting rates for children in their fifth and second years respectively. Children in their first year are the least stunted, with an 18% stunting rate.

Table 1 Section B presents the individual and household baseline characteristics used as controls in our estimations. The average age of children in our sample is slightly above two years. Around 51% of the sample are girls while 49% are boys. The average value of non-agricultural assets for a typical rural household in Malawi is approximately 18,000 Malawian Kwacha, which comes to US$90, giving an idea of the prevalence and severity of the poverty levels in these households. Households in our sample comprise on average six individuals, with two children between the ages of six and 18 years. The average household age across the households in the sample is 17 years while the mean age of the head of household is 37 years. Most of the households, around 84%, are headed by males. Lastly, only 22% of the heads of household have ever had any formal school tuition in their lifetimes.

4. Constructing Rainfall Deviation and Shocks

We aggregate the rainfall measure for each community by agricultural season, which is November to October of the following year. We reference a year by the agricultural season's rainfall measure in this context and derive the yearly rainfall deviation as the deviation of the local rainfall from the 30-year historical rainfall average in the locality. Similar to Maccini and

[7] WAZ and HAZ are obtained using a STATA command developed by Leroy (2011).

Yang (2009), Björkman-Nyqvist (2013) and Rocha and Soares (2015),[8] amongst others, rainfall deviation is constructed as the natural logarithm of the current agricultural season minus the historical average for the same locality.

$$\text{Rainfall Deviation}_{ct} = ln\,\text{Rainfall}_{ct} - ln\,\overline{\text{Rainfall}_c} \tag{1}$$

where Rainfall_{ct} indicates the yearly precipitation for the current agricultural year within the locality for community c, and $\overline{\text{Rainfall}_c}$ is the average historical yearly precipitation of the community over 30 years. Thus, $\text{Rainfall Deviation}_{ct}$ is defined as the deviation between the natural logarithm of the total precipitation in the 12 months of the agricultural season and the natural logarithm of the corresponding average seasonal historical precipitation at the community level. This measure of locality precipitation dynamics essentially denotes a percentage deviation from mean value and is measured in log-points deviation (Maccini and Yang 2009).

Based on equation (1) above, we construct measures of drought and flood shocks for the yearly agricultural cycle within a locality and then match individuals to one of the measures depending on the month of birth. We follow the literature on the creation of drought or flood shock by using a long-term time series of rainfall observations to fit a gamma distribution of rainfall within each community. We then assign each agricultural season's rainfall realisation in that location to its corresponding percentile in the historical distribution of rainfall at the community. We define a drought (flood) shock as a rainfall realisation that is in the bottom (uppermost) 25th percentile of that location's rainfall distribution over the past 30 years. As a robustness check, we calibrate with standard deviation bins below and above 30-year historical rainfall for an understanding of shock patterns below and above historical average (Comfort 2016).

We construct the disaggregated shock components for extreme precipitation measures (drought and flood shock incidence) for localities in the following way:

$$\text{Drought Shock}_{ct} = \begin{Bmatrix} 1 \text{ if rainfall within locality is below 25th percentile of norm} \\ 0 \text{ if rainfall within locality is above 25th percentile of norm} \end{Bmatrix} \tag{2}$$

$$\text{Flood Shock}_{ct} = \begin{Bmatrix} 1 \text{ if rainfall within locality is above 75th percentile of norm} \\ 0 \text{ if rainfall within locality is below 75th percentile of norm} \end{Bmatrix} \tag{3}$$

5. Empirical Strategy

5.1 Conceptual Framework

[8] Although Rocha and Soares (2015) consider alternative shock specification in terms of drought dummy, estimates from the linear rainfall deviation in equation (1) are used for the general interpretation of the results in their paper.

The potential channels for the impact of rainfall shock on welfare outcomes in the literature include agricultural income shock, disease environment and malnutrition (Almond and Currie 2011). Our framework on the impact of shock on both short-term and long-term welfare outcomes provides a unique opportunity to evaluate these existing models on diverse welfare outcomes in agricultural dependent households. While many welfare outcomes have been explored in the literature, additional outcome variables of hospitalisation rates and levels of productivity in our context elaborate the potential mechanisms for the welfare impacts of early life shock in an agricultural dependent setting. The agricultural income channel is mostly explored for outcomes on contemporaneous weather conditions through agricultural yields and livestock production (Bengtsson 2010; Fichera and Savage 2015) while the disease environment link between weather and welfare outcomes is theoretically plausible for both early life and contemporaneous shocks. Lastly, the malnutrition channel for the impact of rainfall shock is widely explored in the medical literature as being determined by caloric intake of individuals as much as by the composition of the nutrients. In this framework, food security risks associated with drought shocks can independently affect any of the above components of nutritional intake of individuals. It is important to note that while contemporaneous drought shocks could be the major contributing factor to nutritional deficiencies, growing evidence on the welfare impact of the first 1,000 days of exposure to shocks presents us with a framework on which to base our estimation strategy.

5.2 Empirical Strategy

The main identification problem in the estimation of impacts of early life shocks on both the short- and long-term social and economic outcomes of individuals is the potential endogeneity of household shocks. In this paper, we exploit the variation of early life precipitation measures as exogenous shock events to overcome this identification problem. As a result, we provide unique evidence on both the short- and long-term effects of the early childhood environment on children's anthropometric, health and labour market outcomes, including age standardised weight and height scores, and an array of health variables and labour productivity. Our empirical strategy is to exploit the exposure to shocks at different stages of early life (focussing on the first 1,000 days) relating to harvests from agricultural seasons for agricultural dependent households to identify the causal effects of children's exposure to nutritional shocks on their childhoods and on adult welfare outcomes. We follow the literature that investigate the impact of shocks on anthropometric indices of children's nutritional health status (e.g. Hidrobo 2014; Rabassa *et al.* 2014; Thai and Falaris 2014) using a reduced form specification for the impact of early life rainfall shock on WAZ and HAZ, as presented in equation (4) below.

In our pooled cross-section data, the effect of early life shocks is identified by comparing the average difference in child growth across communities whose children are born the same number of months apart. This is measured as the average outcome differences of a particular locality for a certain agricultural season as compared to the average differences of the same locality in another season. Identification occurs through children of similar age across these periods in the same community, which may constitute shock-exposed and non-exposed cohorts, or in other words, groups that may be exposed to differential magnitudes or extreme shock events in our disaggregated framework. Insofar as the variables in the error term are

orthogonal to an individual child's early life exposure to rainfall shock, the estimates of the effect of rainfall shock on child outcomes will be unbiased. This identification strategy is similar to the differential exposure to months of crisis in alignment with the month of birth in Hidrobo (2014). The identifying assumption for φ_p in equation (4) to be unbiased is that in the absence of a shock, the average outcome differences across communities whose children are born the same number of months apart would be the same. This means that in the absence of a shock, the average difference in outcomes for children with a similar age gap would be the same in this community. In order for this assumption to hold, the time trends in early outcome variables must be linear.

5.2.1 Linear Rainfall Deviation

$$\text{Child Health}_{ict} = \alpha_c + \gamma_t + \phi_a + \sum_{p=k-1}^{k+1} \varphi_p \text{ Rainfall Deviation}_{c,p} + X_i' \theta_x + Z_{ct}' \theta_z + \varepsilon_{ict} \quad (4)$$

where $\text{Child Health}_{ict}$ represents WAZ and HAZ for children aged six to 59 months for an observation *i* in community *c* for a survey round *t*. The subscript t indicates the survey year in which the child was measured. The z-score measures for each child differ across surveys in the case of the panel survey. $\text{Rainfall Deviation}_{c,p}$ ranges across the agricultural season prior to the year of birth, denoted by subscript *k-1*, first year of birth by *k* and second year of birth by *k+1*. We also consider additional child health outcome variables for the linear rainfall deviation measure in our empirical analysis using underweight, moderate and severe stunting indicators. α_c in equation (4) is the community fixed effect and γ_t is the interview season and the year of interview fixed effect.[9] We use the age (in years) fixed effect ϕ_a in our model to rectify concerns about the inter-age group effect in our regression. φ_p is the parameter of interest, namely the coefficient on community rainfall variation around the time of birth ($\text{Rainfall Deviation}_{c,p}$). φ_p measures the rainfall dynamics of the agricultural seasons around a child's birth, hence directly linking shocks around the period of birth to nutrition. Early life nutrition is an important component of human development which may be linked to critical-period programming of shocks on the short-term and long-term welfare outcomes.

We also use seasonal temperature at the community level as a control due to the adverse effect of excess heat on foetal health, which may impact the child's growth gradients in the short term and their welfare in adulthood (Hancock *et al.* 2007; Martinez *et al.*, 2011; Huang *et al.* 2013b; Wilde *et al.*, 2014; Barreca *et al.*, 2015; Isen *et al.*, 2015). The temperature measure enters into the regression of our preferred model as a deviation from the historical average.[10] *X* is a vector of household and individual level covariate, namely household non-agricultural asset valuation, household size, the gender of the head of household, average household age and the education and occupational categories of the head of household. Individual controls mainly consist of individual demographic characteristics, namely the child's age and gender. *Z* is a vector of community level controls to enhance precision in our

[9] It is important to note that a variation in the month of interview by year fixed effect is alternated during the estimation process with no apparent difference to the estimates of the preferred model.
[10] The use of seasonal temperature in the regression gives the same results as the temperature deviation measure.

estimation.[11] The error term (ε_{ict}) accounts for unobserved time-variant community characteristics not captured by the trend and unobserved individual characteristics. The error term of the model is assumed to be identically and independently distributed (iid) across localities but correlated within localities; hence, standard errors are clustered by locality.

5.2.2 Disaggregated Extreme Weather Shocks: Drought and Flood

We regress child health outcomes on early life drought and flood shock incidences in equation (5) below.

$$\text{Child Health}_{ict} = \alpha_c + \gamma_t + \phi_a + \sum_{p=k-1}^{k+1} D_p \text{ Drought Shock}_{c,p} + \sum_{p=k-1}^{k+1} F_p \text{ Flood Shock}_{c,p} + X_i' \theta_x + Z_{ct}' \theta_z + \varepsilon_{ict} \quad (5)$$

where coefficients D_p and F_p capture the differential impacts of drought and flood shocks from in-utero to second year of birth on child anthropometric health outcomes. Also, general welfare effects of extreme rainfall shocks are examined using equation (6) below.

$$\text{General Welfare}_{ict} = \alpha_c + \gamma_t + \Gamma_a + \sum_{p=k-1}^{k+1} D_p \text{ Drought Shock}_{c,p} + \sum_{p=k-1}^{k+1} F_p \text{ Flood Shock}_{c,p} + X_i' \theta_x + Z_{ct}' \theta_z + \varepsilon_{ict} \quad (6)$$

where Γ_a is the year-of-birth fixed effect (similar to the identification approach in Maccini and Yang 2009; Adhvaryu *et al.* 2014).

6. Results

6.1 Anthropometric Health Outcomes

6.1.1. The Impact of Early Life Linear Rainfall Deviation on WAZ and HAZ

We first present estimates of the regression of WAZ and HAZ on linear rainfall deviation. Results show that rainfall around the period of birth substantively affects average growth trajectories of children between the ages of six and 59 months in Malawi. Coefficient estimates of the linear rainfall deviation around period of birth on anthropometric health measures in Tables 2 and 3 reveal that negative (positive) rainfall movement decreases (increases) WAZ and HAZ respectively. Columns (1) to (5) of Table 2 report the effect of rainfall deviation on the age standardised weight scores of children within the community by systematically controlling for outlined covariates and fixed effects respectively.

[11] This includes indicator variables for access to roads, measured by year-round road usability, and quality of road infrastructure, measured by ease of road passage, the presence of a daily market within the community, the presence of a weekly market within the community, the presence of a phone call centre within the community, the presence of chemists within the community, the presence of a government-run health clinic within the community, the availability of a medical practitioner in the government medical centre, sales of subsidised bed nets within the community, the presence of a bank within the community, a representative from the community at the parliament, and school quality. Other community level controls include the average number of months roads are usable for buses and lorries in a year, number of teachers in government primary schools, number of teachers in government secondary schools, number of pupils in government primary schools, number of pupils in government secondary schools, number of private primary schools, number of private secondary schools, distance to community health clinic, community industry, and the number of churches and mosques.

In column (1), we present the coefficient estimates of a regression which includes a community-level temperature measure (deviation from the 30-year historical average) as well as a community fixed effect, a year fixed effect and a month-of-birth fixed effect. Column (2) adds community, household and individual covariates as control variables to the model. Column (3) includes an interview month-by-year fixed effect to control for discrepancies associated with weather conditions in different months of the year, while column (4) analogously includes interview season by year fixed effect to ensure seasonal variations do not drive our estimates of rainfall deviation on WAZ. Lastly, column (5) additionally includes an age cohort fixed effect to purge our estimates of the inter-age variation of the impact of shocks on WAZ among children.

The richest specification in Table 2 Column (5) reports in-utero, first and second year-of-birth rainfall shock estimates of 1.068, 0.695 and 1.018 respectively, and are significant at the 1 percent level. Rainfall shocks are measured in log-ratio; hence, each measure percentage deviation while WAZ is in standard deviation units of children health scores. A 10% lower than the norm rainfall indicates a negative rainfall shock of approximately 0.1 log-point. Hence, the impact of such a negative shock on WAZ is a reduction of 0.107, 0.070 and 0.102 standard deviation units in average weight for shocks during in-utero, year of birth and year after birth respectively. Given that the average WAZ from our summary statistics is -0.607 standard deviation, a 0.1 log-point in-utero rainfall shock translates to an approximately 18% decrease in the average standardised weight measure for children. The shock effects for birth year and the year after are equally 12% and 17%. The effects are extremely robust across different specifications.

Table 3 reports the coefficient estimates of rainfall shocks around the period of birth on the average age standardised height scores as an alternative measure of child development. As expected, rainfall shock estimates are not significantly different across specifications from Columns (1) to (5) of Table 3. We focus our attention on the standard model in column (5) for the purpose of the interpretation of results. Coefficient estimates of column (5) indicate that a 0.1 log-point negative rainfall shock reduces average standardised height scores by 0.236, 0.176 and 0.160 standard deviation units respectively for in-utero to year-after-birth periods. The impact of these estimates with respect to mean HAZ of -1.594 is an average decrease of 15%, 11% and 10% in HAZ for exposures at in-utero, birth year and year after respectively. Our results, in this case, imply an interpretation consistent with an adverse (beneficial) health effect of negative (positive) rainfall deviations. We investigated this further by examining our main results in a disaggregated framework, using extreme shocks to highlight the potential mechanisms along the types of shock in this context. This allowed us to complement linear rainfall deviation specifications explored for the impact of precipitation patterns in the literature (Maccini and Yang 2009; Rabassa *et al.* 2014; Rocha and Soares 2015).[12]

[12] We would also like to rule out that the results are driven by spatial correlation of rainfall shocks, as elucidated by Lind (2015). Although we make use of less aggregated rainfall data compared to district level measures common in the literature, we want to make sure that village level rainfall shocks are still not serially correlated

6.1.2. The Impact of Early Life Rainfall Deviation on Alternative Child Health Measures

Motivated by the literature on nutritional health effect of shocks (Giles and Satriawan 2015), we examine the impact of early life shocks on indicators for underweightness and stunting. The stunting measure examines two critical indices – moderate and severe stunting. Table 4 Columns (1) to (3) present point estimates of rainfall shocks around the time of birth on underweightness and stunting indicators. The use of underweightness and stunting indicators in this paper help us to gain further insights into the depth of early life malnutrition and child health nexus. While coefficient estimates reveal that underweight and moderate stunting outcomes in columns (1) and (2) are affected by in-utero and year-of-birth rainfall shocks only, the results from column (3) reveal a result consistent with the baseline effects in Tables 2 and 3.

The point estimates of column (1) show that in-utero and year-of-birth rainfall deviation measures have a considerable impact on the proportion of underweight children at the community level. Rainfall deviation estimates are -0.119 and -0.078 respectively (significant at 1 and 5 percent levels). For the purpose of the interpretation of the results, we adopt a benchmark of 0.1 log-point negative rainfall shock for each reference period, as adopted earlier. A 0.1 log-point negative rainfall shock during the pregnancy of a child and the first year translate to an increase in the likelihood of having lower than expected weight by 0.012 and 0.008 percentage points. Given the sample ratio of underweight children of 0.090 in our sample, these estimates indicate a 13% and 9% increase in the average likelihood of underweight children in the event of a 10% decrease in rainfall level relative to normal rainfall at the local level.

With regard to stunting indicators, in-utero and first-year rainfall shock coefficient estimates present -0.337 and -0.235 respectively for moderate stunting outcome in column (2) – both significant at the 1 percent level. This shows that a 0.1 log-point negative rainfall shock during the pregnancy of a child and the first year lead to a corresponding increase in the likelihood of stunting by 0.034 and 0.024 percentage points. In reference to the baseline mean of 0.391, the estimates correspond to an average of a 9% and 6% increase. Also, in-utero, first-year and second-year rainfall deviation coefficient estimates are -0.192, -0.177 and -0.104 for severe stunting outcomes in column (3). A 0.1 log-point negative rainfall shock between the pregnancy period and second year after birth increases severe stunting ratio by 0.019, 0.018 and 0.010 respectively. Given a baseline mean for severe stunting of 0.174, the in-utero rainfall

with the average health outcomes of the children. For this purpose, we regress children nutritional health measures on the village level long-term rainfall variability (measured by the standard deviation of 30-year historical rainfall around the season of birth). Table A1 in the appendix reports the results using both WAZ and HAZ measures of children's nutritional health outcomes. While long-term village level rainfall variability for in-utero period marginally affects WAZ and HAZ respectively, the magnitude of the coefficient estimates are not comparable to corresponding standard model rainfall shock coefficient estimates in Tables 2 and 3. In other words, we do not find any sizeable effect of long-term rainfall variability on these measures, reducing any remaining concerns around spatial correlation of rainfall in our repeated cross-section framework.

deviation estimate leads to an 11% average increase in the severe stunting rate; while 10% and 6% average effects are associated with first and second-year impacts.

6.1.3. The Impact of Drought and Flood Shocks on WAZ and HAZ.

Table 5 repeats the regression of the baseline models on Tables 2 and 3 using drought and flood shocks constructed from equations (2) and (3) respectively. Columns (1) and (2) of Table 5 report coefficient estimates of drought and flood shocks from the in-utero period until the second year of birth on WAZ and HAZ respectively. Coefficient estimates of shocks for WAZ in column (1) show that an incidence of in-utero drought shock decreases WAZ by 0.089 standard deviations while wet shock increases it by 0.194 standard deviations. While the in-utero wet shock is significant at the 1 percent level, the drought shock counterpart is only marginally significant at 10 percent. In contrast, drought shocks for the first and second years of birth correspondingly decrease the standardised weight measure of children by 0.105 and 0.263 standard deviations units (respectively significant at 5 and 1 percent levels), while wet shocks have become insignificant.

The coefficient estimates of drought and wet shocks within the baseline mean of -0.607 standard deviations mean that an incidence of in-utero drought shock decreases the average WAZ by 15%, while wet shock increases it by 32%. Drought shocks in the first and second years further decrease average WAZ at the locality by 17% and 43%. Our results do not show any discernible impact for the wet shock component as the coefficient estimates weaken and turn insignificant.

The in-utero drought shock incidence decreases HAZ by 0.223 standard deviations while the wet shock counterpart increases it by 0.416 standard deviations – both estimates are significant at 1 percent level. First year drought shock incidence significantly decreases HAZ by 0.247 standard deviations while the wet shock counterpart significantly increases it by 0.203 standard deviations. While the drought shock incidence of the second year decreases HAZ by 0.435 standard deviation units, wet shock incidence has no impact. Given the mean HAZ in our sample, in-utero drought and wet shock incidences lead to a corresponding decrease and increase in standardised height scores of 14% and 26%. Also, a first-year drought shock incidence induces a decrease in standardised height scores measure by 15%, while the wet shock component increases it by 13%. Lastly, the second year drought shock incidence decreases the standardised height score by 27%, while the wet shock incidence has no apparent effect.

An important trend in the above results is the apparent asymmetric effects of second year drought and wet shocks on age standardised weight and height scores. Secondly, while both in-utero drought and wet shocks affect our health measures, the drought shock estimates strengthen from the in-utero to second year periods, while the wet shock estimates fade away and become insignificant. The asymmetric pattern in the magnitudes of the coefficient estimates of drought and wet shocks on WAZ outcome – the weight component of child growth trajectory – starting from the first year of birth suggests some evidence to support nutrition as an important transmission mechanism from seasonal rainfall shock to children's growth status

in developing countries. However, the positive impact of in-utero wet shocks supports the potential benefits of sufficient rainfall and not necessarily an excessive dimension in terms of floods (Comfort 2016).

As a robustness check, we use standard deviation movements of precipitation measures above and below a 30-year historical average, similar to Comfort (2016). The results from this exercise show that the asymmetric impacts of negative and positive shocks are more visible for birth year and year after birth respectively (results available from the author upon request). This is similar to the use of bins of rainfall shock to understand the underlying mechanisms of shock on outcomes variables (Sekhri and Storeygard 2014). Contrasting evidence of negative and positive shock patterns between Sekhri and Storeygard (2014) and Comfort (2016) may be attributed to differential contexts and outcome variables. Our findings align with the literature on the adverse impact of drought shocks and the positive, but fading, impact of wet shock on welfare outcomes. Also, we conducted a sensitivity analysis on all the main results by estimating the impact of rainfall deviation and shocks on health using a sample of children aged between six and 35 months, similar to some studies (Rabassa *et al.* 2014). We did not find significantly different coefficient estimates across samples (Table A2 and Table A3).[13]

6.1.4 Heterogeneous Impacts of Early Life Rainfall Deviations (Boys and Girls)

Charts 1 and 2 of Table 6 present the coefficient estimates of the impact of rainfall deviations on children health measures. Panel A of each chart focuses on weight-related outcomes while Panel B centres on height-related health outcomes. The results from Chart 1 for boys show that estimates of rainfall deviation are important for WAZ and HAZ, which are the priority children's health outcomes in this paper. Also, indicators for underweight, moderate and severe stunting particularly show the effects for in-utero and first year exposure to rainfall deviation for boys. Similarly, Chart 2 presents rainfall deviation measures that have a significant impact on girls' growth trajectories in WAZ and HAZ. Deviation estimates by time reference for girls are marginally stronger relative to boys for the same outcome variables.[14] While only in-utero shock affects the underweight dummy, all shock references impact the moderate and severe stunting indicators for the girls. In summary, the above results do not reveal any substantial difference in the response of growth trajectories for boys and girls. This is an indication that health measures between boys and girls do not differentially respond to early life nutritional shocks in our sample.

6.1.5 Other Explanations for the Impact of Rainfall Deviation on Child Health

In addition to potential pathways for the impact of rainfall shocks on health, there could be transmission of health directly from the environmental factors potentially through mothers to foetuses during pregnancy. This perspective negates widely acclaimed nutritional basis for WAZ and HAZ measures. We test if children's health may be directly linked to disease

[13] While the shock estimates slightly reduces for the new focus sample of observations, a pairwise Wald test of the equivalence of coefficient estimates shows that corresponding rainfall shock estimates are not significantly different across sample estimations.

[14] A Wald test of equality of estimates indicates no significant difference exists among boys and girls.

environment of early life rainfall deviation rather than harvest from the weather patterns. To investigate this pathway, we use a non-season rainfall variation as measures of rainfall deviations for a non-nutritional explanation of rainfall effects on WAZ and HAZ. This approach closely follows Rocha and Soares (2015) in constructing shocks for a newer perspective and to investigate other mechanisms of early life rainfall impact beyond nutrition. Panels A and B of Table 7 present coefficient estimates of environmental-oriented rainfall deviations for WAZ and HAZ respectively. We observe that the adoption of non-seasonal rainfall deviation reveals smaller point estimates when compared to coefficient estimates reported for corresponding outcome variables in Tables 2 and 3. However, the significance of associated pre in-utero rainfall deviation coefficient estimates in columns (2) and (4) of Table 7 signal some environmental-driven shock impacts for growth trajectories of rural children in Malawi.

6.2 Health and Labour Market Outcomes

6.2.1. Chronic ailments, health expenditure and rate of hospitalisation

In this section, we focus on the impact of early life rainfall shocks on basic health outcomes of individuals in rural Malawi. The variables of interest in this regard consist of chronic health outcomes and individual level health expenditures. We explore the rich health data in the household survey to create an indicator variable for chronic ailment[15] for individual respondents in our sample, and we use recent four-week health expenditure in various dimensions[16] for the typical health expenditure of individuals in our sample. We also explore the previous year's individual level hospitalisation indicator as an important health outcome to investigate the impact of exposure to early life extreme shock events on the average rate of hospitalisation for concerned groups. Since health outcomes above are demand driven, we include community-level, supply-side health facilities as controls in our estimation to account for differences in availability and access to health facilities across communities.

The results for recent health expenditure and chronic disease are reported in Table A4 in the appendix. We did not find any unique pattern for the impact of early life extreme rainfall shocks on health expenditure patterns or on the average number of people currently suffering from a chronic ailment due to exposure to early life extreme weather events. On the other hand, we found an impact of in-utero rainfall deviation on the average hospitalisation rate of exposed individuals (Table 8). Our result shows that this effect is specific to early life drought shock, while the wet shock component did not have any effect. Table 8 Columns (1) to (3) present the coefficient estimates of the two extreme rainfall shock components of all individuals. We focus our attention on the preferred model in column (3), which includes temperature shock, community of birth, season and year-of-birth fixed effects, and community linear trends, similarly to the approach used for broader health outcomes in the literature (Adhvaryu *et al.* 2014). Lastly, we include individual, household and community level controls. The coefficient estimate for in-utero drought shock shows an average increase of a 0.8 percentage points hospitalisation rate for individuals exposed to drought shock. The estimate is significant at the 5 percent level. The in-utero wet shock estimate is a 0.01 percentage points increase in the hospitalisation rate, with no significance at any level. The coefficient estimates for drought and wet shocks for first and second year are equally weak and insignificant at the traditional levels. The impact of the incidence of drought shock on the hospitalisation rate is measured at 23.5 percent.

We separate the impact of extreme early life shocks on hospitalisation rates by gender difference. Columns (1) to (2) of Table 9 present the coefficient estimates of the extreme rainfall shock events on the hospitalisation rates for male and female samples respectively.

[15] We focus on the potential chronic health conditions that may be related to early life shocks in our sample where 1 represents individual affected by a chronic health disease; 0, otherwise.

[16] The health expenditures are reported in *Tanzanian Shillings* for the recent four weeks. The components of the health spending from the questionnaire include medical, prescription and non-prescription health expenditures in the recent four weeks. The natural logarithm of the health expenditure is used in the regression in line with the common practice in the literature.

Each regression refers to the preferred model in Column (3) of Table 8. In column (1), both in-utero drought and wet shock estimates are weak and insignificant for male respondents whilst the in-utero drought shock estimate is stronger and significant at 1 percent compared to the in-utero wet shock for the female observations in column (2). The in-utero drought shock estimate for females is 0.014. Given the mean hospitalisation rate for females, this coefficient estimate corresponds to a 35 percent impact for the in-utero period drought shock on the hospitalisation rate for females. This heterogeneous result establishes the predominance of the impact of in-utero drought shock on hospitalisation among females.

We investigated the role of intervention programmes on the impact of early life shocks on the rate of hospitalisation. We focused on food intervention programmes or supplementary feeding arrangements for malnourished individuals in the MHS data using the last two waves of the survey with identical social safety net questions. These included questions on free food and supplementary feeding intervention programmes for households. Of the 40,394 observations reported in Table 8, the last two waves comprise 16,026, for which household level social safety net and intervention programme questions are the same and match the hospitalisation context in our data.[17] We formally tested the role of supplementary feeding programmes in an econometric framework using the modified version of equation (6), where drought shock for each reference time was interacted with an indicator of household supplementary feeding in the past twelve months.[18] While the drought shock parameters convey the established impact of adverse early life shocks on the rate of hospitalisation, the interaction term depicts the role of the feeding programme in that regard. The results presented in Table 12 suggest a gender-specific asymmetric effectiveness of food intervention on the impact of early life droughts. Column (1) reveals that the incidence of in-utero drought shock increases the likelihood of hospitalisation by 1.3 percentage points while the interaction term presents a counteractive effect of a reduction in the hospitalisation rate by 2.1 percentage points. This result indicates that households' access to food intervention mediates the impact of in-utero drought shock reported earlier in Table 8. We observe that this pattern holds for the male observations for whom an increased hospitalisation rate for individuals exposed to in-utero drought shock is counteracted by more than a compensatory reduction in the hospitalisation rate for individuals who have access to food intervention (Column 2). On the other hand, while the in-utero drought shock estimate remains roughly the same for female observations, the interaction term is weak and insignificant at the conventional levels.

[17] The wording of the safety net section for the 2004-2005 wave refers to recent years of household access while the same question in the 2010-2011 and 2013 surveys refers to access in the previous 12 months which matches the hospitalisation question timeframe. Inconsistencies across these waves may lead to variable mismatch or reporting and measurement errors, which may bias the interactive term estimates in our model.

[18] $\text{General Welfare}_{ict} = \alpha_c + \gamma_t + \Gamma_a + \sum_{p=k-1}^{k+1} D_p \text{ Drought Shock}_{c,k} + \sum_{p=k-1}^{k+1} I_p \text{ Drought Shock}_{c,k} * \text{Feeding Program}_h + X_i' \theta_x + Z_{ct}' \theta_z + \varepsilon_{ict}$ (7)

6.2.2 Labour outcomes: Hours of productivity

Next we report the coefficient estimates of various productivity hours from our regression in columns (1) – (5) of Table 10[19]. Table 10 Column (1) presents the shock estimates for hours spent in agricultural labour in the past seven days. The result shows an estimate of -0.417 for in-utero drought shock (significant at 5 percent). Although the in-utero wet shock coefficient of -0.202 is large, it is not significant at the traditional levels. On the other hand, the coefficient estimates for first and second years indicate weak impacts of shocks linked to those time references on agricultural productivity. Similarly, column (2) reports an in-utero drought shock estimate of -0.238 for informal business while all other shock estimates including in-utero wet shock are insignificant. The impacts of in-utero drought shock on agricultural and informal business productivity levels given the respective baseline mean are a 5.25 percent and 22 percent decrease. The results for the impact of shocks on other labour market engagements – reported in columns (3) to (5) – do not show a significant effect.

In Table 11, we split the sample observations by gender of respondents for agricultural and informal business engagements. We restrict our analysis to these two outcomes due to the established impact of in-utero drought shock on them. Columns (2) and (4) reveal stronger and significant in-utero drought shock coefficient estimates[20] in the productivity hours of female within the agricultural and informal business sectors respectively, similar to findings in the overall sample, while estimates for males are generally weak and insignificant. The impacts of the in-utero drought shock on agricultural and informal business engagements are 9 percent and 38 percent relative to the baseline mean for females. This heterogeneous pattern is generally consistent with previous results on hospitalisation rates in Table 9.

7. Discussion and Conclusion

This paper re-examines the dynamics of early life weather shocks on the anthropometric health measures of children and later life welfare outcomes of rural households in Malawi. The study contributes to the literature in four major ways. First, the paper emphasises disaggregated extreme weather events with respect to drought and wet shocks. This exercise directly extends the context of numerous linear rainfall deviation models used in the existing literature for both the short-term and long-term impacts of weather patterns (Maccini and Yang 2009; Rabassa *et al.* 2014; Thai and Falaris 2014). Second, the paper contributes to the literature with estimates on welfare outcomes, such as productivity and hospitalisation rates, which have been previously ignored due to the lack of adequate data to capture these in the literature. Third, the paper provides evidence for both the short-term and medium-term impact of extreme early life

[19] We use the number of hours spent on each economic activity as a more accurate measure of productivity at the individual level. We use the hours of economic engagement from both the formal and informal sectors, which include agricultural, informal business, household chores, paid formal labour and unpaid apprenticeship programmes (as expected, more individuals partake in the agricultural sector and informal business activities while an insignificant fraction of the sample takes part in formal jobs and unpaid apprenticeship programs). The sample size of observations that fall within each category are 30,585; 30,585; 30,590; 30,589 and 13,172 respectively (observations investigated are restricted to individuals above five years of age who report hours worked on specific economic activity in the previous seven days).

[20] For the agricultural sector, our estimates also reveal that in-utero wet shock has a deleterious effect on the productivity of females of a similar magnitude as drought shock – significant at the 5 percent level.

weather events in a developing country setting. Lastly, the paper provides a gender specific differential impact of early life shocks on later life welfare.

Using repeated cross-section data from the World Bank household surveys in Malawi, we find that early life rainfall deviation and extreme shock events affect age standardised weight and height scores of children aged six to 59 months. Coefficient estimates from our disaggregated extreme shock model reveal that the effect of extreme early life shock events is prominent for drought shocks. The results from the linear rainfall deviation specification regarding children's standardised growth status reported in Tables 2 and 3 show that negative (positive) rainfall shock decreases (increases) standardised weight and height scores of children. Specifically, estimates show that a 0.1 log-point adverse (positive) rainfall shock at the in-utero, first and second years of life decreases (increases) the age standardised weight scores of children by 18 percent, 12 percent and 17 percent respectively. Corresponding effects of the shocks on age standardised height scores are 15 percent, 11 percent and 10 percent. This finding is consistent with results from prominent papers in related literature. While the interpretation of the linear shock framework is unambiguous, this study focuses more on disaggregated extreme weather shock patterns. The disaggregated extreme shock model reveals that drought shock leads to a resultant average decrease of 15%, 17% and 43% in WAZ for shocks experienced at the in-utero stage, in the first and second years respectively. Also, the impacts of an incident of drought shock on HAZ are 14%, 15% and 27% respectively. While the impacts of drought shock strengthen progressively from in-utero to the second-year period and remain significant, the impact of wet shock deteriorates and becomes insignificant. Our findings on disaggregated shocks impacts are robust for alternative shock specifications, such as standard deviation movements below and above the historical rainfall norm.

We look at the long-term outcomes for all individuals given that we have access to information on the place of birth of individuals in the MHS data. The results from long-term outcomes show an impact of drought shocks on welfare indicators as measured by the hospitalisation rate and hours of work in the informal economic sector. Our findings in this regard show that in-utero drought shock increases the hospitalisation rate and reduces the productivity level of females while no effect is found for males. Also, there is no evidence of an impact of the incidence of drought or wet shocks on the hospitalisation rate and productivity level for the first and second years of birth respectively. The gender-specific heterogeneous findings align with the long-term impact of shocks at the time of birth on adult socioeconomic outcomes as revealed in Maccini and Yang (2009). Also, our generalised results are consistent with the findings by Adhvaryu *et al.* (2014) and Majid (2015), which investigate the adulthood impact of early life shocks in other developing settings. We investigate the role of food intervention programmes on the adverse effects of drought shock on the hospitalisation rate. Our result in this regard reveals that access to nutrition intervention programmes mediates the persistent impact of in-utero drought shock on the hospitalisation rate. While our result documents the cushioning effect for the male observations, we did not find the food intervention programme to be useful in mediating the adverse effect of early life drought shock for females.

Our results for children's anthropometric health measures do not reveal any gender-specific heterogeneous response of children growth progression to early life rainfall. This short-term health results corroborate the findings in Rabassa *et al.* (2014) for Nigeria. Although multiple agricultural cultivation references for rainfall shocks in their paper do not correspond to periods of birth shocks, our findings complement this literature by specifically linking the effects of rainfall shock to the incidence of drought shock in the early life period as a way of formulating a vibrant policy to cushion nutrition shocks at the early stage of life, which is an important component of child growth. The persistent widening of gender specific in-utero drought shock estimates for other welfare outcomes in the absence of differential short-run evidence should not be mixed as the sample of observations are from entirely different cohorts.

Lastly, this paper contributes to the small but growing evidence on the vulnerability of rural households to exogenous weather patterns and how this imposes short-term and long-term future costs on welfare of individuals. While momentary effects persist due to a lack of consumption smoothing outside the agricultural sector in these areas, indirect long-term effects of exposure to early life shocks seem to be similarly prevalent. As revealed in our results, drought shock may be relatively more impactful on welfare outcomes than wet shock since irrigation systems used to mitigate the impact of drought can be quite expensive to manage and technical to handle, while excess rainfall can be easily channelled in such a manner that will not adversely affect agricultural produce in rural areas. Given that the most important potential pathway of our effect is nutrition at the early life period, more attention is required to address the malnutrition of pregnant mothers and babies in the Sub-Saharan African countries during extreme weather conditions – especially drought. In this context, our paper further strengthens the stance of the economics literature in alignment with the established biomedical background of the welfare effect of in-utero nutritional deficits (Wu *et al.* 2004; Zhu *et al.* 2006; Abu-Saad and Fraser 2010). Actions in this direction will help stabilise women during pregnancy periods and reduce the high rate of maternal mortality cases, as revealed by Comfort (2016). Similarly, this step will be helpful for protecting childhood and adulthood welfare outcomes of foetuses and new-borns.

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Figures and Tables

Figure 1: Weight-for-age Z Scores Distribution for Children in Malawi.

Figure 2: Height-for-age Z Scores Distribution for Children in Malawi.

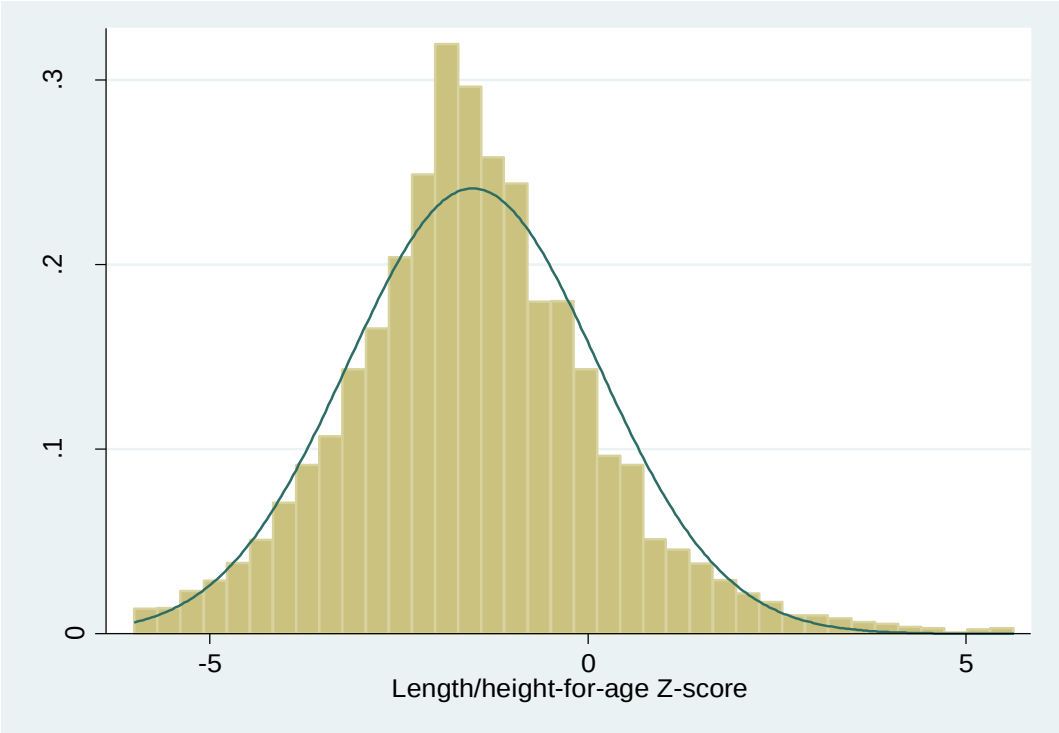

Table 1: Summary Statistics for Children Aged 6 to 59 Months and Household Covariates.

Variables	Mean	Std. Dev.	Obs.
Section A: WAZ and HAZ			
Total Sample			
WAZ	-0.607	1.109	6,422
HAZ	-1.594	1.623	6,695
Boys			
WAZ	-0.666	1.120	3,159
HAZ	-1.680	1.644	3,300
Girls			
WAZ	-0.549	1.095	3,263
HAZ	-1.510	1.600	3,395
6 – 11 months			
WAZ	-0.136	1.297	742
HAZ	-0.536	1.865	784
12 – 24 months			
WAZ	-0.538	1.186	1,419
HAZ	-1.494	1.721	1,493
25 – 36 months			
WAZ	-0.628	1.096	1,330
HAZ	-1.884	1.554	1,391
37 – 48 months			
WAZ	-0.680	0.990	1,589
HAZ	-1.812	1.401	1,646
49 – 59 months			
WAZ	-0.831	0.965	1,342
HAZ	-1.750	1.425	1,381
Section B: Ind and HH characteristics			
Age (in years)	2.195	1.315	
Female (dummy)	0.507	0.500	
Total value of household assets ('000 Malawi Kwacha)	17.847	377.304	
Household Size	5.889	2.333	
Number of children	2.042	1.727	
Average household age	16.568	4.679	
Age of the head of household	37.494	12.363	
Male head of household (dummy)	0.839	0.367	
Head of household educated (dummy)	0.220	0.414	

Notes: Table 1 above reports the summary statistics of WAZ and HAZ in Section A; and individuals and household characteristics in Section B. Observations are restricted to those living in rural areas of Malawi. Total value of household assets in Panel B is measured in thousands of Malawian Kwacha.

Table 2: The Impact of Early Life Rainfall Deviation on Weight-for-Age Z-Scores of Children In Malawi.

	Dependent Variable : WAZ				
Variables	(1)	(2)	(3)	(4)	(5)
In-utero deviation	0.979***	0.973***	0.992***	0.979***	1.068***
	(0.143)	(0.142)	(0.142)	(0.142)	(0.142)
First year deviation	0.692***	0.685***	0.693***	0.688***	0.695***
	(0.124)	(0.125)	(0.125)	(0.125)	(0.124)
Second year deviation	0.876***	0.873***	0.904***	0.882***	1.018***
	(0.139)	(0.137)	(0.137)	(0.136)	(0.142)
Temperature deviation	Yes	Yes	Yes	Yes	Yes
Community FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	-
Month of birth FE	Yes	Yes	Yes	Yes	Yes
Controls (Ind, HH and Comm)	No	Yes	Yes	Yes	Yes
Interview month X Year FE	No	No	Yes	No	-
Interview season X Year FE	No	No	No	Yes	Yes
Cohort FE	No	No	No	No	Yes
Observations	6,422	6,422	6,422	6,422	6,422
R-squared	0.232	0.244	0.252	0.244	0.257

Notes: Table 2 above presents coefficient estimates for the impact of early life 1,000 days agricultural season's rainfall deviation on WAZ for 6,422 observations of children aged 6 to 59 months. All estimations focus on observations resident in rural areas in line with the literature on the impact of weather shocks on welfare outcomes in developing countries. Rainfall deviation for each period is constructed as the deviation of the natural log of the community level rainfall from the corresponding 30-year historical average. Yearly precipitation measures refer to the agricultural season's rainfall for a locality, measured as the total precipitation for wet and dry seasons, corresponding to November-April and May-October respectively. All estimations include are clustered at the community level, with a total of 590 communities comprising the focus sample. Community level controls include indicator variables for access to roads, measured by year-round road usability, and quality of road infrastructure, measured by ease of road passage, the presence of a daily market within the community, the presence of a weekly market within the community, the presence of a phone call centre within the community, the presence of chemist within the community, the presence of a government-run health clinic within the community, the availability of a medical practitioner in the government medical centre, sales of subsidised bed nets within the community, the presence of a bank within the community, a representative at the parliament from the community, and school quality. Other community level controls include average number of months roads are usable for buses and lorries in a year, number of teachers in government primary schools, number of teachers in government secondary schools, numbers of pupils in government primary schools, number of pupils in government secondary schools, number of private primary schools, number of private secondary schools, distance to community health clinic, community industry, and the number of churches and mosques. Household controls include household non-agricultural assets in Malawi Kwacha and household demographic characteristics, such as household size, gender of the head of household, average household age, and the education and occupational categories of the head of household. Individual controls mainly consist of individual demographic characteristics, namely child's age and gender. Robust standard errors (clustered at the community level) are reported in parentheses. ***,**,* represent significance at the 1 percent, 5 percent and 10 percent levels respectively.

Table 3: The Impact of Early Life Rainfall Deviation on Height-for-Age Z-Scores for Children In Malawi.

	Dependent Variable : HAZ				
Variables	(1)	(2)	(3)	(4)	(5)
In-utero deviation	2.244***	2.281***	2.303***	2.282***	2.357***
	(0.213)	(0.214)	(0.213)	(0.214)	(0.216)
First year deviation	1.768***	1.764***	1.775***	1.764***	1.762***
	(0.176)	(0.175)	(0.175)	(0.175)	(0.172)
Second year deviation	1.497***	1.508***	1.540***	1.511***	1.601***
	(0.208)	(0.207)	(0.208)	(0.207)	(0.212)
Temperature shock	Yes	Yes	Yes	Yes	Yes
Community FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	-
Month of birth FE	Yes	Yes	Yes	Yes	Yes
Controls (Ind, HH and Comm)	No	Yes	Yes	Yes	Yes
Interview month X Year FE	No	No	Yes	No	-
Interview season X Year FE	No	No	No	Yes	Yes
Cohort FE	No	No	No	No	Yes
Observations	6,695	6,695	6,695	6,695	6,695
R-squared	0.299	0.309	0.317	0.309	0.318

Notes: Table 3 above presents coefficient estimates for the impact of early life 1,000 days agricultural season's rainfall deviation on HAZ for 6,695 observations of children aged 6 to 59 months. See Table 2 above for more notes and a list of additional controls. Robust standard errors (clustered at the community level) are reported in parentheses.
*** indicates significance at 1 percent level
** indicates significance at 5 percent level
* indicates significance at 10 percent level

Table 4: The Impact of Early Life Rainfall Deviation on Children Underweight and Stunting Indicators In Malawi.

	Dependent Variables :		
	Underweight	Moderate Stunting	Severe Stunting
Variables	(1)	(2)	(3)
In-utero deviation	-0.119***	-0.337***	-0.192***
	(0.034)	(0.060)	(0.047)
First year deviation	-0.078**	-0.235***	-0.177***
	(0.030)	(0.049)	(0.041)
Second year deviation	-0.041	-0.031	-0.104**
	(0.034)	(0.055)	(0.045)
Temperature shock	Yes	Yes	Yes
Community FE	Yes	Yes	Yes
Month of birth FE	Yes	Yes	Yes
Controls (Ind, HH and Comm)	Yes	Yes	Yes
Interview season X Year FE	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes
Observations	6,422	6,695	6,695
R-squared	0.256	0.202	0.174

Notes: Table 4 above presents coefficient estimates for the impact of early life 1,000 days agricultural season's rainfall deviation on stunting and underweight indicators for 6,695 and 6,422 observations of children aged 6 to 59 months. Moderate stunting and severe stunting indicators are the ratio of children with HAZ below -2 and -3 standard deviations respectively while underweight indicator measures the ratio of children below -2 standard deviation WAZ. Baseline mean of underweight, moderate stunted and severe stunted children is 0.090, 0.391 and 0.174 respectively. Each column is a separate regression of the preferred model of Tables 2 and 3 presented above. Linear Probability Model is used in the estimation process for each column. See Table 2 above for more notes and a list of additional controls. Robust standard errors (clustered at the community level) are reported in parentheses.

*** indicates significance at 1 percent level

** indicates significance at 5 percent level

* indicates significance at 10 percent level

Table 5: Impacts of Disaggregated Early Life Extreme Rainfall Shocks on WAZ and HAZ In Malawi.

	Dependent Variables :	
	WAZ	HAZ
Variables	(1)	(2)
In-utero drought shock	-0.089*	-0.223***
	(0.053)	(0.069)
In-utero flood shock	0.194***	0.416***
	(0.046)	(0.064)
First year drought shock	-0.105**	-0.247***
	(0.052)	(0.079)
First year flood shock	0.045	0.203***
	(0.047)	(0.064)
Second year drought shock	-0.263***	-0.435***
	(0.053)	(0.077)
Second year flood shock	0.034	-0.040
	(0.049)	(0.068)
Temperature shock	Yes	Yes
Community FE	Yes	Yes
Month of birth FE	Yes	Yes
Controls (Individual, Household and Community)	Yes	Yes
Interview season X Year FE	Yes	Yes
Cohort FE	Yes	Yes
Observations	6,422	6,695
R-squared	0.255	0.313

Notes: Table 5 above presents coefficient estimates for the impact of early life 1,000 days agricultural season's extreme rainfall shocks on WAZ and HAZ for 6,695 and 6,422 observations of children aged 6 to 59 months. Each column is a separate regression of the preferred model of Tables 2 and 3 presented above. Drought shock is an indicator variable measured as 1 for locality rainfall measures below 25th percentile of 30-year historical rainfall distribution; and 0 otherwise. Analogously, flood shock is an indicator variable measured as 1 for locality rainfall measures above 75th percentile of 30-year historical rainfall distribution; and 0 otherwise See Table 2 above for detailed notes and a list of additional controls. Robust standard errors (clustered at the community level) are reported in parentheses.

*** indicates significance at 1 percent level

** indicates significance at 5 percent level

* indicates significance at 10 percent level

Table 6: The Impact of Early Life Rainfall Deviation on Children Health Trajectories In Malawi by Gender.

	Panel A:		Panel B:		
	WAZ	Underweight	HAZ	Moderate Stunting	Severe Stunting
Variables	(1)	(2)	(3)	(4)	(5)
Chart 1: Boys					
In-utero deviation	0.917***	-0.115*	2.321***	-0.392***	-0.230***
	(0.218)	(0.062)	(0.322)	(0.090)	(0.075)
First year deviation	0.553***	-0.086	1.672***	-0.209***	-0.197***
	(0.198)	(0.055)	(0.274)	(0.081)	(0.066)
Second year deviation	0.843***	-0.034	1.428***	0.048	-0.105
	(0.215)	(0.053)	(0.314)	(0.089)	(0.068)
R-squared	0.336	0.284	0.384	0.330	0.303
Observations	3,159	3,159	3,300	3,300	3,300
Chart 2: Girls					
In-utero deviation	1.388***	-0.134***	2.616***	-0.337***	-0.171***
	(0.208)	(0.047)	(0.319)	(0.088)	(0.066)
First year deviation	0.871***	-0.057	1.931***	-0.291***	-0.185***
	(0.180)	(0.044)	(0.245)	(0.076)	(0.060)
Second year deviation	1.325***	-0.047	1.922***	-0.144*	-0.131*
	(0.218)	(0.052)	(0.299)	(0.086)	(0.069)
R-squared	0.343	0.249	0.384	0.335	0.284
Observations	3,263	3,263	3,395	3,395	3,395

Notes: Table 6 above presents coefficient estimates for the impact of early life 1,000 days agricultural season's rainfall deviation on health trajectories of children between 6 to 59 months by gender. Charts A and B respectively presents results for boys and girls. Each column is a separate regression of the preferred model of Tables 2 and 3 presented above including temperature shock and controls. The regressions also include community fixed effect, year fixed effect, month of birth fixed effect, interview month by year fixed effect, interview season by year fixed effect and cohort fixed effect respectively. See Tables 2 and 4 above for a list of controls and more notes. Robust standard errors (clustered at the community level) are reported in parentheses.

*** indicates significance at 1 percent level

** indicates significance at 5 percent level

* indicates significance at 10 percent level

Table 7: The Impact of Direct Rainfall Deviation Measures on WAZ and HAZ

	Panel A:		Panel B:	
	WAZ		HAZ	
Variables	(1)	(2)	(3)	(4)
Rainfall deviation measures				
12 – 24 months before birth		0.359**		0.491**
		(0.145)		(0.206)
0 – 12 months before birth	0.244**	0.418***	0.066	0.241
	(0.105)	(0.142)	(0.153)	(0.209)
1 – 12 months after birth		0.138		-0.352
		(0.147)		(0.216)
Constant	71.832	179.544*	42.974	68.025
	(110.205)	(104.411)	(153.897)	(160.603)
R-squared	0.247	0.261	0.295	0.309

Notes: Table 7 above presents estimates of rainfall deviation with reference to the exact month of birth of children. This is different from the use of agricultural cycle for deviation computations. Deviations are constructed as log-deviation from norm exactly as constructed in Rocha and Soares (2015). Each column is a separate regression of the preferred model of Tables 2 and 3 presented above including temperature deviation and controls. The regressions also include community fixed effect, month of birth fixed effect, interview season by year fixed effect and cohort fixed effect respectively. See Table 2 for a list of controls and more notes. Robust standard errors (clustered at the community level) are reported in parentheses.

*** indicates significance at 1 percent level

** indicates significance at 5 percent level

* indicates significance at 10 percent level

Table 8: Impacts of Disaggregated Early Life Extreme Rainfall Shocks on Rate of Hospitalisation In Malawi.

	Dependent variable: Hospitalisation indicator		
Variables	(1)	(2)	(3)
In-utero drought shock	0.009**	0.009**	0.008**
	(0.003)	(0.003)	(0.003)
In-utero flood shock	0.001	0.001	0.001
	(0.003)	(0.003)	(0.003)
First year drought shock	0.004	0.004	0.004
	(0.004)	(0.004)	(0.004)
First year flood shock	-0.000	-0.000	-0.000
	(0.003)	(0.003)	(0.003)
Second year drought shock	0.005	0.005	0.004
	(0.003)	(0.003)	(0.003)
Second year flood shock	0.001	0.001	0.001
	(0.003)	(0.003)	(0.003)
R-squared	0.039	0.039	0.043
Observations	40,394	40,394	40,394
Temperature deviation	Yes	Yes	Yes
Community of birth fixed effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
Year of Birth Fixed Effect	Yes	Yes	Yes
Community of Birth Linear Trend	No	No	Yes
Controls	No	No	Yes

Notes: Table 8 above presents linear probability model coefficient estimates of the impact of early life extreme rainfall shocks on hospitalisation rate of individuals. See notes in Tables 2 and 5 above for a list of all controls and additional information on the construction of disaggregated extreme rainfall shocks. Robust standard errors (clustered at the community level) are reported in parentheses.
*** indicates significance at 1 percent level
** indicates significance at 5 percent level
* indicates significance at 10 percent level

Table 9: Impacts of Disaggregated Early Life Extreme Rainfall Shocks on Rate of Hospitalisation In Malawi by Gender.

	Dependent variable: Hospitalisation indicator	
	Males	Females
Variables	(1)	(2)
In-utero drought shock	0.003	0.014***
	(0.004)	(0.005)
In-utero flood shock	0.003	0.001
	(0.004)	(0.005)
First year drought shock	0.002	0.007
	(0.004)	(0.005)
First year flood shock	-0.001	0.000
	(0.004)	(0.004)
Second year drought shock	0.002	0.007
	(0.004)	(0.005)
Second year flood shock	0.006	-0.003
	(0.004)	(0.005)
R-squared	0.064	0.065
Observations	20,113	20,281

Notes: Table 9 above presents linear probability model coefficient estimates of the impact of early life extreme rainfall shocks on hospitalisation indicator of individuals. Each column is a separate regression of the preferred model in Table 8 column 3 above. Each regression includes locality of birth fixed effect, year of interview fixed effect, year of birth fixed effect, village of birth linear trend, village and household covariates; and temperature deviation. See notes in Tables 2 and 5 above for a list of all controls and additional information on the construction of disaggregated extreme rainfall shocks. Robust standard errors (clustered at the community level) are reported in parentheses.

*** indicates significance at 1 percent level

** indicates significance at 5 percent level

* indicates significance at 10 percent level

Table 10: Impacts of Disaggregated Early Life Extreme Rainfall Shocks on Productivity in Malawi.

	Dependent Variables (hours per week):				
	Agriculture	Informal business	HH chores	Formal jobs	Apprentice
VARIABLES	(1)	(2)	(3)	(4)	(5)
In-utero drought shock	-0.417**	-0.238**	0.028	-0.130	0.017
	(0.203)	(0.115)	(0.037)	(0.128)	(0.039)
In-utero flood shock	-0.202	0.102	0.013	-0.015	-0.036
	(0.211)	(0.124)	(0.034)	(0.121)	(0.033)
First year drought shock	-0.047	-0.060	-0.036	0.000	0.036
	(0.186)	(0.120)	(0.032)	(0.129)	(0.043)
First year flood shock	-0.092	-0.167	0.047	-0.007	-0.017
	(0.205)	(0.110)	(0.045)	(0.122)	(0.013)
Second year drought shock	-0.012	0.105	0.016	-0.151	0.014
	(0.199)	(0.118)	(0.027)	(0.128)	(0.034)
Second year flood shock	0.071	-0.083	0.032	-0.055	0.021
	(0.199)	(0.120)	(0.052)	(0.119)	(0.038)
R-squared	0.447	0.100	0.095	0.071	0.030
Observations	30,585	30,585	30,590	30,589	13,172

Notes: Table 10 above presents coefficient estimates of the impact of early life extreme rainfall shocks on weekly productivity hours of individuals aged 5 years and above for diverse labour outcomes. Each column is a separate regression of the preferred model in Table 8 Column (3) above. Each regression includes locality of birth fixed effect, year of interview fixed effect, year of birth fixed effect, village of birth linear trend, village and household covariates; and temperature deviation. See notes in Tables 2 and 5 above for a list of all controls and additional information on the construction of disaggregated extreme rainfall shocks. Robust standard errors (clustered at the community level) are reported in parentheses.

*** indicates significance at 1 percent level

** indicates significance at 5 percent level

* indicates significance at 10 percent level

Table 11: Impacts of Disaggregated Early Life Extreme Rainfall Shocks on Productivity in Malawi by Gender.

	Dependent Variables (in hours per week):			
	Agriculture		Informal business	
	Males	Females	Males	Females
Variables	(1)	(2)	(3)	(4)
In-utero drought shock	-0.274	-0.684***	-0.175	-0.317**
	(0.275)	(0.261)	(0.179)	(0.143)
In-utero flood shock	0.211	-0.657**	0.123	-0.076
	(0.290)	(0.281)	(0.198)	(0.139)
First year drought shock	0.036	-0.178	-0.044	-0.112
	(0.281)	(0.258)	(0.195)	(0.147)
First year flood shock	0.248	-0.385	-0.449**	0.050
	(0.285)	(0.278)	(0.188)	(0.130)
Second year drought shock	-0.062	0.114	0.227	-0.063
	(0.288)	(0.255)	(0.210)	(0.138)
Second year flood shock	0.257	-0.256	-0.016	-0.232*
	(0.303)	(0.260)	(0.196)	(0.126)
Observations	15,238	15,347	15,239	15,346
R-squared	0.466	0.465	0.139	0.123

Notes: Table 11 above presents coefficient estimates of the impact of early life extreme rainfall shocks on weekly productivity hours of individuals aged 5 years and above for agricultural and informal business engagements by gender. Each column is a separate regression of the preferred model in Table 8 Column (3) above. Each regression includes locality of birth fixed effect, year of interview fixed effect, year of birth fixed effect, village of birth linear trend, village and household covariates; and temperature deviation. See notes in Tables 2 and 5 above for a list of all controls and additional information on the construction of disaggregated extreme rainfall shocks. Robust standard errors (clustered at the community level) are reported in parentheses.

*** indicates significance at 1 percent level

** indicates significance at 5 percent level

* indicates significance at 10 percent level

Table 12: Nutrition Intervention and Gender Asymmetric Impact on Hospitalization Rate.

	Dependent variable: Hospitalisation indicator		
	Total sample	Male	Female
Variables	(1)	(2)	(3)
In-utero drought shock	0.013***	0.013**	0.013*
	(0.004)	(0.006)	(0.007)
In-utero drought shock X Food intervention	-0.021*	-0.027*	-0.017
	(0.012)	(0.014)	(0.019)
First year drought shock	-0.002	0.003	-0.006
	(0.005)	(0.006)	(0.008)
First year drought shock X Food intervention	0.008	-0.011	0.035
	(0.021)	(0.022)	(0.029)
Second year drought shock	0.002	-0.003	0.007
	(0.005)	(0.006)	(0.007)
Second year drought shock X Food intervention	0.007	0.044	-0.027
	(0.017)	(0.028)	(0.023)
Observations	16,026	7,935	8,091
R-squared	0.038	0.064	0.062

Notes: Table 12 above presents coefficient estimates of the impact early life drought shocks and interaction terms with access to food intervention program on hospitalisation rate. Columns (2) and (3) separate the sample observations by gender of respondents. Each column is a separate regression of the preferred model in Table 8 Column (3) above. Each regression includes locality of birth fixed effect, year of interview fixed effect, year of birth fixed effect, village of birth linear trend, village and household covariates; and temperature deviation. See notes in Tables 2 and 5 above for a list of all controls and additional information on the construction of drought shock. Robust standard errors (clustered at the community level) are reported in parentheses.

*** indicates significance at 1 percent level

** indicates significance at 5 percent level

* indicates significance at 10 percent level

Appendix

Table A1: Spatial Correlation between Rainfall and Children Growth

	Dependent Variable :	
	WAZ	HAZ
VARIABLES	(1)	(2)
Long-term rainfall variation		
In-utero shock	-0.006*	-0.020***
	(0.004)	(0.005)
First year shock	0.001	0.004
	(0.002)	(0.003)
Second year shock	-0.005	0.010
	(0.005)	(0.006)
Observations	6,422	6,695
R-squared	0.247	0.298

Notes: Table A1 above presents coefficient estimates of the regression of long term rainfall shocks around the period of birth on WAZ and HAZ. Long-term shocks are computed as the standard deviation of 30-year historical rainfall distribution at the community level from UDel precipitation data. Each column is a separate regression of the preferred model of Tables 2 and 3 presented above including temperature deviation and controls. The regressions also include community fixed effect, month of birth fixed effect, interview season by year fixed effect and cohort fixed effect respectively. See Table 2 for a list of controls and more notes. Robust standard errors (clustered at the community level) are reported in parentheses. ***, ** and * indicate significance at 1 percent, 5 percent and 10 percent levels respectively.

Table A2: The Impact of Early Life Rainfall Deviation on Children Health Trajectories In Malawi (6 – 35 months).

	Panel A:		Panel B:		
	WAZ	Under weight	HAZ	Moderate Stunting	Severe Stunting
Variables	(1)	(2)	(3)	(4)	(5)
In-utero deviation	0.832***	-0.063	2.630***	-0.440***	-0.213***
	(0.198)	(0.046)	(0.336)	(0.082)	(0.059)
First year deviation	0.406**	-0.083*	1.787***	-0.260***	-0.165***
	(0.191)	(0.048)	(0.267)	(0.074)	(0.059)
Second year deviation	0.604**	-0.006	1.670***	-0.086	-0.093
	(0.268)	(0.062)	(0.426)	(0.101)	(0.082)
Observations	3,491	3,491	3,668	3,668	3,668
R-squared	0.365	0.267	0.405	0.323	0.273

Notes: Table A2 above reports coefficient estimates for the impact of early life 1,000 days agricultural season's rainfall deviations on health trajectories of children between 6 to 35 months. Each column is a separate regression of the preferred specifications of Tables 2 and 3 presented above including temperature deviation and controls. The regressions also include community fixed effect, month of birth fixed effect, interview season by year fixed effect and cohort fixed effect respectively. See Tables 2 and 4 above for a list of controls and more notes. Robust standard errors (clustered at the community level) are reported in parentheses. ***, ** and * indicate significance at 1 percent, 5 percent and 10 percent levels respectively.

Table A3: Impacts of Disaggregated Early Life Extreme Rainfall Shocks on WAZ and HAZ In Malawi by Age Divisions.

	Panel A: 6 – 35 months		Panel B: 36 – 59 months	
	WAZ	HAZ	WAZ	HAZ
Variables	(1)	(2)	(3)	(4)
In-utero drought shock	-0.147**	-0.395***	-0.047	0.014
	(0.074)	(0.099)	(0.089)	(0.117)
In-utero flood shock	0.081	0.433***	0.082	0.129
	(0.093)	(0.123)	(0.101)	(0.146)
First year drought shock	-0.185**	-0.478***	0.142*	0.111
	(0.082)	(0.121)	(0.084)	(0.121)
First year flood shock	-0.090	0.134	0.023	0.109
	(0.085)	(0.115)	(0.122)	(0.162)
Second year drought shock	-0.348***	-0.843***	0.004	0.086
	(0.120)	(0.180)	(0.076)	(0.101)
Second year flood shock	-0.090	-0.144	0.170**	0.118
	(0.096)	(0.129)	(0.075)	(0.109)
Constant	-0.017	-3.486**	-0.083	-1.183**
	(0.830)	(1.433)	(0.392)	(0.569)
Observations	3,491	3,668	2,931	3,027
R-squared	0.367	0.406	0.322	0.399

Notes: Table A3 above reports coefficient estimates for the impact of early life 1,000 days rainfall shocks on WAZ and HAZ of children by age divisions. Panels A and B reports disaggregated shock estimates for WAZ and HAZ for children aged 6 to 35 months and children aged 36 – 59 months respectively. Each column is a separate regression of the preferred specifications of Tables 2 and 3 presented above including temperature deviation and controls. The regressions also include community fixed effect, month of birth fixed effect, interview season by year fixed effect and cohort fixed effect respectively. See Tables 2 and 4 above for a list of controls and more notes. Robust standard errors (clustered at the community level) are reported in parentheses. ***, ** and * indicate significance at 1 percent, 5 percent and 10 percent levels respectively.

Table A4: Impacts of Disaggregated Early Life Extreme Rainfall Shocks on Health Expenditures and Chronic Illness In Malawi.

	Dependent variables:			
	Illness expenditure	Prescription expenditure	Preventative expenditure	Chronic illness (dummy)
Variables	(1)	(2)	(3)	(4)
In-utero drought shock	0.023	-0.000	-0.001	0.002
	(0.018)	(0.007)	(0.026)	(0.004)
In-utero flood shock	0.022	-0.000	-0.005	0.000
	(0.017)	(0.005)	(0.024)	(0.004)
First year drought shock	0.005	-0.001	0.055**	0.001
	(0.016)	(0.005)	(0.023)	(0.004)
First year flood shock	-0.003	-0.003	0.001	-0.009**
	(0.017)	(0.006)	(0.023)	(0.004)
Second year drought shock	0.010	-0.007	0.043*	-0.004
	(0.015)	(0.007)	(0.025)	(0.004)
Second year flood shock	0.024	-0.006	0.001	-0.003
	(0.017)	(0.006)	(0.024)	(0.004)
Observations	40,376	40,389	40,253	40,385
R-squared	0.069	0.058	0.116	0.126

Notes: Table A4 above presents coefficient estimates of the impact of early life disaggregated extreme rainfall shocks on the natural logarithm of diverse categories of health expenditure from Column (1) – (3) and indicator variable of chronic illness of individuals in Column (4). Each column is a separate regression of the preferred model in Table 8 Column 3 above. Each regression includes locality of birth fixed effect, year of interview fixed effect, year of birth fixed effect, village of birth linear trend, village and household covariates; and temperature deviation. See notes in Tables 2 and 5 above for a list of all controls and additional information on the construction of disaggregated extreme rainfall shocks. Robust standard errors (clustered at the community level) are reported in parentheses. ***, ** and * indicate significance at 1 percent, 5 percent and 10 percent levels respectively.