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# Estimating the short-term effects and seasonal dynamics of Malawi's 2015/16 drought on household food insecurity and child malnutrition

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## Abstract

In 2015, Southern Africa experienced a drought that affected approximately 30 million people across seven countries. Using a nationally representative household panel survey dataset and a remotely sensed measure of drought intensity during the 2015/16 farming season, we rigorously estimate the short-term effects of the drought on food consumption and child malnutrition in Malawi. We capitalize on the coincidence of the drought with the roll-out of the 2016 survey wave to examine how its impacts on household dietary patterns, food insecurity coping mechanisms, and child nutritional outcomes evolved over the year as households depleted their food stocks. Our fixed effects models reveal significant adverse impacts on dietary quality and acute child malnutrition, particularly soon after the failed harvest. Affected households initially responded by lowering the quality of their diets, before adopting more severe coping mechanisms as the year progressed. Children exposed to the drought lost weight immediately following harvest. However, the dietary quality and nutritional outcomes of drought- and non-drought-exposed households converged later in the year. Despite initial weight loss, drought-exposed children had lower probabilities of wasting during the rainy season, likely because households restricted adult food consumption and prioritized children during this period of the year.

**Key words**: Drought, child nutrition, food consumption, Malawi, seasonality, short term effects

**JEL codes:** I38, O12, O15

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**Estimating the short-term effects and seasonal dynamics of Malawi's 2015/16 drought on household food insecurity and child malnutrition**

## 1. Introduction

Over the past two decades, the majority of developing countries have made progress in improving their human capital through, among other interventions, investments in nutrition, health and education programs (UNDP 2022; World Bank 2021). However, weather shocks, which are becoming increasingly frequent and unpredictable due to climate change (Masson-Delmotte et al., 2021; Helden et al., 2021) are threatening to reverse the human capital development gains by exposing individuals to conditions that undermine long-term health and longevity. The majority of rural households in low-income countries rely on primary agricultural production for food and incomes, have little off-farm income opportunities and operate in contexts characterized by missing or incomplete insurance and credit markets. As a result, weather shocks that occur during the main farming season have grave effects on welfare. Children are particularly affected, since shocks experienced in early childhood do not only affect them in the short term, but also tend to have lifelong consequences (Barker, 1994; Currie and Almond 2011). Generally, children who are exposed to negative shocks in early childhood are found to have poorer human development outcomes in adulthood compared to other children. The literature shows that these children are significantly shorter (Rosales-Rueda 2018; Dercon and Porter 2014; Akresh et al., 2011; Aguilar and Vicarelli 2011; Hoddinott and Kinsey 2001), attain lower educational levels (Maccini and Yang 2009; Alderman et al., 2006), have lower lifetime incomes (Rosales-Rueda 2018), and are more prone to diseases (Maccini and Yang 2009).

In recent years, the number of empirical studies analysing the impacts of climate change and extreme weather events on child malnutrition has been growing rapidly. Belesova et al., (2019) provide a review of the effects of drought exposure on child undernutrition, Agabiirwe et al., (2022) review studies on the impact of floods, and other review studies evaluate the effect of various weather shocks or climate variability on child nutrition (e.g. Lieber et al., 2022; Brown et al., 2020; Hellden et al., 2021; Headey and Venkat, 2024). Despite the large number of studies, the quality of the causal effect identification is not assured in all studies, and evidence on the immediate and short-term effects, the analysis of pathways, and the role of seasonality remains limited (Headey and Venkat, 2024).

Most studies in this literature evaluate the impact on child stunting using anthropometric measurements sooner or later after the weather shock. Measuring the effect on acute malnutrition, reflected in lower weight-for-height scores or increased wasting, requires frequent survey waves (e.g. Bloem et al., 2003; Freudenreich et al., 2022) or data that is collected during or soon after the event, which is typically not an easy time for survey roll-out.

Few studies provide an analysis of the pathways and timing of the effects of shocks on malnutrition outcomes, which are important to design effective and timely relief measures. Dietary pathways, in the form of households' food consumption choices in response to weather shocks, or adjustments in the intra-household allocation of food remain largely unstudied. Only very few studies assess effects on indicators like food groups consumed, dietary quality or food security responses (Headey and Venkat, 2024), but effects are usually observed only several months or years after the shocks, and not able to identity households' short-term responses.

Finally, the interaction of shocks with the seasonal nature of consumption and livelihoods has not received much attention. The importance of seasonality in food consumption, incomes and labour market participation in most tropical countries has been recognized since long (see Chambers and Maxwell, 1981; Readorn and Matlon, 1989) and gained renewed interest in recent years (Chirwa et al., 2013; Gilbert et al., 2017; Zanello et al., 2019; Dimitrova, 2021; De Janvry et al., 2022). Also, child growth and the relation between weight and hight gain has been shown to be seasonal, especially in poor, tropical settings (e.g. Brown et al., 1982). For Malawi, Maleta et al., (2003) find that weight gains were highest after main harvest and were lowest in the rainy season, when incidents of infectious diseases are most common and food security poor. The timing of shocks in relation to the typical household calendar, including their reliance on food stocks versus markets and the onset of the lean season, can thus be expected to significantly influence the impact of shocks on child nutrition.

With this paper, we aim to contribute to this literature by evaluating the effects of the El-Niño-induced drought that hit Malawi during the 2015/16 farming season on households' immediate food insecurity experiences and responses and acute child undernourishment as the effects of the drought and the seasons unfold. Using Malawi's Living Standard Measurement Surveys – Integrated Household Panel Survey (LSMS-IHPS)[3], of which the 2016 round coincided with the drought-affected harvest period and the months immediately after the harvest, we examine how the effects of the drought on food insecurity and child malnutrition vary as the year progresses from a failed harvest period through lean season to the next harvest. Using the variation in timing of interviews, we are able to identify how and when households activate

[3] Household data were collected under The World Bank's Living Standards Measurement Survey-Integrated Household Panel Survey (LSMS-IHPS).

various food consumption coping strategies in response to shocks and when acute effects on child malnutrition are observed.

Our econometric strategy exploits the exogenous geographical variation in the intensity of drought, measured as the deviation of climatic water balance from its long-run averages during the 2015/16 faming season. We use a Standardized Precipitation Evapotranspiration Index (SPEI) dataset by Peng et al., (2019) to measure the soil water balance. Peng's SPEI for Africa is a high-resolution satellite dataset with a spatial resolution of 5 km by 5 km and a monthly temporal resolution starting from January 1981 to December 2016. Combining these data with Malawi's LSMS-IHPS household survey panel allows us to identify locations that experienced agricultural drought conditions in our farming season of interest, thus enabling us to estimate how diets, food insecurity experience and child nutrition outcomes responded to intensifying drought conditions in these locations. We use panel fixed effects models with Conley (1999) standard errors to account for spatial correlation across observations.

Our analysis shows that the 2015/16 drought had significant negative effects on dietary quality, particularly during the dry season, corresponding to the months immediately following the failed harvest. Measuring dietary quality using the food consumption score (FCS), we estimate that a 1SD increase in relative dryness led to an average 8.5 percent decline in FCS compared to its mean value. The effect is larger during the dry season when FCS drops by about 12 percent relative to its mean. However, the drought effect on dietary quality disappears during the rainy season when all households face the lean season. We find similar overall result when we use household dietary diversity score (HDDS) as an alternative measure of dietary quality, although we do not see any seasonal differences in dietary composition due to the drought with this measure. Additional analyses reveal that the decline in dietary quality is due to drought-induced increase in consumption of cereals and decreases in consumption of fish, vegetables and fats and oils.

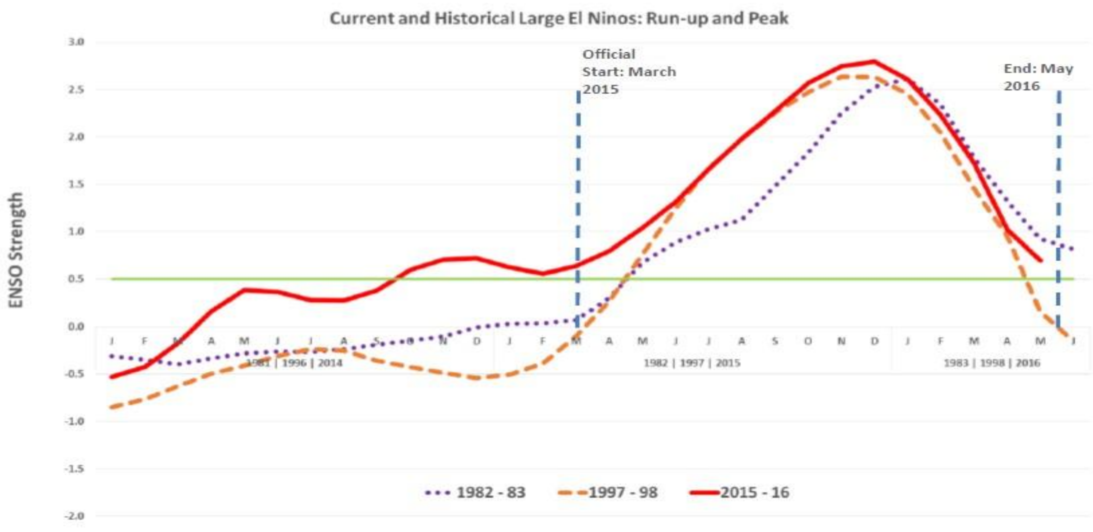
Furthermore, our analysis shows that the change in diet composition during the dry season was just a first response to the drought. We find evidence that as the year progressed and households exhausted food stocks, they resorted to more drastic coping mechanisms such as reallocating food consumption from adults to children. Additionally, we find evidence of significant increases in acute malnutrition in under-five children in the immediate aftermath of the drought. We estimate that, on average, a 1SD increase in relative dryness during the 2015/16 farming season resulted in a 0.34SD decline in child weight-for-height Z-scores (WHZ). Again, the effects are concentrated in the dry season when the drought led to a 0.36SD decline in WHZ scores. However, the drought impact is not statistically different from zero during the subsequent rainy season, when the usual lean period starts. Interestingly, our analysis shows a negative and significant relationship between the drought and probability of child wasting during the rainy season. We find that a 1SD increase in relative dryness resulted in an about 8 percent reduction in probability of a child being categorized as wasted. This effect is only significant during the rainy season, a period when adults restricted their food consumption and increased the number of meals that children took per day.

The rest of the paper develops as follows. Section 2 provides a brief background to the 2015/16 drought in Malawi. Section 3 outlines our conceptual framework in which we specify the hypotheses, followed by our methodology in section 4. We report our main results in section 5 while section 6 assesses the robustness of our results. We give concluding remarks in section 7.

## 2. The 2015/16 drought in Malawi

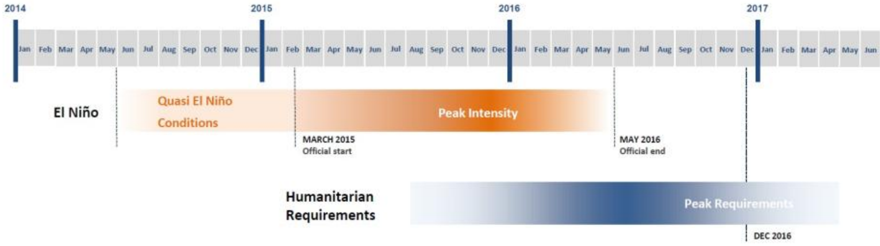
The Southern Africa region experienced the strongest El Niño event of the last 50 years (Figure 1). The El Niño caused intense drought in Botswana, Lesotho, Madagascar, Malawi, Mozambique, South Africa, Swaziland, Zambia and Zimbabwe, resulting in famine conditions in parts of these countries in 2016 and 2017 (FAO, 2020). According to FAO (2020), about 30 million people were rendered food insecure by the drought, with 23 million of them requiring immediate humanitarian assistance to avoid welfare losses. In conjunction with national and international organizations, the various countries mounted humanitarian assistance programs aimed at saving the situation, with the Southern Africa Development Community estimating that US$2.7 billion was needed to respond to the emergency.

**Figure 1. The 2015/16 El Niño event is the most intense Southern Africa has experienced in recorded history.**




Source: WFP (2016).

**Figure 2. Timing of the 2015/16 El Niño and intensity of humanitarian needs.**




Source: WFP (2016).

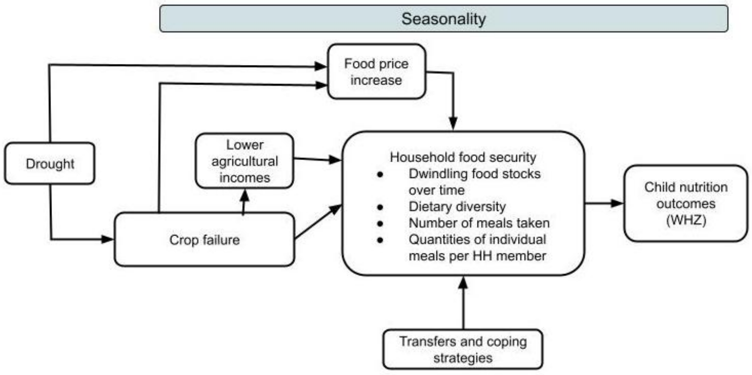
The 2016/17 famine was dire in Malawi as it followed low agricultural production during 2014/15 season due to late onset of rainfall, erratic rains in some parts of the country and floods in others. Consequently, in 2015, about 2.8 million people were already in need of humanitarian aid. The El Niño-induced drought worsened that already precarious situation, as the drought hit the country during the main farming months of November 2015 and March 2016, with the Southern and Central regions receiving 50 percent and 80 percent of normal rainfall, respectively (Babu et al., 2018). As illustrated in Figure 2, this resulted in widespread food insecurity in 2016 and early 2017 that saw about 40 percent of the Malawi population in 24 of the Malawi’s 28 districts requiring emergency food and cash assistance (Babu et al., 2018). The Government of Malawi, together with its humanitarian and development partners, responded to the famine through a Food Insecurity Response Plan (FIRP) that targeted affected households with cash and food transfers between July of 2016 and March of 2017, just soon before the 2017 harvest.

## 3. Conceptual framework and hypotheses

Figure 3 illustrates a conceptual framework outlining the main channels through which an agricultural drought, like the one in Malawi in 2015/16, could affect child nutrition. In a context where household food security relies on both own food production and food purchases, a drought might affect child nutrition primarily through crop failure at the household level as well as through unusually high food prices.

Droughts during critical crop growth stages, such as silking in maize, can cause significant yield losses (Wollburg, et al., 2024). Therefore, for households reliant on own food production for part or all of their food consumption, drought-induced crop failure in the main farming season significantly reduces the stock of food available for consumption between the current and the next harvest. At the same time, agricultural droughts drive up food prices through forces of demand and supply, as well as through speculative hoarding of food stocks. Anticipating poor food supplies after the harvest, households might start hoarding stocks of food that they would otherwise have sold during the growing season (Conte et al., 2023) and traders could hoard food to sell when prices are high after the failed harvest, thereby driving up food prices already during the growing season, before the failed harvest comes in (Osborne, 2004). Additionally, droughts have negative effects on agricultural incomes both through reduced crop sales and lower employment opportunities and wages for agricultural workers, further lowering food consumption for those households relying on market purchases.

**Figure 3. Possible pathways through which the 2015/16 could have affected child nutrition.**

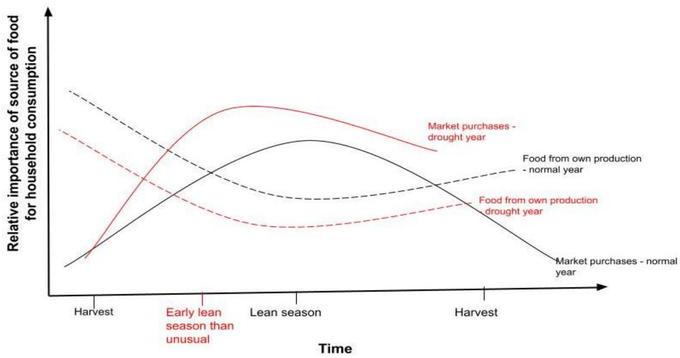



Source: Authors.

Figure 4 illustrates, in black, the seasonal variation in food stocks, reliance on own-produced food, and dependence on food markets during a normal year. Typically, households have the highest food stocks immediately after harvest (dry season). During this period, food prices are at their lowest as farmers supply markets with their produce. Consequently, farm households experience their highest annual incomes from selling farm produce, while non-farm households benefit from access to affordable food during this period. As the year progresses and food stocks dwindle, households increasingly rely on market purchases for food, and market prices increase. Food insecurity gradually worsens, peaking during the lean season between December and March, and driving households towards different strategies, ranging from eating less preferred food, reducing meals or selling household assets to manage the situation.

In the presence of strong weather shocks, such as the 2015/16 drought, the same sequence can be expected to occur, but households will run out of food stocks and rely on markets earlier in the year, in combination with an anticipated increase in food prices. As a result, affected households experience lean season conditions earlier than usual (illustrated in red in Figure 4) resulting in prolonged periods of food insecurity. These households are forced to adopt negative coping strategies earlier and sustain them for longer compared to their non-drought-affected counterparts, resulting in worse outcomes for their members. This can be expected to manifest itself in reduced daily per capita caloric intake and reduced dietary quality at the household level. Under five children, depending on age, sex, exposure to chronic diseases, and other individual and household factors, may bear the brunt of the food insecurity as their bodies are sensitive to any drops in both energy and nutrient availability. Therefore, children might experience wasting in the short run and stunting if the food insecurity persists.

**Figure 4. Seasonal variation in food stocks, reliance on own-produced food, and dependence on food markets**




Source: Authors.

We will test these hypothesized outcomes following the 2015/16 drought in Malawi. More specifically, we will examine the effect of the drought on dietary quality and household food security responses, and on acute child nutrition and wasting. We will explore these effects during two different seasons, to empirically evaluate the timing of household responses and malnutrition outcomes over the year.

## 4. Empirical strategy

### 4.1 Data

#### 4.1.1 Living Standards Measurement Survey - Integrated Household Panel Survey Data

We use household- and child-level data from the 2013 and 2016 waves of Malawi's Living Standards Measurement Survey - Integrated Household Panel Survey (LSMS-IHPS, or IHPS hereafter). The IHPS is a ten-year-long nationally representative panel dataset collected every three years since 2010 by the National Statistics Office in Malawi with technical support from the World Bank.

The data are collected using a stratified two stage sampling approach. The sampling frames for both 2013 and 2016 IHPS rounds are based on the listings from Malawi's 2008 decennial

Population and Housing Census (PHC); include the three major regions of Malawi namely North, Centre and South; and are stratified into rural and urban strata. The urban stratum is composed of three cities, while the rural stratum covers the rural areas of the country's 28 districts. Within each city and district, enumeration areas (EA) were randomly selected from the census, and 16 households were randomly selected within each EA. The initial, 2010/11 round sampled 3,246 households in 204 enumeration areas (EAs). A subsample of about 1,500 households from 102 EAs (out of the initial 204 EAs) have been selected in 2010 for re-interviewing every three years to build a multi-year panel, with the sample size growing as the households split. For this study, we rely on this multi-year panel, which consists of 1,990 households in the 2013 wave and increased to 2,508 households in the 2016 wave.

The IHPS collects comprehensive data on household composition, food and non-food consumption, asset ownership, individual household member education, household and labour market participation, experience of idiosyncratic and covariate shocks, access to social safety nets, credit and remittances. The survey also collects detailed information on agricultural production, community attributes and health outcomes including anthropometric data for under-five children.

### 4.1.2 Seasonality and timing of IHPS data collection

The IHPS data in Malawi are collected over a one-year period such that they capture the seasonality of agricultural production and its implications for livelihoods. Malawi has two seasons. The rainy season starts mid-October and ends mid-April the next year, with the dry season spanning from April to early October (FEWSNET, n.d). The main harvest period spans from late March to July, while December to March represents the lean season when majority of households have exhausted their food stocks and rely on markets and formal and informal social safety nets for food. To cover this seasonality, sampled households in IHPS are visited twice per survey round, once after planting and once after harvest. The first visit asks farm households agricultural questions pertaining to the ongoing season while the second visit asks post-harvest related questions. To collect consumption data in an evenly spread manner across the panel period, since the 2010 survey round, the (non-agriculture-related) household and individual questionnaire modules – including food consumption data and child anthropometric measurements - are administered to about half of the households during the first, post-planting visit (referred to as the dry season sample later on) and to about half of the households during the second, post-harvest visit (rainy season sample). The EAs were randomly assigned to either the dry or rainy subsamples at baseline (2010), such that their assignment does not influence our results. Nonetheless, we conduct balancing tests to formally confirm the comparability of non-seasonally-related characteristics across the two subsamples. We present results of our balancing tests in table 9 in the appendix.

In the 2013 and 2016 rounds, the first visit took place between the months April and July, while the second visit took place between August and December. Note that for about one percent of the households in the 2016 survey the second interview was delayed due to difficulties tracking them, resulting in them being interviewed only between January and April of 2017.

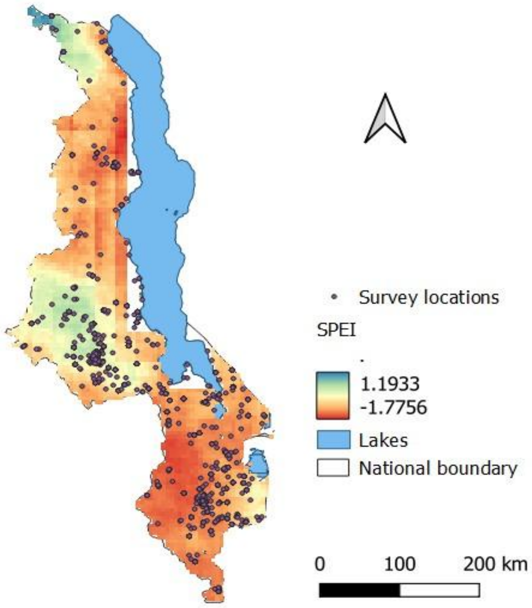
### 4.1.3 Climatic data and drought indicator

We use Standardized Precipitation Evapotranspiration Index (SPEI) to measure the intensity of the 2015/16 drought. SPEI allows calculating climatic water balance by taking the difference between precipitation and potential evapotranspiration covering periods between 1 and 48 months. SPEI is expressed in standard deviations from a long-run mean for each grid (Vicente-Serrano et al., 2010). We use a SPEI dataset for Africa constructed by Peng et al. (2019)[4]. The dataset has a spatial resolution 0.05° across Africa and lies on satellite data over weather station data, which are sparse and of variable quality in Africa. The higher resolution allows us to measure the intensity of drought at 5 kilometre by 5-kilometre grid cell level and to reliably match it to the geographical locations of EAs in the IHPS survey data. Figure 5 is a map of Malawi summarizing the distribution of SPEI during the 2015/16 main farming season. As we can see from the map, the whole country experienced drought conditions between December of 2015 to March of 2016. The main exceptions are some districts in the central region and Chitipa district at the northern tip of the country.

The Standardized Precipitation and Evapotranspiration Index measures climatic water balance in a given grid cell from its long-term mean (1981 to 2016 in our case). It is standardized to have a mean of zero and a standard deviation of one. Hence, a realization of zero implies that the water availability in a specified point in time does not deviate from the grid's long-term average, while negative (positive) values imply water deficiencies (surpluses) compared to the grid cell's long-term average. Peng et al. (2019) categorize droughts as moderate if SPEI lies between -1 and -1.49, severe if it lies between -1.5 and -1.99, and extreme if it is -2 or less.

[4] The SPEI variable uses precipitation data from Climate Hazards group InfraRed Precipitation with Station data (CHIRPS) and Potential Evapotranspiration (PET) estimates from Global Land Evaporation Amsterdam Model (GLEAM). The PET are calculated using Priestley–Taylor equation.

**Figure 5. Deviations in climatic water balance from long-run mean in each location during the 2015/16 production season (December-March) measured using Standardized Precipitation Evapotranspiration Index (SPEI).**




Note: The dots are survey locations. Source: Authors

To assess the impact of the 2015/16 drought, we construct an indicator of the intensity of drought for each enumeration area, following Hidrobo et al (2024) and Hirvonen et al (2023). After matching the SPEI grids with the location of the EAs, we modify the SPEI variable by setting positive values equal zero so that we only focus on areas that have negative water balances and hence experienced relative drought conditions. Then, we multiply the SPEI variable by -1 to transform the negative values to positive values, to facilitate interpretation of our results. With our transformation, larger positive values of the drought indicator imply more severe drought conditions while zero values imply non-drought conditions.

### 4.1.4 Outcome variables

We are interested in assessing the effects of Malawi's 2015/16 drought on food security and child nutrition. To measure the effects on food security, we are using indicators of dietary quality and household food insecurity response. We measure dietary quality using Household Dietary Diversity Score (HDDS) and Food Consumption Score (FCS). The HDDS is the number of food groups (0 to 12) consumed by household members based on a 7-day recall (Kennedy et al., 2011). Being a simple sum of food groups consumed at the household level, HDDS puts equal weights of importance on all the 12 food groups, which is problematic nutritionally. Additionally, it does not account for frequency of consumption of the food groups in the reference period. Therefore, we complement the HDDS with the FCS. The FCS is a composite score, ranging from 0 to 112, accounting for dietary diversity, food frequency and the relative nutritional value of food groups. It is calculated based on households' frequency of consuming 8 food groups over a 7-day recall period (Wiesmann et al., 2009). To understand how diets shift in response to the drought we also assess the effects of the droughts on the households' probability of consuming each of the 12 food groups used in the HDDS.

Furthermore, we use household responses to nine questions asking how households coped with food insecurity in the previous 7 days. These questions are based on the HFIAS (Household Food Insecurity Access Scale) module (Coates et al., 2007), and include (1) whether household worried about not having enough food; (2) number of days that household ate less preferred food in the past 7 days; (3) number of days household limited meal portion sizes in past 7 days; (4) number of days household reduced number of meals per day in the past 7 days; (5) number of days household reduced adult consumption in the past 7 days; (6) number of days household borrowed or was gifted food in the past 7 days; (7) number of meals taken by adults per day; (8) number of meals taken by children (6-59 months old); and (9) whether household faced food insecurity issues in the past 12 months.

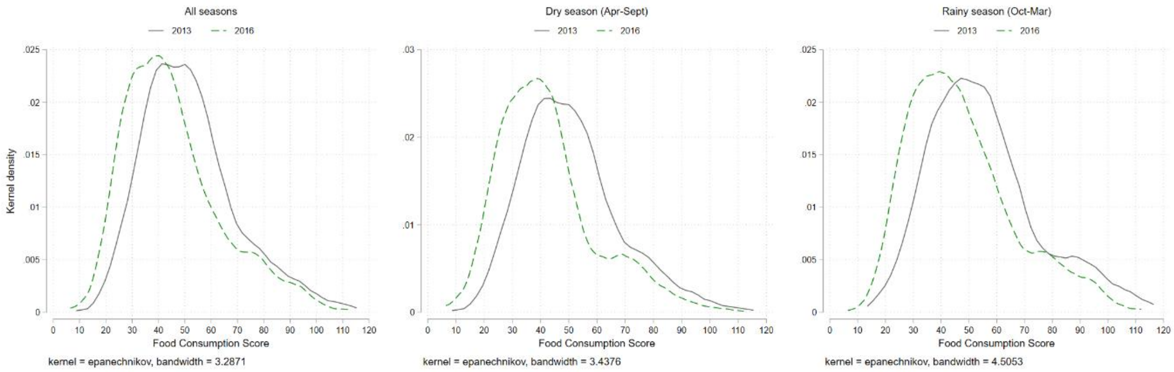
As a measure of children's nutritional status, we use anthropometric data on weight and height for children aged between 6 and 59 months old. We construct Weight-for-Height Z-scores (WHZ), a measure of acute undernourishment, that captures how child weights-to-height ratio compares with that of a median child of the same sex and age. However, we restrict the Weight-for-Height Z scores to between -5 and 5 so as to operate within a range that is biologically plausible for child anthropometric outcomes. We use this standardized measure first as a continuous variable, but also as a dummy variable whereby we categorize all children with WHZ scores of less than -2 as wasted. Possible longer term negative effects on children's height are not expected to materialize in the months immediately after the drought. The commonly used Height-for-Age Z-score (HAZ) capturing chronic malnutrition and child stunting, is therefore not considered.

## 4.2 Descriptive statistics

In this section we describe the main characteristics of the sample, and present a graphical descriptive analysis of our key outcome variables. Table 6 and Table 7 in the appendix describe the main socio-economic variables and tests of statistical differences by survey round. About 80% of our sample lives in rural areas, household size is composed of 5 members on average of which 1 child is under the age of 5. The average FCS is 51.9 in 2013 and 54.57 in 2016, and on average 8.3 and 8.7 out of 12 food groups were consumed in 2013 and 2016, respectively.

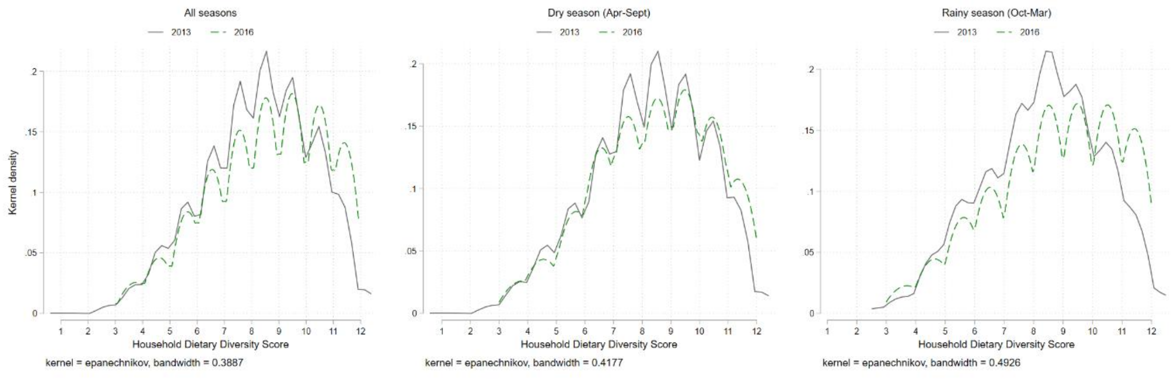
Figure 6 shows the distribution of FCS by season between 2013 and 2016 and indicates that a large share of households has a FCS that is considered poor (<21) or borderline (<35). Generally, over all seasons, the graph shows that dietary quality was considerably better in 2013 than in 2016. Disaggregating the analysis by season suggests that this holds similarly for both seasons. Using HDDS as an alternative measure of dietary quality (Figure 7), the difference between 2013 and 2016 is less clear, with the density of households that reported consuming over ten food groups being slightly higher in 2016.

**Figure 6. Food Consumption Score distributions by survey round, disaggregated by season.**




Note: Sample comprises 1990 households in 2013 and 2508 households in 2016. Analysis uses sampling weights.

**Figure 7. Household Dietary Diversity Score distributions by survey round, disaggregated by season.**




Note: Sample comprises 1990 households in 2013 and 2508 households in 2016. Analysis uses sampling weights.

Table 1 describes households experience of food insecurity. 34.2% in 2013 and 51.9% in 2016 reported being worried about not having enough food. The number of days in the past week on which households ate less preferred food, limited portion sizes, reduced the number of meals in a day, restricted consumption of adults, and borrowed food from others was reported to be higher in 2016 than in 2013. The number of meals taken by adults and by children under

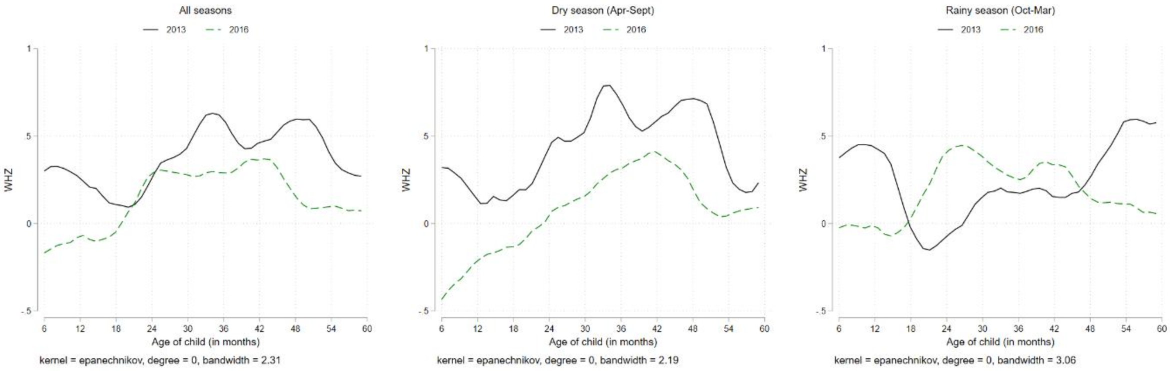
5 was lower in 2016 compared to 2013. Households reporting having faced food insecurity situations in the past year, was similar for both years.

**Table 1. Household experience of food insecurity by survey round .**

| | All | 2013 | 2016 | Difference |
|---|---|---|---|---|
| Household worried about not having enough food (0/1) | 0.442 | 0.342 | 0.519 | 0.179*** |
| | (0.497) | (0.475) | (0.500) | |
| Number of days ate less preferred food in the past 7 days | 1.570 | 1.271 | 1.801 | 0.554*** |
| | (2.128) | (2.059) | (2.151) | |
| Number of days household limited portion sizes at mealtimes in the past 7 days | 1.122 | 0.860 | 1.323 | 0.515*** |
| | (1.899) | (1.684) | (2.027) | |
| Number of days household reduced number of meals eaten in a day in the past 7 days | 0.977 | 0.588 | 1.277 | 0.736*** |
| | (1.814) | (1.385) | (2.036) | |
| Number of days household restricted consumption for adults in the past 7 days | 0.383 | 0.243 | 0.492 | 0.296*** |
| | (1.078) | (0.772) | (1.253) | |
| Number of days household borrowed food or help from others in the past 7 days | 0.440 | 0.355 | 0.506 | 0.183*** |
| | (1.049) | (0.868) | (1.164) | |
| Number of meals taken by adults per day in the household | 2.529 | 2.613 | 2.465 | -0.134*** |
| | (0.630) | (0.526) | (0.693) | |
| Number of meals taken by children (6-59 months old) per day in household | 2.409 | 2.601 | 2.266 | -0.259*** |
| | (1.223) | (1.003) | (1.347) | |
| Household faced food insecurity situations in the past 12 months (0/1) | 0.638 | 0.624 | 0.648 | 0.037 |
| | (0.481) | (0.484) | (0.478) | |

Figure 8 summarizes the WHZ-age relationship for children aged between 6 and 59 months old in our dataset. Overall, children measured in the aftermath of the drought in 2016 have worse nutritional outcomes compared to under-five children measured in 2013. Importantly, the WHZ for children measured in 2016 seems to be worse in the dry season compared to the rainy season. Children aged between 18 and 46 months old have higher WHZ scores during the rainy season in 2016 compared to those in the 2013 wave.

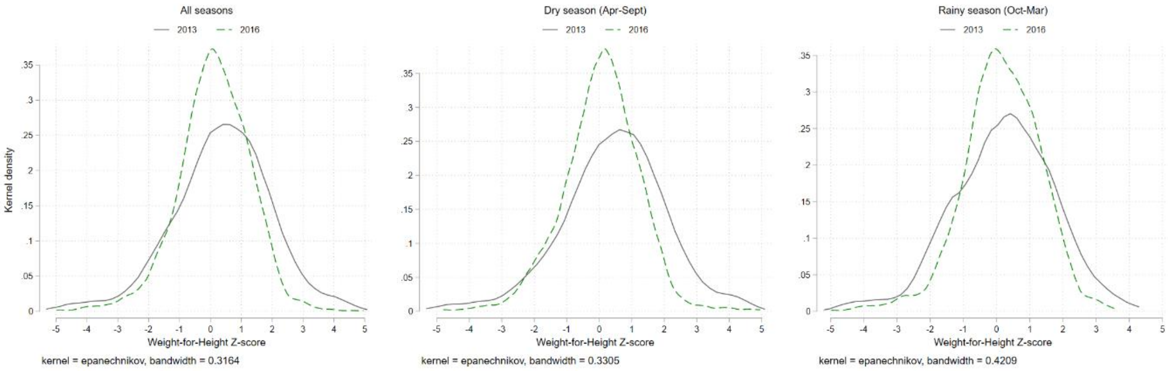
**Figure 8. Local polynomial regression of Weight-for-height Z-score by child age, disaggregated by season.**




Note: Sample comprises 1315 children in 2013 and 1372 children in 2016. Analysis uses sampling weights.

In Figure 9 we show the distribution of WHZ by survey round and season. Generally, the WHZ scores for children in 2016 are somewhat poorer than for children in 2013, with the differences seeming to be slightly larger during the dry season.

**Figure 9. Weight-for-Height Z-score distributions by survey round and season.**




Note: Sample comprises 1315 children in 2013 and 1372 children in 2016. Analysis uses sampling weights.

In the remainder of this paper, we formally analyse the effects of the 2016 drought on these outcome variables using proper econometric estimation techniques, controlling for all relevant factors that affect the relationships among droughts, dietary quality, food insecurity responses and child nutrition.

## 4.3 Econometric model

We start by estimating the effects of the 2015/16 drought on household food security. To this end, we estimate the following equation:

$$Y_{hct} = \alpha_f + \gamma_t + \beta_1 drought_c^{16} + u_{hct}, \quad (1)$$

where $Y_{hct}$ is the food security indicator for household $h$ in enumeration area $c$ in year $t$, $\alpha_f$ are fixed effects, with *f* referring to the household or enumeration area (EA), depending on the specification, and $\gamma_t$ are survey round fixed effects. $u_{hct}$ is an error term which we construct as explained in section 4.4 below. In this model, $drought_c^{16}$ is our variable of interest as it measures the intensity of drought in enumeration area $c$ during the 2015/16 farming season, while $\beta_1$ is our parameter of interest. We test the null hypothesis that the 2015/16 drought did not affect household-level food security ($\beta_1 = 0$) against the alternative hypothesis that the drought impacted consumption ($\beta_1 \neq 0$). We will do so for both indicators of dietary quality (FCS and HDDS), for households' probability of consuming each of the 12 food groups, and for each of the nine questions on household food insecurity experience.

For each food security indicator, we estimate the following three versions of equation 1:

$$Y_{hct} = \alpha + \beta_1 drought_c^{16} + u_{hct} \tag{1a}$$

$$Y_{hct} = \alpha_f + \gamma_t + \beta_1 drought_c^{16} + u_{hct} \tag{1b}$$

$$Y_{hct} = \alpha_f + \gamma_t + X_{ht}\delta + \beta_1 drought_c^{16} + u_{hct}. \tag{1c}$$

Equation (1a) assesses the simple correlation of the intensity of the 2015/16 drought with food security without controlling for any household characteristics nor fixed effects. It pools together 2013 and 2016 data and treats them as a pooled cross-section. Equation (1b) introduces the panel nature of our dataset by including either household or EA fixed effects ($\alpha_f$). It also includes survey round fixed effects ($\gamma_t$) that control for nationwide changes that vary over time. Finally, equation (1c) additionally controls for important time-variant household level factors $X_{ht}$ that may affect household food consumption, including education level of the most educated member of the household, gender of household head, region of residence, residence in rural or urban areas and access to infrastructure.

Furthermore, we modify model (1) to estimate effects of the drought on acute child malnutrition during the 2016 consumption season as follows:

$$Y_{ihct} = \alpha_f + \gamma_t + \tau_1 drought_c^{16} + u_{ihct}. \tag{2}$$

Here, $Y_{icht}$ is the Weight-for-Height Z-score or an indicator variable for wasting[5] for child $i$ in household $h$ of enumeration area $c$ in year $t$, while the rest of the variables and parameters are as defined above. $\alpha_f$ again represents household- or EA-level fixed effects, depending on the specification. As anthropometric measurements were only taken for children up to the age of 5, the panel of children measured in both 2013 and 2016 is very small. We therefore do not include a specification with child-level fixed effects. In model (2), we are interested in $\tau_1$ as it measures the relationship between the 2015/16 drought and acute child malnutrition. We test the null hypothesis that the 2015/16 drought did not affect short-term child nutrition $(\tau_1 = 0)$ against the alternative hypothesis that the drought affected short-term child nutrition $(\tau_1 \neq 0)$. We estimate the following versions of equation (2):

$$Y_{ihct} = \alpha + \tau_1 drought_c^{16} + u_{ihct} \quad \text{(2a)}$$

$$Y_{ihct} = \alpha_f + \gamma_t + \tau_1 drought_c^{16} + u_{ihct} \quad \text{(2b)}$$

$$Y_{ihct} = \alpha_f + \gamma_t + X_{ht}\delta + \tau_1 drought_c^{16} + u_{ihct}, \quad \text{(2c)}$$

where we start by assessing the association between the drought and acute malnutrition in equation (3a) and include household or EA-level and survey round fixed effects in equation (3b) as well as the two fixed effects and control variables in equation (3c). Equation (3c) controls for age of the child in months and its square; sex of the child, age and sex of household head; number of years of education of the most educated household member; whether household uses a safe water source; whether household resides in a rural area; region of residence of the household; district to the nearest road; and distance to the district centre.

One of the main considerations when assessing the effects of the drought on child nutrition, is that we have to ensure that our estimates do not suffer from *survivorship bias* (Alderman et al., 2011). Survivorship bias could bias our estimates if weaker children died as a result of the drought such that we only observe outcomes of children who were strong enough to survive the drought. In such cases, the negative effects of the drought would be underestimated or even positive estimates could be obtained, misleading our conclusions. The household dataset that we use does not have data on child mortality. Therefore, we cannot directly test whether the 2015/16 drought caused excess child mortality. Instead, in line with equations (2a-b-c), we regress variables for numbers of children under 24 months and under 60 months old in the

[5] Coded as 1 if a child has a WHZ of less than -2 and zero if otherwise.

household on our drought indicator to test whether the drought changed household composition.

We estimate all the models using an ordinary least squares (OLS) estimator. Considering that Conley (1999) standard errors are not suitable for nonlinear models, we use an OLS estimator instead of probit or logit estimators in all specifications with binary outcome variables. Therefore, the coefficients are given a linear interpretation since we estimate Linear Probability Models in such cases.

Finally, by definition, our SPEI-based indicator of drought is an exogenous variable in our application such that the 2015/16 drought enters our models exogenously. Hence, our parameters of interest $\beta_1$ and $\tau_1$ are given a causal interpretation. After the modification we discussed in section 4.1.3, our drought variable has a median value of 0.8SD. Thus, we interpret the two parameters as the *average effect of being exposed to a moderate (-1SD) drought*.

## 4.4 Calculation of standard errors

Ordinarily, studies that use the LSMS data cluster standard errors at the enumeration area level, which is the primary sampling unit (PSU) for these data. Beyond being the PSU, clustering at this level may also seem appropriate in our application because the EA is the level at which the climate data are linked with the LSMS data. However, clustering at the EA is plausibly invalid given the spatial dependencies across EAs due to use of weather data (see Hirvonen et al., (2023)). In practice, drought shocks in a farming season tend to cover a much large geographical region than an EA such that effects might be spatially correlated across several EAs. We address this concern by using Conley (1999) spatial heteroskedastic and autocorrelation consistent standard errors with a 50 km distance cutoff. The Conley standard errors use a weighting matrix to weight households that are close to each other more than those far apart within a specified distance. The 50 km distance cutoff in our application means that we assume the spatial correlation to extend up to 50 kilometres such that observations beyond 50 kilometres of each other have zero spatial correlation. For further robustness checking, we also cluster the standard errors at the enumeration area and district-year levels.

# 5. Results

## 5.1 Impacts of the 2015/16 drought on dietary quality

We start by assessing the effect of the drought on dietary quality in the household. Table 2 summarizes estimates of a 1SD increase in relative dryness on the household food consumption score (in Panel A) and household dietary diversity score (in Panel B) using enumeration area fixed effects. The results using household fixed effects are presented in Table 10 in the appendix. Starting with food consumption score (FCS) and focusing on column (3), which is our preferred specification, we find that, on average, exposure to a -1SD drought reduced FCS by about 4.289 points ($p < 0.001$). Considering that the mean FCS in this specification is 50.22, this result represents an 8.5 percent reduction in the food consumption score. However, the effect of the drought on FCS was seasonal, with the effect being significant in the dry season ($p < 0.001$) (column 6) and disappearing in the rainy season (column 9). The FCS dropped by about 5.845 points or about 12 percent in the dry season.

Panel B of table 2 summarizes the impact of the drought on household dietary diversity score (HDDS). Again, focusing on our preferred specification (column 3), we find a significant reduction in HDDS of about 0.296 points on average ($p < 0.1$). This is equivalent to a reduction in HDDS of about 3 percent relative to mean HDDS. In line with our finding for FCS, the point estimates for the HDDS are higher in the dry than in the rainy season, but are measured with larger error, and not significantly different from zero.

To understand the effect of the drought on the dietary quality better, we run linear probability models whose results we report in Table 3. We regress our drought indicator on 12 food groups that constitute HDDS to identify the food groups that responded to the drought. We find that a 1SD increase in relative dryness increased the probability of consuming cereals by about 0.5 percent ($p < 0.1$); but it reduced the probability of consuming vegetables by about 0.9 percent ($p < 0.05$); fish by about 7 percent ($p < 0.1$); and oils and fats by about 7 percent ($p < 0.01$).

**Table 2. Effect of 2015/16 drought on food consumption (using 2013 and 2016 data).**

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
|---|---|---|---|---|---|---|---|---|---|
| *Panel A – Outcome Variable is FCS* | All seasons | | | Dry season (Apr – Sept) | | | Rainy season (Oct – Mar) | | |
| Drought ($\beta_1$) | -5.853** | -3.827*** | -4.289*** | -9.139*** | -6.311*** | -5.845*** | -4.548 | 0.677 | 0.690 |
| | (2.289) | (1.216) | (1.145) | (2.116) | (1.617) | (1.533) | (2.927) | (2.057) | (1.652) |
| Enumeration area fixed effects? | No | Yes | Yes | No | Yes | Yes | No | Yes | Yes |
| Survey wave fixed effects? | No | Yes | Yes | No | Yes | Yes | No | Yes | Yes |
| Control variables? | No | No | Yes | No | No | Yes | No | No | Yes |
| Observations | 4,450 | 4,450 | 4,296 | 2,329 | 2,329 | 2,292 | 2,121 | 2,121 | 2,004 |
| R-squared | 0.022 | 0.002 | 0.115 | 0.049 | 0.006 | 0.100 | 0.013 | 0.000 | 0.126 |
| Mean of outcome variable | 50.22 | 50.22 | 50.22 | 49.42 | 49.42 | 49.42 | 51.08 | 51.08 | 51.08 |
| Std. dev. Of outcome variable | 19.60 | 19.60 | 19.60 | 19.07 | 19.07 | 19.07 | 20.12 | 20.12 | 20.12 |
| *Panel B – Outcome variable is HDDS* | | | | | | | | | |
| Drought ($\beta_1$) | 0.306 | -0.273* | -0.296* | 0.230 | -0.260 | -0.169 | 0.261 | -0.141 | -0.182 |
| | (0.215) | (0.164) | (0.160) | (0.240) | (0.214) | (0.204) | (0.278) | (0.245) | (0.218) |
| Enumeration area fixed effects? | No | Yes | Yes | No | Yes | Yes | No | Yes | Yes |
| Survey wave fixed effects? | No | Yes | Yes | No | Yes | Yes | No | Yes | Yes |
| Control variables? | No | No | Yes | No | No | Yes | No | No | Yes |
| Observations | 4,450 | 4,450 | 4,296 | 2,329 | 2,329 | 2,292 | 2,121 | 2,121 | 2,004 |
| R-squared | 0.005 | 0.001 | 0.121 | 0.003 | 0.001 | 0.111 | 0.004 | 0.000 | 0.131 |
| Mean of outcome variable | 8.613 | 8.613 | 8.613 | 8.474 | 8.474 | 8.474 | 8.763 | 8.763 | 8.763 |
| Std. dev. Of outcome variable | 2.130 | 2.130 | 2.130 | 2.059 | 2.059 | 2.059 | 2.195 | 2.195 | 2.195 |

Note: Drought is measured by multiplying SPEI by -1 and setting negative values to zero such that larger values mean dire drought conditions. Control variables used are sex of household head; age of household head; education level of the most educated household member; household size; whether household resides in a rural area; region of residence; distance in kilometres to the nearest road; and distance in kilometres to the district centre. Numbers in parentheses are Conley(1999) Spatial-HAC standard errors with a Bartlett kernel decay weights and a 50 km distance cutoff. *** indicates 1% significance level; ** indicates 5% significance level; and * indicates 10% significance level.

**Table 3. Effect of the 2015/16 drought on consumption of foods from various groups (using 2013 and 2016 data).**

| *Outcome variables:* | (1) Cereals (0/1) | (2) Roots & tubers (0/1) | (3) Vegetables (0/1) | (4) Fruits (0/1) | (5) Meats (0/1) | (6) Pulses & nuts (0/1) | (7) Eggs (0/1) | (8) Fish/seafood (0/1) | (9) Dairy (0/1) | (10) Oils & fats (0/1) | (11) Sugar (0/1) | (12) Condiments & other foods (0/1) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Drought ($\beta_1$) | 0.00478* | -0.0160 | -0.00858** | -0.0513 | -0.0326 | -0.0101 | 0.0255 | -0.0689* | -0.0286 | -0.0742*** | -0.0300 | -0.00571 |
| | (0.00259) | (0.0228) | (0.00355) | (0.0375) | (0.0347) | (0.0185) | (0.0278) | (0.0353) | (0.0264) | (0.0209) | (0.0205) | (0.00384) |
| EA fixed effects? | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Survey fixed round effects? | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Control variables? | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 4,296 | 4,296 | 4,296 | 4,296 | 4,296 | 4,296 | 4,296 | 4,296 | 4,296 | 4,296 | 4,296 | 4,296 |
| R-squared | 0.002 | 0.026 | 0.003 | 0.019 | 0.044 | 0.010 | 0.059 | 0.020 | 0.068 | 0.057 | 0.057 | 0.002 |
| Mean of outcome variable | 0.998 | 0.751 | 0.997 | 0.663 | 0.530 | 0.889 | 0.434 | 0.476 | 0.260 | 0.826 | 0.790 | 0.999 |
| Std. dev. of outcome variable | 0.0447 | 0.433 | 0.0537 | 0.473 | 0.499 | 0.315 | 0.496 | 0.500 | 0.439 | 0.379 | 0.407 | 0.0365 |

Note: Drought is measured by multiplying SPEI by -1 and setting negative values to zero such that larger values mean dire drought conditions. Control variables used are sex of household head; age of household head; education level of the most educated household member; household size; whether household resides in a rural area; region of residence; distance in kilometres to the nearest road; and distance in kilometres to the district centre. Numbers in parentheses Conley SE refer to Conley(1999) Spatial heteroskedastic and autocorrelation consistent standard errors with a Bartlett kernel decay weights and a 50 km distance cutoff. *** indicates 1% significance level; ** indicates 5% significance level; and * indicates 10% significance level.

## 5.2 Effect of the drought on food security

Table 4 summarizes results from model (1) which estimates the effect of the 2015/16 drought on household responses to food insecurity including enumeration area fixed effects. The results using household fixed effects are presented in Table 12 in the appendix. We find that the intensity of the drought resulted in adults reducing their food consumption. We find that, on average, exposure to a moderate (-1SD) drought in the 2015/16 farming season resulted in a 0.179 increase in number of days in a week that adult household members restricted food consumption so that children in the household could eat ($p<0.05$) (column 5). Given a mean value of 0.371, our estimate means that the drought resulted in a 48 percent increase in the number of days adults restricted food consumption. One way in which adults can restrict their food consumption, is by reducing the number of meals per day. Indeed, column (7) shows that the drought resulted in adults in the household reducing the number of meals they ate per day by 0.141 or 5.39 percent ($p<0.01$).

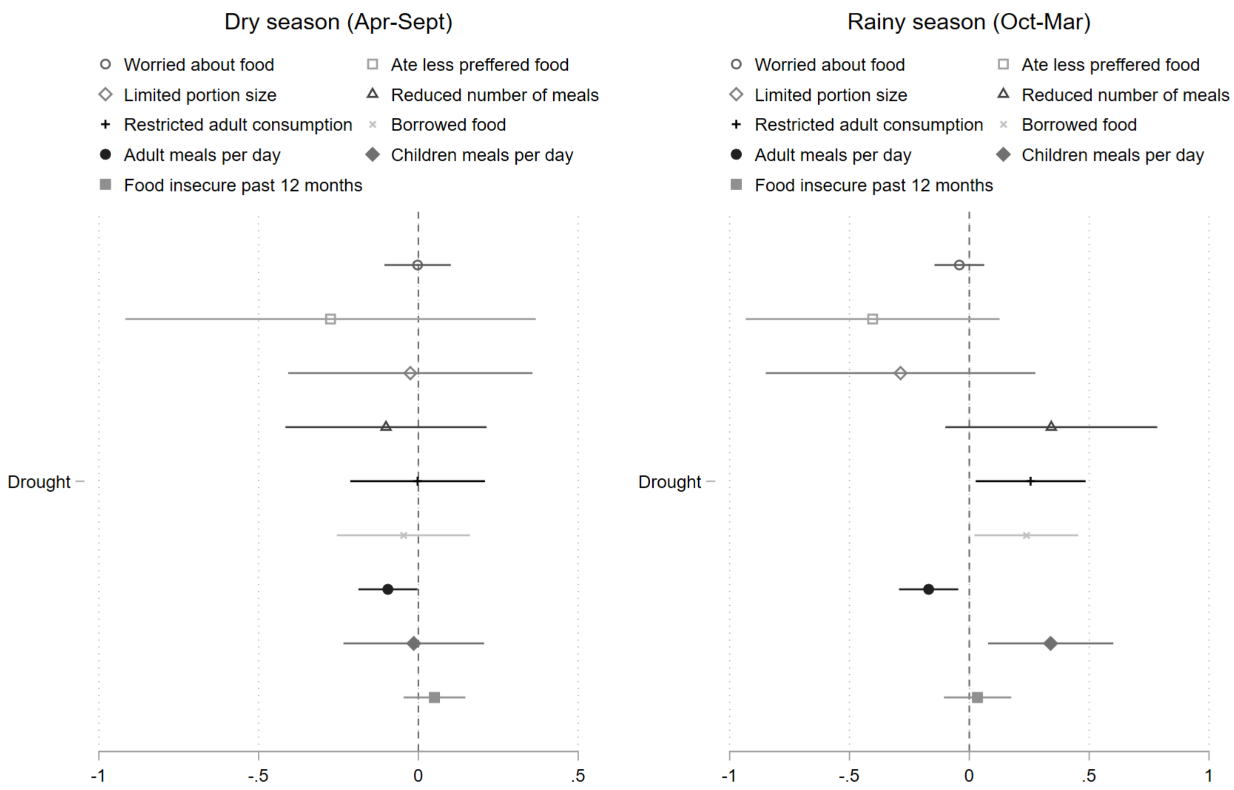
Considering the importance of seasonality of consumption in Malawi, we disaggregate our analysis by season to estimate how the effects of the drought varies in dry and rainy seasons. We summarize our results in figure 10. We do not find significant effects of the drought on most of our 9 indicators of household food insecurity responses during the dry season, immediately following the failed harvest. However, we find that the aggregate effect we found on adults restricting their consumption (5) and the number of meals per day (7) is entirely driven by households' responses during the rainy season, at least 5 months after the failed 2016 harvest. Moreover, we find that during the rainy season households borrowed food and/or relied on food gifts more (6), and for households with under-five children, the number of meals that children ate per day increased (8), as a result of the drought.

Table 4. Effect of 2015/16 drought on household food security (using 2013 and 2016 data).

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
|---|---|---|---|---|---|---|---|---|---|
| Outcome variables: | Worried about not having enough food (0/1) | Number of days HH ate less preferred food in the past 7 days | Number of days limited meal portion sized past 7 days | Number of days HH reduced number of meals per day in the past 7 days | Number of days HH reduced adult consumption in the past 7 days | Number of days HH borrowed or was gifted food in the past 7 days | Number of meals taken by adults per day | Number of meals taken by children (6-59 months old) | HH faced food insecurity issue in the past 12 months (0/1) |
| Drought ($\beta_1$) | -0.00659 | -0.283 | -0.0865 | 0.0283 | 0.179** | 0.0230 | -0.141*** | -0.0323 | 0.0217 |
| | (0.0488) | (0.242) | (0.170) | (0.131) | (0.0845) | (0.0641) | (0.0310) | (0.100) | (0.0481) |
| Enumeration area fixed effects? | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Survey wave fixed effects? | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Control variables? | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 4,296 | 4,295 | 4,295 | 4,295 | 4,294 | 4,295 | 4,293 | 2,924 | 4,296 |
| R-squared | 0.044 | 0.045 | 0.028 | 0.032 | 0.031 | 0.021 | 0.069 | 0.122 | 0.055 |
| Mean of outcome variable | 0.447 | 1.558 | 1.125 | 0.980 | 0.371 | 0.443 | 2.559 | 2.468 | 0.621 |
| Std. dev. of outcome variable | 0.497 | 2.119 | 1.905 | 1.818 | 1.058 | 1.065 | 0.644 | 1.216 | 0.485 |

Note: Drought is measured by multiplying SPEI by -1 and setting negative values to zero such that larger values mean dire drought conditions. Control variables used are sex of household head; age of household head; education level of the most educated household member; household size; whether household resides in a rural area; region of residence; distance in kilometres to the nearest road; and distance in kilometres to the district centre. Numbers in parentheses are Conley(1999) Spatial-HAC standard errors with a 50 km distance cutoff. *** indicates 1% significance level; ** indicates 5% significance level; and * indicates 10% significance level.

**Figure 10. Coefficient plots summarizing effect of the 2015/16 drought on household food security outcomes, by season (using 2013 and 2016 data).**




Note: Drought is measured by multiplying SPEI by -1 and setting negative values to zero such that larger values mean dire drought conditions. Control variables used are sex of household head; age of household head; education level of the most educated household member; household size; whether household resides in a rural area; region of residence; distance in kilometres to the nearest road; and distance in kilometres to the district centre. Analysis uses Conley(1999) Spatial-HAC standard errors with a 50 km distance cutoff.

### 5.3 Effect of the drought on child malnutrition

#### 5.3.1 Testing for potential survivorship bias

We now assess the effect of a 1SD increase in relative dryness during the 2015/16 farming season on child nutritional outcomes. For this analysis, we focus on short-term effects by using WHZ scores in the months following the failed 2016 harvest.

We first test for survivorship bias, by regressing the number of children under 24 months and under 60 months old in the household on our drought indicator. We report the results in Table 5, where we do not find any effect of the drought on number of children in the household. Therefore, we conclude that our subsequent analyses of the drought's child nutrition effects will not suffer from survivorship bias. The results using household fixed effects are presented in Table 13 in Appendix.

**Table 5. Assessing potential presence of survivorship bias in our estimations of drought impacts on child nutrition (using 2013 and 2016 data).**

| VARIABLES | (1)<br>Number of children less than 24 months old | (2)<br>Number of children less than 60 months old |
|---|---|---|
| Drought ($\tau_1$) | -0.0237 | -0.00344 |
| | (0.0328) | (0.0586) |
| Enumeration area fixed effects? | Yes | Yes |
| Survey round fixed effects? | Yes | Yes |
| Observations | 4,977 | 4,977 |
| R-squared | 0.000 | 0.000 |
| Mean of outcome variable | 0.353 | 0.880 |
| Std. dev. of outcome variable | 0.521 | 0.886 |

Note: Drought is measured by multiplying SPEI by -1 and setting negative values to zero such that larger values mean dire drought conditions. Control variables used are child age(in months); square of child age; child sex (male = 1); sex of household head (female = 1); age of household head; education level of the most educated household member; household size; whether households uses safe water sources; whether household resides in a rural area; region of residence; distance in kilometres to the nearest road; and distance in kilometres to the district centre. Numbers in parentheses are Conley(1999) Spatial-HAC standard errors with a 50km cutoff. *** indicates 1% significance level; ** indicates 5% significance level; and * indicates 10% significance level.

#### 5.3.2 Impact of the drought on acute malnutrition

Having established that our estimates will not suffer from survivorship bias, we turn to evaluating the impact of the drought on acute child malnutrition. Table 6 summarizes the estimates of models (2a) to (2c) using enumeration area fixed effects for the WHZ indicator (Panel A) and for the probability of a child being identified as wasted (Panel B). The results using household fixed effects are presented in Table 14 in Appendix. Columns 1 to 3 of Panel (A) summarize impacts of the drought on WHZ score, where we start by assessing the association between a moderate (-1SD) drought and short-term malnutrition by pooling 2013 and 2016 survey waves as cross-sections. We find a negative and significant association between the drought and child nutrition ($p < 0.01$). The coefficient doubles in magnitude when we introduce EA and survey round fixed effects in column 2 but the magnitude drops somewhat when we control for relevant, time-varying child and household characteristics such as child age and its square, child sex, and education in the household (column 3). On average, we find that exposure to a moderate drought reduced child weight for height by about 0.344SD ($p < 0.01$).

Similar to the drought's impacts on food consumption, we hypothesize that the effects of the droughts on child nutritional outcomes may differ over the months following the failed harvest. We find that the negative effects are concentrated in the dry season only (columns 4 to 6). When we account for EA and survey round fixed effects as well as child and household characteristics, we find a 0.364SD reduction in WHZ score ($p < 0.05$). In the rainy reason the effect is negative and not statistically different from zero, regardless of whether we estimate equation (3a), (3b) or (3c). We hypothesize that household coping mechanisms in response to the drought, for example, by adults prioritizing children in the distribution when the lean season (rainy season) approaches, may contribute to reducing the gap in WHZ between more and less drought-affected regions. At the same time, also in the non-drought affected regions, the normal seasonal pattern of consumption reaches the lean season around this time, and children may lose weight irrespective of the local intensity of drought.

Panel B of table 6 summarizes linear probability model estimates of exposure to a -1SD drought in 2015/16 on child wasting, where a child is considered wasted if it has a WHZ score of less than -2. We do not find evidence of the drought causing wasting in under-five children. The negative association being wasting and the drought in column 1 disappears when we introduce community and survey round fixed effects and remains insignificant when we include relevant child and household characteristics in the model. However, we find a negative and significant relationship between the drought and wasting in the rainy season (columns 8 and 9). Our preferred specification in column 9 shows that exposure to the drought reduced a child's probability of being wasted during the rainy season by about 8 percent ($p < 0.01$). This finding suggests that coping strategies that households with children used in the rainy season (as estimated in figure 11) might have been effective in hedging the children against negative nutritional impacts of the drought[6]. As wasting is defined by an extremely low WHZ score, we

[6] In section 5.1.1 we found that adults reduced consumption and children increased consumption in the rainy season due to the drought.

hypothesize that the catching up of drought-affected regions in the WHZ-score of children by the time of the rainy season (through adults prioritizing children, humanitarian support, or community level measures), was especially strong for the weakest children, bringing them above the -2 Z-score. As our sample size is getting small, no further heterogeneity analysis to investigate this in more detail has been performed.

## 6. Robustness

We have conducted a number of robustness checks to assess the sensitivity of our findings. First, given that exposure to the drought in our dataset is at the enumeration area (EA) level, one concern that may arise pertains to appropriate fixed effects to use in our regressions. We use EA fixed effects for our main results because the EA is the level at which we merge our IHPS and climatic data sets. However, we test the sensitivity of our food security and child nutrition results to using household fixed effects instead. Tables 10 and 12 in the appendix show that regardless of the fixed effects that we use, the drought had negative effects on food security. Tables 13 and 14 shows the same for child nutrition, with seasonality playing an important role in all cases.

Second, droughts characteristically affect large areas of a country. Although most earlier studies that answer our type of questions using similar datasets ordinarily cluster standard errors at the EA level, we follow Hirvonen et al (2023) in using Conley (1999) standard errors to account for any spatial correlation across observations, thus clustering our standard errors at a much larger spatial magnitude. We test the sensitivity of our results to how we constructed our standard errors by using cluster robust standard errors. As summarized in Tables 11 and 15 in the appendix, we find that our results are robust to alternative ways of calculating standard errors.

Third, our main results are based on data from 2013 and 2016 waves of the IHPS program in Malawi. This is because we want to use available data from immediately before the drought and during the failed 2016 harvest to estimate short-term effects. However, we pool all data from the 2010 to 2019 to test if any unaccounted-for long-term trends bias our estimates. We still find the same negative effects of the drought on dietary quality (figures 12 and 13) and child nutrition outcomes (figures 14 in the appendix).

Lastly, we estimate effects of the drought on short-term child nutrition outcomes separately for girls and boys and report the results in table 16. We still find the negative effect of exposure to the drought on WHZ for both girls and boys. In line with Block et al., (2022) and Headey and Ruel (2023), we find the negative effect being generally stronger for boys than girls. Due to the small numbers of children in our sample, we cannot disaggregate this analysis by season.

**Table 6. Impact of Malawi's 2015/16 drought on acute malnutrition (using 2013 and 2016 data).**

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
|---|---|---|---|---|---|---|---|---|---|
| *Panel A - Outcome variable is WHZ* | All seasons | | | Dry season (Apr- Sept) | | | Rainy season (Oct - Mar) | | |
| Drought ($\tau_1$) | -0.211*** | -0.432*** | -0.344*** | -0.294*** | -0.365** | -0.364** | -0.0860 | -0.121 | -0.0768 |
| | (0.0759) | (0.116) | (0.117) | (0.112) | (0.159) | (0.160) | (0.0936) | (0.214) | (0.229) |
| Enumeration area fixed effects? | No | Yes | Yes | No | Yes | Yes | No | Yes | Yes |
| Survey wave fixed effects? | No | Yes | Yes | No | Yes | Yes | No | Yes | Yes |
| Control variables? | No | No | Yes | No | No | Yes | No | No | Yes |
| Observations | 2,576 | 2,576 | 2,576 | 1,406 | 1,406 | 1,406 | 1,170 | 1,170 | 1,170 |
| R-squared | 0.006 | 0.005 | 0.024 | 0.008 | 0.002 | 0.026 | 0.001 | 0.000 | 0.011 |
| Mean of outcome variable | 0.244 | 0.244 | 0.244 | 0.305 | 0.305 | 0.305 | 0.172 | 0.172 | 0.172 |
| Std. dev. of outcome variable | 1.385 | 1.385 | 1.385 | 1.476 | 1.476 | 1.476 | 1.266 | 1.266 | 1.266 |
| *Panel B - Outcome variable is Wasting (0/1)* | | | | | | | | | |
| Drought ($\tau_1$) | -0.0199** | 0.00626 | 0.00715 | -0.0219 | 0.0155 | 0.0162 | -0.0106 | -0.0755*** | -0.0760*** |
| | (0.00883) | (0.0147) | (0.0148) | (0.0147) | (0.0204) | (0.0204) | (0.0130) | (0.0220) | (0.0217) |
| Observations | 2,650 | 2,650 | 2,650 | 1,457 | 1,457 | 1,457 | 1,193 | 1,193 | 1,193 |
| R-squared | 0.002 | 0.000 | 0.020 | 0.002 | 0.000 | 0.027 | 0.001 | 0.005 | 0.021 |
| Enumeration area fixed effects? | No | Yes | Yes | No | Yes | Yes | No | Yes | Yes |
| Survey wave fixed effects? | No | Yes | Yes | No | Yes | Yes | No | Yes | Yes |
| Control variables? | No | No | Yes | No | No | Yes | No | No | Yes |
| Mean of outcome variable | 0.0491 | 0.0491 | 0.0491 | 0.0570 | 0.0570 | 0.0570 | 0.0397 | 0.0397 | 0.0397 |
| Std. dev. of outcome variable | 0.216 | 0.216 | 0.216 | 0.232 | 0.232 | 0.232 | 0.195 | 0.195 | 0.195 |

Note: Drought is measured by multiplying SPEI by -1 and setting negative values to zero such that larger values mean dire drought conditions. Control variables used are child age(in months); square of child age; child sex (male = 1); sex of household head (female = 1); age of household head; education level of the most educated household member; household size; whether households uses safe water sources; whether household resides in a rural area; region of residence; distance in kilometres to the nearest road; and distance in kilometres to the district centre. Numbers in parentheses are Conley(1999) Spatial-HAC standard errors with a 50 km distance cutoff. *** indicates 1% significance level; ** indicates 5% significance level; and * indicates 10% significance level.

## 7. Summary and concluding remarks

Weather shocks pose significant threats to welfare and human capital in most developing countries. Shocks that hit during the main farming season tend to have grave effects in communities that rely on rain-fed agriculture as they disrupt current livelihoods, but also have long-term effects when affecting children during early stages of growth. While several studies have examined the impacts of weather shocks, including drought, on child malnutrition, these studies mostly focus on child stunting in the months or years after the drought, and are unable to provide insights into the pathways, coping strategies and short-term effects during or in the immediate aftermath of the event.

This paper evaluated food consumption and child nutrition effects of an El Niño-induced drought that hit seven southern African countries and affected about 30 million people during the 2015/16 farming season. Using two rounds of a nationally representative panel survey dataset collected in 2013 and 2016 in Malawi, and a remotely sensed indicator of the intensity of the drought, our panel fixed effects models provide evidence of negative impacts on food security, dietary quality and short-term child malnutrition as a result of exposure to a moderate (-1SD) drought in the 2015/16 farming season. Capitalizing on variation in the timing of data collection of the household survey over the two seasons in which the effects of the droughts were most strongly experienced, we are able to measure household food consumption, food insecurity responses and child malnutrition as the consequences of the drought unfold. We found that the effects of the drought were strongly seasonal, with households first reducing the quality of their diets during the dry season months of April to September, and resorting to more severe coping strategies in the form of reduced food consumption of adults in favour of children in the months after that. We find that child malnutrition is negatively affected by the drought in the dry season months, a period of the year in which – in normal years – the largest gains in weight and height would be observed (Maleta et al., 2007). No significant difference in acute child undernutrition as compared to non-drought affected areas was found in the rainy season, a period when Maleta et al., (2007) found child growth to be typically slowing down, and corresponding to the months in which we found households to prioritize children over adults in the allocation of food.

We conducted a number of checks to ascertain the robustness of our results and found that our results are robust to (1) using clustered standard errors instead of Conley (1999) standard errors; (2) using household fixed effects instead of enumeration area fixed effects; (3) disaggregating short-term nutrition effects by child sex; and, (4) pooling together all four waves of the panel dataset from 2010 to 2019 instead of using 2013 and 2016 data only.

Our results confirm that weather shocks during the main farming season can have severe consequences for household food security, coping strategies, and acute child malnutrition. We believe that our analysis can help in optimizing timing of interventions during humanitarian emergencies. Yet, further studies are needed on how and when these short-term responses translate into longer term effects on child growth and stunting levels, and how these effects vary across households operating in different context, with different access to markets, resilience mechanisms or social transfers.

Unfortunately, current climate change models predict increasing frequencies and intensities of these shocks as a result of human activities and natural climatic processes. Therefore, the need for interventions that help households cope with current shocks while building resilience to future shocks has never been more urgent. In order to design appropriate and timely interventions to cushion negative shocks to food insecurity and its possible implications on child malnutrition and growth, a better understanding is needed of how households respond and at what moment in the months following such shocks. Especially for small children, in the crucial first months of their lives, understanding this timing is crucial.

### CRediT authorship contribution statement.

**Edwin Kenamu**: Conceptualization, Data curation, Formal analysis, Methodology, Software, Writing – original draft, Writing – review & editing. **Liesbeth Colen**: Conceptualization, Methodology, Resources, Supervision, Validation, Writing – review & editing.

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# Appendices

## Seasonal agricultural calendar

**Figure 11. Seasonal calendar for an average year in Malawi.**


Source: FEWSNET (n.d).

**Table 7. Household-level summary statistics by survey round.**

| | N | All | 2013 | 2016 | Difference | Prob>F |
|---|---|---|---|---|---|---|
| Food Consumption Score | 4,489 | 48.340 | 51.929 | 45.576 | -6.356 | 0.000 |
| | | (18.588) | (17.965) | (18.591) | | |
| Household Dietary Diversity Score (0-12) | 4,489 | 8.494 | 8.258 | 8.676 | 0.435 | 0.000 |
| | | (2.110) | (1.973) | (2.194) | | |
| Household worried about not having enough food (0/1) | 4,489 | 0.442 | 0.342 | 0.519 | 0.179 | 0.000 |
| | | (0.497) | (0.475) | (0.500) | | |
| Number of days ate less preferred food in the past 7 days | 4,488 | 1.570 | 1.271 | 1.801 | 0.554 | 0.000 |
| | | (2.128) | (2.059) | (2.151) | | |
| Number of days household limited portion sizes at mealtimes in the past 7 days | 4,488 | 1.122 | 0.860 | 1.323 | 0.515 | 0.000 |
| | | (1.899) | (1.684) | (2.027) | | |
| Number of days household reduced number of meals eaten in day in the past 7 days | 4,488 | 0.977 | 0.588 | 1.277 | 0.736 | 0.000 |
| | | (1.814) | (1.385) | (2.036) | | |
| Number of days household restricted consumption for adults in the past 7 days | 4,487 | 0.383 | 0.243 | 0.492 | 0.296 | 0.000 |
| | | (1.078) | (0.772) | (1.253) | | |
| Number of days household borrowed food or help from others in the past 7 days | 4,488 | 0.440 | 0.355 | 0.506 | 0.183 | 0.001 |
| | | (1.049) | (0.868) | (1.164) | | |
| Number of meals taken by adults per day in the household | 4,486 | 2.529 | 2.613 | 2.465 | -0.134 | 0.000 |
| | | (0.630) | (0.526) | (0.693) | | |
| Number of meals taken by children (6-59months old) per day in household | 3,026 | 2.409 | 2.601 | 2.266 | -0.259 | 0.000 |
| | | (1.223) | (1.003) | (1.347) | | |
| Household faced food insecurity situations in the past 12 months (0/1) | 4,489 | 0.638 | 0.624 | 0.648 | 0.037 | 0.271 |
| | | (0.481) | (0.484) | (0.478) | | |
| Household consumed cereals in the past week (0/1) | 4,489 | 0.998 | 0.999 | 0.996 | -0.003 | 0.139 |
| | | (0.048) | (0.025) | (0.060) | | |
| Household consumed roots and tubers in the past week (0/1) | 4,489 | 0.750 | 0.789 | 0.721 | -0.074 | 0.001 |
| | | (0.433) | (0.408) | (0.449) | | |
| Household consumed eggs in the past week (0/1) | 4,489 | 0.404 | 0.397 | 0.410 | 0.008 | 0.483 |
| | | (0.491) | (0.489) | (0.492) | | |
| Household consumed fish in the past week (0/1) | 4,489 | 0.486 | 0.093 | 0.788 | 0.719 | 0.000 |
| | | (0.500) | (0.291) | (0.409) | | |
| Household consumed vegetables in the past week (0/1) | 4,489 | 0.997 | 0.996 | 0.997 | 0.000 | 0.618 |
| | | (0.055) | (0.061) | (0.050) | | |
| Household consumed fruits in the past week (0/1) | 4,489 | 0.635 | 0.666 | 0.612 | -0.039 | 0.029 |
| | | (0.481) | (0.472) | (0.487) | | |
| Household consumed meats in the past week (0/1) | 4,489 | 0.514 | 0.556 | 0.482 | -0.067 | 0.000 |
| | | (0.500) | (0.497) | (0.500) | | |
| Household consumed pulses in the past week (0/1) | 4,489 | 0.886 | 0.946 | 0.839 | -0.105 | 0.000 |
| | | (0.318) | (0.226) | (0.367) | | |
| Household consumed dairy in the past week (0/1) | 4,489 | 0.231 | 0.214 | 0.243 | 0.026 | 0.076 |
| | | (0.421) | (0.411) | (0.429) | | |
| Household consumed oils and fats in the past week (0/1) | 4,489 | 0.815 | 0.795 | 0.830 | 0.024 | 0.019 |
| | | (0.389) | (0.404) | (0.376) | | |
| Household consumed sugars in the past week (0/1) | 4,489 | 0.780 | 0.808 | 0.758 | -0.055 | 0.000 |
| | | (0.414) | (0.394) | (0.428) | | |
| Household consumed condiments in the past week (0/1) | 4,489 | 0.998 | 0.998 | 0.999 | 0.001 | 0.534 |
| | | (0.039) | (0.047) | (0.032) | | |
| Number of under 5 children in the HH | 4,489 | 0.725 | 0.808 | 0.661 | -0.137 | 0.000 |
| | | (0.772) | (0.807) | (0.739) | | |

| | | | | | | |
|---|---|---|---|---|---|---|
| Number of under 2 children in the HH | 4,489 | 0.288<br>(0.479) | 0.334<br>(0.508) | 0.253<br>(0.452) | -0.079 | 0.000 |
| Received cash or food transfer (0/1) | 4,489 | 0.081<br>(0.273) | 0.089<br>(0.284) | 0.075<br>(0.264) | -0.009 | 0.451 |
| Received cash transfer (0/1) | 4,489 | 0.035<br>(0.184) | 0.012<br>(0.109) | 0.053<br>(0.224) | 0.038 | 0.000 |
| Received food transfer (0/1) | 4,489 | 0.049<br>(0.215) | 0.080<br>(0.271) | 0.024<br>(0.155) | -0.048 | 0.000 |
| Received food and cash transfer (0/1) | 4,489 | 0.003<br>(0.052) | 0.003<br>(0.057) | 0.002<br>(0.047) | -0.002 | 0.493 |
| Female HH head (0/1) | 4,489 | 0.255<br>(0.436) | 0.241<br>(0.428) | 0.266<br>(0.442) | 0.022 | 0.007 |
| Age of household head | 4,324 | 42.260<br>(14.708) | 42.037<br>(14.636) | 42.441<br>(14.766) | 0.605 | 0.155 |
| Maximum HH education (years) | 4,489 | 8.150<br>(3.573) | 7.979<br>(3.601) | 8.282<br>(3.547) | 0.223 | 0.001 |
| Education (in years) of highest educated female | 4,307 | 6.408<br>(3.701) | 6.185<br>(3.735) | 6.581<br>(3.665) | 0.333 | 0.000 |
| Education (in years) of highest educated male | 4,181 | 7.320<br>(3.892) | 7.191<br>(3.908) | 7.421<br>(3.878) | 0.135 | 0.005 |
| Education level of household head (years) | 3,832 | 6.099<br>(4.207) | 5.904<br>(4.228) | 6.210<br>(4.192) | 0.203 | 0.003 |
| Household size | 4,489 | 4.903<br>(2.261) | 4.959<br>(2.264) | 4.860<br>(2.258) | -0.066 | 0.115 |
| Household uses a safe source of drinking water (0/1) | 4,489 | 0.858<br>(0.349) | 0.855<br>(0.352) | 0.860<br>(0.347) | 0.011 | 0.759 |
| Rainy season (0/1) | 4,489 | 0.464<br>(0.499) | 0.246<br>(0.431) | 0.632<br>(0.482) | 0.351 | 0.000 |
| Distance (km) to nearest road | 4,489 | 7.713<br>(9.226) | 7.850<br>(9.290) | 7.608<br>(9.176) | -0.115 | 0.116 |
| HH Distance in (KMs) to Nearest ADMARC Outlet | 4,489 | 7.263<br>(5.290) | 7.217<br>(5.235) | 7.298<br>(5.333) | 0.116 | 0.457 |
| Distance (km) to district centre | 4,489 | 22.057<br>(17.065) | 21.923<br>(16.806) | 22.161<br>(17.264) | 0.553 | 0.497 |
| Residence in a rural area (0/1) | 4,489 | 0.811<br>(0.392) | 0.810<br>(0.393) | 0.812<br>(0.391) | 0.013 | 0.850 |
| Northern region (0/1) | 4,489 | 0.109<br>(0.311) | 0.111<br>(0.314) | 0.107<br>(0.310) | -0.005 | 0.401 |
| Central region (0/1) | 4,489 | 0.412<br>(0.492) | 0.399<br>(0.490) | 0.422<br>(0.494) | 0.034 | 0.008 |
| Southern region (0/1) | 4,489 | 0.479<br>(0.500) | 0.491<br>(0.500) | 0.471<br>(0.499) | -0.029 | 0.011 |

Notes: Standard deviations are in parentheses. Sample comprises 1990 households in 2013 and 2508 households in 2016. Analysis uses sampling weights.

**Table 8. Child-level summary statistics by survey round.**

| | N | All | 2013 | 2016 | Difference | Prob>F |
|---|---|---|---|---|---|---|
| Weight for Height Z Score | 2,597 | 0.255 | 0.375 | 0.149 | -0.248 | 0.005 |
| | | (1.381) | (1.590) | (1.153) | | |
| Wasted (0/1) | 2,671 | 0.049 | 0.063 | 0.036 | -0.024 | 0.010 |
| | | (0.216) | (0.243) | (0.186) | | |
| Child weight (kilogram) | 2,685 | 12.879 | 13.242 | 12.536 | -0.843 | 0.144 |
| | | (12.526) | (17.301) | (4.729) | | |
| Child height (centimetre) | 2,681 | 87.256 | 87.177 | 87.331 | 0.258 | 0.812 |
| | | (15.677) | (18.926) | (11.809) | | |
| Age of child (in months) | 2,687 | 31.155 | 30.844 | 31.450 | 0.683 | 0.359 |
| | | (15.900) | (15.819) | (15.976) | | |
| Child is male (0/1) | 2,687 | 0.475 | 0.481 | 0.470 | -0.015 | 0.562 |
| | | (0.499) | (0.500) | (0.499) | | |
| Child participates in underfive clinic (0/1) | 2,687 | 0.737 | 0.722 | 0.752 | 0.021 | 0.191 |
| | | (0.440) | (0.448) | (0.432) | | |
| Child participates in nutrition program (0/1) | 2,684 | 0.079 | 0.074 | 0.083 | 0.003 | 0.597 |
| | | (0.270) | (0.262) | (0.276) | | |
| Child is at least than 36 months old (0/1) | 2,687 | 0.426 | 0.422 | 0.430 | 0.006 | 0.679 |
| | | (0.495) | (0.494) | (0.495) | | |

Notes: Standard deviations are in parentheses. Sample comprises 1315 children in 2013 and 1372 children in 2016. Analysis uses sampling weights.

**Table 9. Baseline balance by IHPS subsample (using 2010 data).**

| | N | All | Panel A households | Panel B households | Difference | P-value |
|---|---|---|---|---|---|---|
| Number of under 5 children in the HH | 953 | 1.436 (0.600) | 1.418 (0.597) | 1.460 (0.604) | 0.022 | 0.346 |
| Number of under 2 children in the HH | 953 | 0.588 (0.552) | 0.597 (0.532) | 0.575 (0.578) | -0.042 | 0.563 |
| Received cash or food transfer (0/1) | 1,599 | 0.025 (0.155) | 0.030 (0.171) | 0.018 (0.132) | -0.009 | 0.412 |
| Received cash transfer (0/1) | 1,599 | 0.006 (0.075) | 0.005 (0.074) | 0.006 (0.077) | -0.001 | 0.925 |
| Received food transfer (0/1) | 1,599 | 0.020 (0.139) | 0.026 (0.159) | 0.012 (0.109) | -0.010 | 0.344 |
| Received food and cash transfer (0/1) | 1,599 | 0.001 (0.024) | 0.001 (0.032) | 0.000 (0.000) | -0.001 | 0.321 |
| Female head | 1,599 | 0.225 (0.418) | 0.215 (0.411) | 0.238 (0.426) | 0.015 | 0.425 |
| Age of household head | 1,599 | 41.782 (15.038) | 41.253 (15.165) | 42.443 (14.862) | 0.554 | 0.287 |
| Maximum HH education (years) | 1,599 | 7.325 (3.717) | 7.378 (3.803) | 7.258 (3.608) | -0.240 | 0.779 |
| Education (in years) of highest educated female | 1,532 | 5.446 (3.757) | 5.507 (3.799) | 5.371 (3.706) | -0.273 | 0.762 |
| Education (in years) of highest educated male | 1,491 | 6.676 (3.970) | 6.632 (4.110) | 6.729 (3.793) | -0.111 | 0.822 |
| Education level of household head (years) | 1,597 | 5.604 (4.284) | 5.740 (4.365) | 5.433 (4.176) | -0.445 | 0.515 |
| Household size | 1,599 | 4.751 (2.213) | 4.659 (2.245) | 4.866 (2.168) | 0.076 | 0.261 |
| Household uses a safe source of drinking water (0/1) | 1,599 | 0.826 (0.379) | 0.873 (0.333) | 0.767 (0.423) | -0.102 | 0.038 |
| Distance (km) to nearest road | 1,599 | 7.862 (9.053) | 8.031 (9.088) | 7.650 (9.011) | -1.108 | 0.843 |
| HH Distance (km) to Nearest ADMARC Outlet | 1,599 | 7.242 (5.276) | 6.940 (4.922) | 7.621 (5.669) | 0.143 | 0.566 |
| Distance (km) to district centre | 1,599 | 51.584 (27.734) | 51.842 (27.757) | 51.262 (27.720) | 0.246 | 0.925 |
| Residence in a rural area (0/1) | 1,599 | 0.826 (0.379) | 0.812 (0.391) | 0.844 (0.363) | -0.001 | 0.698 |
| Northern region (0/1) | 1,599 | 0.122 (0.328) | 0.102 (0.302) | 0.149 (0.356) | 0.001 | 0.594 |
| Central region (0/1) | 1,599 | 0.379 (0.485) | 0.403 (0.491) | 0.349 (0.477) | 0.004 | 0.623 |
| Southern region (0/1) | 1,599 | 0.499 (0.500) | 0.496 (0.500) | 0.503 (0.500) | -0.005 | 0.953 |

Notes: Standard deviations are in parentheses. Analysis uses sampling weights.

**Table 10. Replicating table 2, but using HH fixed effects instead of enumeration area fixed effects.**

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
|---|---|---|---|---|---|---|---|---|---|
| Variables | All seasons | | | Dry season (Oct - Mar) | | | Rainy season (Apr - Sept) | | |
| *Panel B – Outcome variable is FCS* | | | | | | | | | |
| Drought ($\beta_1$) | -5.853** | -4.190*** | -4.644*** | -9.139*** | -6.670*** | -6.755*** | -4.548 | 0.300 | -0.0479 |
| | (2.289) | (0.939) | (1.014) | (2.116) | (1.371) | (1.352) | (2.927) | (1.587) | (1.445) |
| Household fixed effects? | No | Yes | Yes | No | Yes | Yes | No | Yes | Yes |
| Survey wave fixed effects? | No | Yes | Yes | No | Yes | Yes | No | Yes | Yes |
| Control variables? | No | No | Yes | No | No | Yes | No | No | Yes |
| Observations | 4,450 | 4,450 | 4,296 | 2,329 | 2,329 | 2,292 | 2,121 | 2,121 | 2,004 |
| R-squared | 0.022 | 0.005 | 0.064 | 0.049 | 0.014 | 0.063 | 0.013 | 0.000 | 0.069 |
| Mean of outcome variable | 50.22 | 50.22 | 50.22 | 49.42 | 49.42 | 49.42 | 51.08 | 51.08 | 51.08 |
| Std. dev. of outcome variable | 19.60 | 19.60 | 19.60 | 19.07 | 19.07 | 19.07 | 20.12 | 20.12 | 20.12 |
| *Panel B – Outcome variable is HDDS* | | | | | | | | | |
| Drought ($\beta_1$) | 0.306 | -0.312** | -0.337** | 0.230 | -0.235 | -0.178 | 0.261 | -0.146 | -0.303 |
| | (0.215) | (0.145) | (0.151) | (0.240) | (0.205) | (0.206) | (0.278) | (0.221) | (0.226) |
| Household fixed effects? | No | Yes | Yes | No | Yes | Yes | No | Yes | Yes |
| Survey wave fixed effects? | No | Yes | Yes | No | Yes | Yes | No | Yes | Yes |
| Control variables? | No | No | Yes | No | No | Yes | No | No | Yes |
| Observations | 4,450 | 4,450 | 4,296 | 2,329 | 2,329 | 2,292 | 2,121 | 2,121 | 2,004 |
| R-squared | 0.005 | 0.002 | 0.075 | 0.003 | 0.001 | 0.069 | 0.004 | 0.000 | 0.096 |
| Mean of outcome variable | 8.613 | 8.613 | 8.613 | 8.474 | 8.474 | 8.474 | 8.763 | 8.763 | 8.763 |
| Std. dev. of outcome variable | 2.130 | 2.130 | 2.130 | 2.059 | 2.059 | 2.059 | 2.195 | 2.195 | 2.195 |

Note: Drought is measured by multiplying SPEI by -1 and setting negative values to zero such that larger values mean dire drought conditions. To only focus on the 2016 drought SPEI values for 2013 are set to zero. Control variables used are sex of household head; age of household head; education level of the most educated household member; household size; whether household resides in a rural area; region of residence; distance in kilometres to the nearest road; and distance in kilometres to the district centre. Numbers in parentheses are Conley(1999) Spatial-HAC standard errors with a Bartlett kernel decay weights and a 50 km distance cutoff. *** indicates 1% significance level; ** indicates 5% significance level; and * indicates 10% significance level.

**Table 11. Replicating table 2, but using cluster standard errors instead of Conley (1999) Spatial HAC standard errors.**

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
|---|---|---|---|---|---|---|---|---|---|
| | All seasons | | | Dry season (Apr - Sept) | | | Rainy season (Oct - Mar) | | |
| *Panel A – Outcome variable is FCS* | | | | | | | | | |
| Drought ($\beta_1$) | -5.853*** | -3.827** | -4.289*** | -9.139*** | -6.311*** | -5.845*** | -4.548** | 0.677 | 0.690 |
| | (1.101) | (1.511) | (1.553) | (1.298) | (2.177) | (2.102) | (1.773) | (2.411) | (2.295) |
| Enumeration area fixed effects? | No | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Survey fixed round effects? | No | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Control variables? | No | No | No | No | No | No | No | No | No |
| Observations | 4,450 | 4,449 | 4,295 | 2,329 | 2,318 | 2,280 | 2,121 | 2,121 | 2,002 |
| R-squared | 0.022 | 0.267 | 0.352 | 0.049 | 0.296 | 0.361 | 0.013 | 0.292 | 0.384 |
| Mean of outcome variable | 50.24 | 50.24 | 50.30 | 49.42 | 49.41 | 49.49 | 51.14 | 51.14 | 51.21 |
| Std. dev. of outcome variable | 19.65 | 19.65 | 19.56 | 19.07 | 19.07 | 19.14 | 20.23 | 20.23 | 20 |
| *Panel B – Outcome variable is HDDS* | | | | | | | | | |
| Drought ($\beta_1$) | 0.306** | -0.273 | -0.296* | 0.230 | -0.260 | -0.169 | 0.261 | -0.141 | -0.182 |
| | (0.128) | (0.175) | (0.178) | (0.171) | (0.258) | (0.261) | (0.197) | (0.255) | (0.248) |
| Enumeration area fixed effects? | No | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Survey fixed round effects? | No | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Control variables? | No | No | Yes | No | No | Yes | No | No | Yes |
| Observations | 4,450 | 4,449 | 4,295 | 2,329 | 2,318 | 2,280 | 2,121 | 2,121 | 2,002 |
| R-squared | 0.005 | 0.265 | 0.356 | 0.003 | 0.287 | 0.363 | 0.004 | 0.292 | 0.392 |
| Mean of outcome variable | 8.616 | 8.616 | 8.616 | 8.474 | 8.472 | 8.464 | 8.772 | 8.772 | 8.784 |
| Std. dev. of outcome variable | 2.135 | 2.135 | 2.125 | 2.059 | 2.053 | 2.052 | 2.204 | 2.204 | 2.186 |

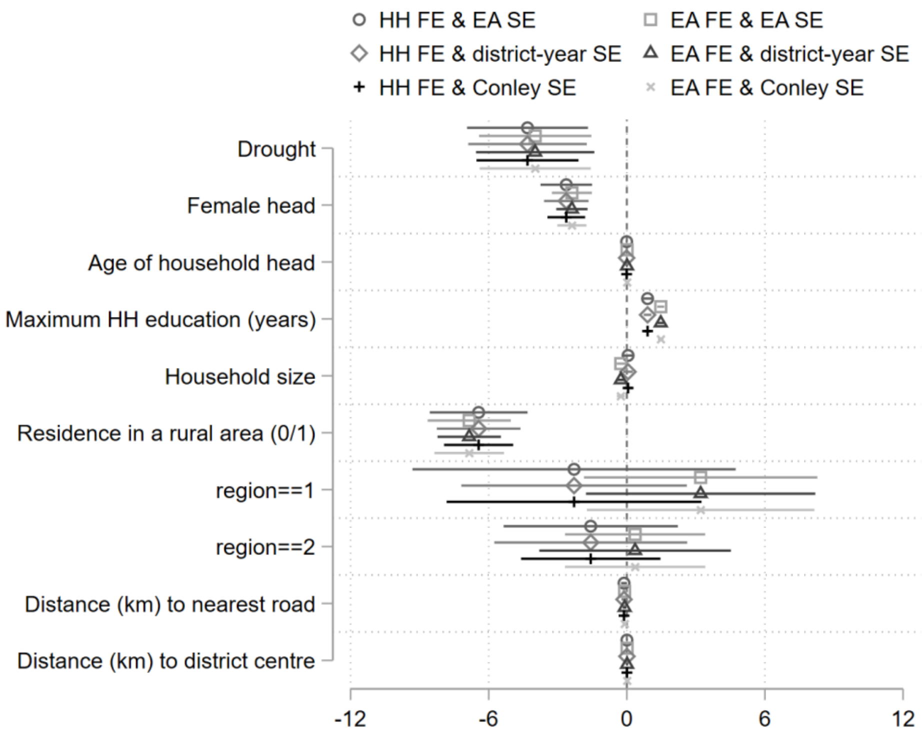
Note: Drought is measured by multiplying SPEI by -1 and setting negative values to zero such that larger values mean dire drought conditions. Control variables used are sex of household head; age of household head; education level of the most educated household member; household size; whether household resides in a rural area; region of residence; distance in kilometres to the nearest road; and distance in kilometres to the district centre. Numbers in parentheses are robust standard errors clustered at the enumeration area level. *** indicates 1% significance level; ** indicates 5% significance level; and * indicates 10% significance level.

**Table 12. Replicating table 4, but using household fixed effects instead of EA fixed effects (using 2013 and 2016 data).**

| VARIABLES | (1) Worried about not having enough food (0/1) | (2) Number of days HH ate less preferred food in the past 7 days | (3) Number of days limited meal portion sized past 7 days | (4) Number of days HH reduced number of meals per day in the past 7 days | (5) Number of days HH reduced adult consumption in the past 7 days | (6) Number of days HH borrowed or was gifted food in the past 7 days | (7) Number of meals taken by adults per day | (8) Number of meals taken by children (6-59 months old) | (9) HH faced food insecurity issue in the past 12 months (0/1) |
|---|---|---|---|---|---|---|---|---|---|
| Drought ($\beta_1$) | -0.0146 | -0.278 | -0.0861 | 0.0771 | 0.202** | 0.0258 | -0.128*** | -0.00653 | 0.0438 |
| | (0.0462) | (0.241) | (0.167) | (0.121) | (0.0857) | (0.0640) | (0.0286) | (0.0866) | (0.0442) |
| Observations | 4,296 | 4,295 | 4,295 | 4,295 | 4,294 | 4,294 | 4,291 | 2,920 | 2,920 |
| R-squared | 0.019 | 0.021 | 0.015 | 0.017 | 0.021 | 0.006 | 0.030 | 0.084 | 0.029 |
| Household fixed effects? | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Survey wave fixed effects? | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Control variables? | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Mean of outcome variable | 0.447 | 1.558 | 1.125 | 0.980 | 0.371 | 0.443 | 2.559 | 2.467 | 0.639 |
| Std. dev. of outcome variable | 0.497 | 2.119 | 1.905 | 1.818 | 1.058 | 1.065 | 0.644 | 1.217 | 0.480 |

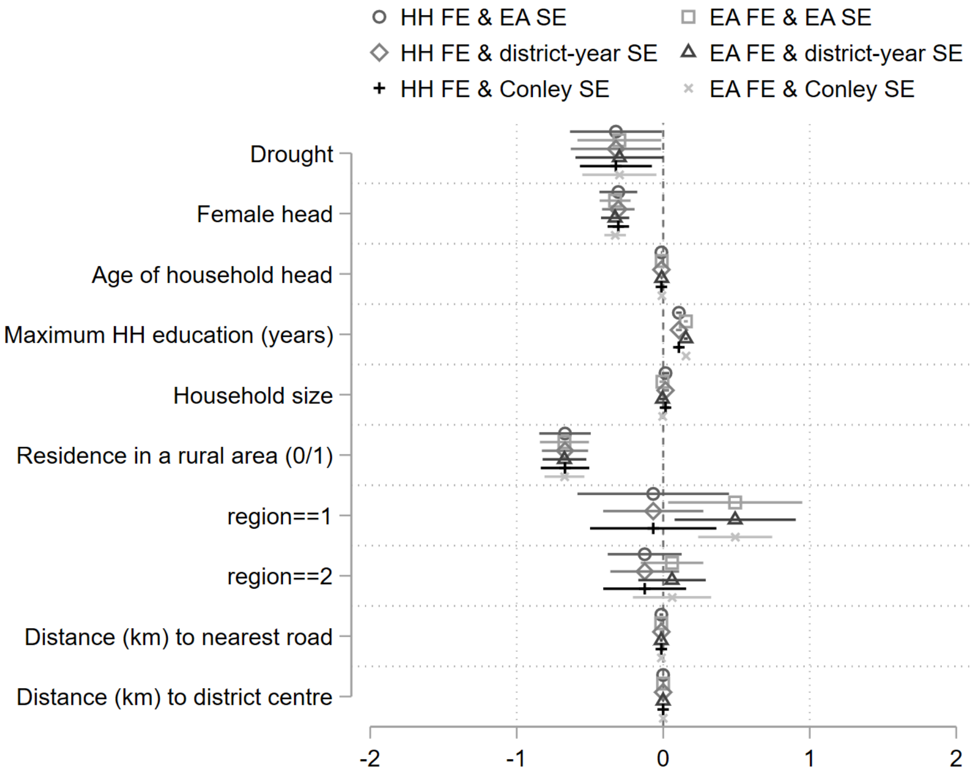
Note: Drought is measured by multiplying SPEI by -1 and setting negative values to zero such that larger values mean dire drought conditions. Control variables used are sex of household head; age of household head; education level of the most educated household member; household size; whether household resides in a rural area; region of residence; distance in kilometres to the nearest road; and distance in kilometres to the district centre. Numbers in parentheses are Conley(1999), Spatial-HAC standard errors with a 50km cutoff. *** indicates 1% significance level; ** indicates 5% significance level; and * indicates 10% significance level.

**Figure 12. Coefficient plot replicating table 2 - Panel A (FCS), but pooling all data from 2010 to 2020 and using different fixed effects and standard errors instead of 2013 and 2016 data.**




Note: Drought is measured by multiplying SPEI by -1 and setting negative values to zero such that larger values mean dire drought conditions. All specifications use year fixed effects. HH = household, EA = Enumeration area, FE = fixed effect and SE = Standard error. Conley SE refer to Conley(1999) Spatial heteroskedastic and autocorrelation consistent standard errors with a Bartlett kernel decay weights and a Bartlett kernel decay weights and a 50 km distance cutoff.

**Figure 13. Coefficient plot replicating table 2 – Panel B (HDDS), but pooling all data from 2010 to 2020 and using different fixed effects and standard errors instead of 2013 and 2016 data only.**




Note: Drought is measured by multiplying SPEI by -1 and setting negative values to zero such that larger values mean dire drought conditions. All specifications use year fixed effects. HH = household, EA = Enumeration area, FE = fixed effect and SE = Standard error. Conley SE refer to Conley(1999) Spatial heteroskedastic and autocorrelation consistent standard errors with a Bartlett kernel decay weights and a 50 km distance cutoff.

**Table 13. Replicating table 5, but using household fixed effects instead of household fixed effects (using 2013 and 2016 data).**

| VARIABLES | (1)<br>Number of children less than 24 months old | (1)<br>Number of children less than 60 months old |
|---|---|---|
| Drought ($\tau_1$) | -0.0166 | -0.0107 |
| | (0.0259) | (0.0188) |
| Household fixed effects? | Yes | Yes |
| Survey round fixed effects? | Yes | Yes |
| Observations | 4,450 | 4,450 |
| R-squared | 0.000 | 0.000 |
| Mean of outcome variable | 0.292 | 0.718 |
| Std. dev. of outcome variable | 0.482 | 0.769 |

Note: Drought is measured by multiplying SPEI by -1 and setting negative values to zero such that larger values mean dire drought conditions. Control variables used are child age(in months); square of child age; child sex (male = 1); sex of household head (female = 1); age of household head; education level of the most educated household member; household size; whether households uses safe water sources; whether household resides in a rural area; region of residence; distance in kilometres to the nearest road; and distance in kilometres to the district centre. Numbers in parentheses are Conley(1999) Spatial-HAC standard errors with a 50 km distance cutoff. *** indicates 1% significance level; ** indicates 5% significance level; and * indicates 10% significance level.

**Table 14. Replicating table 6, but using household fixed effects instead of enumeration area fixed effects.**

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
|---|---|---|---|---|---|---|---|---|---|
| *Panel A: Outcome variable is WHZ* | All seasons | | | Dry season (Apr - Sept) | | | Rainy season (Oct - Mar) | | |
| Drought ($\tau_1$) | -0.211*** | -0.360*** | -0.344*** | -0.294*** | -0.209 | -0.225 | -0.0860 | -0.0714 | -0.0122 |
| | (0.0759) | (0.111) | (0.117) | (0.112) | (0.197) | (0.193) | (0.0936) | (0.224) | (0.247) |
| Household fixed effects? | No | Yes | Yes | No | Yes | Yes | No | Yes | Yes |
| Survey wave fixed effects? | No | Yes | Yes | No | Yes | Yes | No | Yes | Yes |
| Control variables? | No | No | Yes | No | No | Yes | No | No | Yes |
| Observations | 2,576 | 2,576 | 2,576 | 1,406 | 1,406 | 1,406 | 1,170 | 1,170 | 1,170 |
| R-squared | 0.006 | 0.005 | 0.024 | 0.008 | 0.001 | 0.043 | 0.001 | 0.000 | 0.015 |
| Mean of outcome variable | 0.244 | 0.244 | 0.244 | 0.305 | 0.305 | 0.305 | 0.172 | 0.172 | 0.172 |
| Std. dev. of outcome variable | 1.385 | 1.385 | 1.385 | 1.476 | 1.476 | 1.476 | 1.266 | 1.266 | 1.266 |
| *Panel B: Outcome variable is wasting (0/1)* | | | | | | | | | |
| Drought ($\tau_1$) | -0.0199** | 0.0241* | 0.0207 | -0.0219 | 0.0403 | 0.0366 | -0.0106 | -0.0444 | -0.0477 |
| | (0.00842) | (0.0140) | (0.0140) | (0.0146) | (0.0261) | (0.0253) | (0.0125) | (0.0271) | (0.0290) |
| Enumeration area fixed effects? | No | Yes | Yes | No | Yes | Yes | No | Yes | Yes |
| Survey wave fixed effects? | No | Yes | Yes | No | Yes | Yes | No | Yes | Yes |
| Control variables? | No | No | Yes | No | No | Yes | No | No | Yes |
| Observations | 2,650 | 2,650 | 2,650 | 1,457 | 1,457 | 1,457 | 1,193 | 1,193 | 1,193 |
| R-squared | 0.002 | 0.001 | 0.027 | 0.002 | 0.002 | 0.036 | 0.001 | 0.002 | 0.041 |
| Mean of outcome variable | 0.0491 | 0.0491 | 0.0491 | 0.0570 | 0.0570 | 0.0570 | 0.0397 | 0.0397 | 0.0397 |
| Std. dev. of outcome variable | 0.216 | 0.216 | 0.216 | 0.232 | 0.232 | 0.232 | 0.195 | 0.195 | 0.195 |

Note: Drought is measured by multiplying SPEI by -1 and setting negative values to zero such that larger values mean dire drought conditions. Control variables used are child age(in months); square of child age; child sex (male = 1); sex of household head (female = 1); age of household head; education level of the most educated household member; household size; whether households uses safe water sources; whether household resides in a rural area; region of residence; distance in kilometres to the nearest road; and distance in kilometres to the district centre. Numbers in parentheses are Conley(1999) Spatial-HAC standard errors with a 50 km distance cutoff. *** indicates 1% significance level; ** indicates 5% significance level; and * indicates 10% significance level.

**Table 15. Replicating table 6, but using cluster standard errors instead of Conley (1999) Spatial HAC standard errors.**

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
|---|---|---|---|---|---|---|---|---|---|
| *Panel A: Outcome variable is WHZ* | All seasons | | | Dry season (Apr - Sept) | | | Rainy season (Oct - Mar) | | |
| Drought ($\tau_1$) | -0.211*** | -0.432** | -0.425** | -0.294*** | -0.365 | -0.364 | -0.0860 | -0.121 | -0.0768 |
| | (0.0708) | (0.169) | (0.179) | (0.0984) | (0.235) | (0.249) | (0.0911) | (0.250) | (0.261) |
| Enumeration area fixed effects? | No | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Survey fixed round effects? | No | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Control variables? | No | No | Yes | No | No | Yes | No | No | Yes |
| Observations | 2,576 | 2,575 | 2,575 | 1,406 | 1,395 | 1,395 | 1,170 | 1,162 | 1,162 |
| R-squared | 0.006 | 0.082 | 0.095 | 0.008 | 0.124 | 0.144 | 0.001 | 0.126 | 0.135 |
| Mean of outcome variable | 0.243 | 0.243 | 0.243 | 0.305 | 0.303 | 0.303 | 0.168 | 0.168 | 0.168 |
| Std. dev. of outcome variable | 1.385 | 1.386 | 1.386 | 1.476 | 1.480 | 1.480 | 1.265 | 1.266 | 1.266 |
| *Panel B: Outcome variable is wasting (0/1)* | | | | | | | | | |
| Drought ($\tau_1$) | -0.0199** | 0.00626 | 0.00715 | -0.0219 | 0.0155 | 0.0162 | -0.0106 | -0.0755** | -0.0760** |
| | (0.00954) | (0.0195) | (0.0200) | (0.0149) | (0.0299) | (0.0308) | (0.0108) | (0.0310) | (0.0326) |
| Enumeration area fixed effects? | No | Yes | Yes | No | Yes | Yes | No | Yes | Yes |
| Survey wave fixed effects? | No | Yes | Yes | No | Yes | Yes | No | Yes | Yes |
| Control variables? | No | No | Yes | No | No | Yes | No | No | Yes |
| Observations | 2,650 | 2,649 | 2,649 | 1,457 | 1,445 | 1,445 | 1,193 | 1,185 | 1,185 |
| R-squared | 0.002 | 0.044 | 0.063 | 0.002 | 0.069 | 0.094 | 0.001 | 0.089 | 0.104 |
| Mean of outcome variable | 0.0487 | 0.0487 | 0.0487 | 0.0570 | 0.0574 | 0.0574 | 0.0386 | 0.0388 | 0.0388 |
| Std. dev. of outcome variable | 0.215 | 0.215 | 0.215 | 0.232 | 0.233 | 0.233 | 0.193 | 0.193 | 0.193 |

Note: Drought is measured by multiplying SPEI by -1 and setting negative values to zero such that larger values mean dire drought conditions. To only focus on the 2016 drought SPEI values for 2013 are set to zero. Control variables used are sex of household head; age of household head; education level of the most educated household member; household size; whether household resides in a rural area; region of residence; distance in kilometres to the nearest road; and distance in kilometres to the district centre. Numbers in parentheses are robust standard errors clustered at the enumeration area level. *** indicates 1% significance.

**Table 16. Replicating table 6, but disaggregating by sex of child instead of seasons.**

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
|---|---|---|---|---|---|---|---|---|---|
| *Panel A: Outcome variable is WHZ* | All children | | | Female children only | | | Male children only | | |
| Drought ($\tau_1$) | -0.211*** | -0.432*** | -0.427*** | -0.238** | -0.393*** | -0.341** | -0.183** | -0.415** | -0.424** |
| | (0.0752) | (0.114) | (0.116) | (0.0939) | (0.131) | (0.136) | (0.0905) | (0.178) | (0.180) |
| Enumeration area fixed effects? | No | Yes | Yes | No | Yes | Yes | No | Yes | Yes |
| Survey wave fixed effects? | No | Yes | Yes | No | Yes | Yes | No | Yes | Yes |
| Control variables? | No | No | Yes | No | No | Yes | No | No | Yes |
| Observations | 2,576 | 2,576 | 2,576 | 1,339 | 1,339 | 1,339 | 1,237 | 1,237 | 1,237 |
| R-squared | 0.006 | 0.005 | 0.018 | 0.008 | 0.004 | 0.024 | 0.004 | 0.004 | 0.027 |
| Mean of outcome variable | 0.244 | 0.244 | 0.244 | 0.254 | 0.254 | 0.254 | 0.233 | 0.233 | 0.233 |
| Std. dev. of outcome variable | 1.385 | 1.385 | 1.385 | 1.328 | 1.328 | 1.328 | 1.444 | 1.444 | 1.444 |
| *Panel B: Outcome variable is wasting (0/1)* | | | | | | | | | |
| Drought ($\tau_1$) | -0.0199** | 0.00626 | 0.00796 | -0.0181* | 0.00755 | -0.000131 | -0.0218 | 0.00496 | 0.0114 |
| | (0.00882) | (0.0149) | (0.0150) | (0.0102) | (0.0162) | (0.0170) | (0.0138) | (0.0264) | (0.0258) |
| Enumeration area fixed effects? | No | Yes | Yes | No | Yes | Yes | No | Yes | Yes |
| Survey wave fixed effects? | No | Yes | Yes | No | Yes | Yes | No | Yes | Yes |
| Control variables? | No | No | Yes | No | No | Yes | No | No | Yes |
| Observations | 2,650 | 2,650 | 2,650 | 1,378 | 1,378 | 1,378 | 1,272 | 1,272 | 1,272 |
| R-squared | 0.002 | 0.000 | 0.017 | 0.002 | 0.000 | 0.027 | 0.002 | 0.000 | 0.022 |
| Mean of outcome variable | 0.0491 | 0.0491 | 0.0491 | 0.0389 | 0.0389 | 0.0389 | 0.0602 | 0.0602 | 0.0602 |
| Std. dev. of outcome variable | 0.216 | 0.216 | 0.216 | 0.194 | 0.194 | 0.194 | 0.238 | 0.238 | 0.238 |

Note: Drought is measured by multiplying SPEI by -1 and setting negative values to zero such that larger values mean dire drought conditions. To only focus on the 2016 drought SPEI values for 2013 are set to zero. Control variables used are child age (in months); square of child age; sex of household head (female = 1) ; age of household head; education level of the most educated household member; household size; whether households uses safe water sources; whether household resides in a rural area; region of residence; distance in kilometres to the nearest road; and distance in kilometres to the district area centre. Numbers in parentheses are Conley(1999) Spatial-HAC standard errors with a 50 km distance cutoff. *** indicates 1% significance level; ** indicates 5% significance level; and * indicates 10% significance level.

**Figure 14. Coefficient plot replicating table 6, but pooling all data from 2010 to 2020 and using different fixed effects and standard errors instead of 2013 and 2016 data only**