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Working Paper

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WIDER Working Paper, No. 36/25

Provided in Cooperation with:

United Nations University (UNU), World Institute for Development Economics Research (WIDER)

Suggested Citation: Kenamu, Edwin; Colen, Liesbeth (2025) : Estimating the effects and seasonal dynamics of Malawi's 2015-16 drought and humanitarian transfers on household food insecurity and child malnutrition, WIDER Working Paper, No. 36/25, ISBN 978-92-9256-595-4, The United Nations University World Institute for Development Economics Research (UNU-WIDER), Helsinki, <https://doi.org/10.35188/UNU-WIDER/2025/595-0>

This Version is available at:

<https://hdl.handle.net/10419/322161>

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Estimating the effects and seasonal dynamics of Malawi's 2015–16 drought and humanitarian transfers on household food insecurity and child malnutrition

Edwin Kenamu¹ and Liesbeth Colen²

May 2025

Abstract: In 2015, Southern Africa experienced a drought that affected approximately 30 million people across seven countries. Using a nationally representative household panel survey data set 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 insecurity and child malnutrition in Malawi, and the mitigating effect of a humanitarian transfer programme. 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, food security, and acute child malnutrition, particularly soon after the failed harvest. The dietary quality and nutritional outcomes of drought- and non-drought-exposed households converged later in the year. Humanitarian transfers made in the aftermath of the drought had positive but insignificant mitigation effects on diets and acute child malnutrition.

Key words: drought, child nutrition, food consumption, Malawi, seasonality, short-term effects

JEL classification: I38, O12, O15

Acknowledgements: This research was financially supported by the German Research Foundation through grant number RTG 2654, ‘Sustainable food systems’. The paper also benefitted from the support of UNU-WIDER’s ‘Strengthening safety nets in post-conflict and humanitarian contexts’, funded by the Ministry for Foreign Affairs of Finland. We thank Kalle Hirvonen, Rodrigo Oliveira, Krisztina Kis-Katos, Jan Duchoslav, Petros Mkandawire, Jasmin Wehner, members of RTG 2654 at the University of Goettingen, and attendees of the 2024 Global Food Security Conference in Leuven, Belgium, for comments that helped to improve this paper.

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This study has been prepared within the UNU-WIDER project **Strengthening safety nets in post-conflict and humanitarian contexts**, funded by the Ministry for Foreign Affairs of Finland. The project is part the research area **From conflict to cohesion – pathways for peace and inclusive statebuilding**.

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ISSN 1798-7237 ISBN 978-92-9256-595-0

<https://doi.org/10.35188/UNU-WIDER/2020/595-0>

Typescript prepared by Merl Fluin.

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The Institute is funded through income from an endowment fund with additional contributions to its work programme from Finland, Sweden, and the United Kingdom as well as earmarked contributions for specific projects from a variety of donors.

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The views expressed in this paper are those of the author(s), and do not necessarily reflect the views of the Institute or the United Nations University, nor the programme/project donors.

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 programmes (UNDP 2022; World Bank 2021). However, weather shocks, which are becoming increasingly frequent and unpredictable due to climate change (Hellden et al. 2021; Masson-Delmotte 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 few 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 not only affect them in the short term but also tend to have lifelong consequences (Barker 1990; 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 with other children. The literature shows that these children are significantly shorter (Aguilar and Vicarelli 2022; Akresh et al. 2011; Dercon and Porter 2014; Hoddinott and Kinsey 2001; Rosales-Rueda 2018), attain lower educational levels (Alderman et al. 2006; Maccini and Yang 2009), 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., Brown et al. 2020; Headey and Venkat 2024; Hellden et al. 2021; Lieber et al. 2022). Despite the large number of studies, the quality of the causal effect identification is not assured in all studies, and evidence remains limited on the immediate and short-term effects, the analysis of pathways, and the role of seasonality (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 are 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 is important for the design of effective and timely relief measures. Dietary pathways, in the form of households' food consumption choices in response to weather shocks or adjustments in the intrahousehold allocation of food, remain largely unstudied. A very few studies assess effects on indicators such as food groups consumed, dietary quality, or food security responses (Headey and Venkat 2024), but they evaluate the effects only several months or years after the shocks and are not able to identify households' short-term responses.

Furthermore, 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 long been recognized (Chambers and Maxwell

1981; Readorn and Matlon 1989) and has gained renewed interest in recent years (Chirwa et al. 2013; De Janvry et al. 2022; Dimitrova 2021; Gilbert et al. 2017; Zanello et al. 2019).

Also, child growth and the relationship between weight and height gain have 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 are highest after the main harvest and lowest in the rainy season, when incidents of infectious diseases are most common and food security is poor. The timing of shocks in relation to the typical seasonal calendar, including 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.

Finally, there is scant evidence on the immediate effects of humanitarian transfers in mitigating weather shocks. The nature of the shocks and the humanitarian response, which targets those most severely affected, makes it very difficult to unambiguously identify the causal impact. The current evidence is based on a limited number of specific social protection programmes (e.g., Hidrobo et al. 2024; Hirvonen et al. 2023), or on studies that assess the effects of regular (food) aid (e.g., Quisumbing 2003), which may differ from the effects of emergency responses.

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 unfolded. Using Malawi's Living Standards Measurement Study— Integrated Household Panel Survey (LSMS-IHPS),¹ of which the 2016 round coincides 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 the lean season to the next harvest. Using the variation in timing of the interviews, we are able to identify how and when households activate various food consumption coping strategies in response to shocks, and when acute effects on child malnutrition are observed. Additionally, we assess the effectiveness of humanitarian transfers distributed during the drought in mitigating the effects of the drought.

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 farming season. We use a Standardized Precipitation Evapotranspiration Index (SPEI) data set by Peng et al. (2019) to measure the climatic water balance. Peng's SPEI for Africa is a high-resolution satellite data set with a spatial resolution of five kilometres by five kilometres and a monthly temporal resolution from January 1981 to December 2016. Combining these data with Malawi's IHPS household survey panel allows us to identify locations that experience agricultural drought conditions in our farming season of interest, thus enabling us to estimate how diets, food insecurity experiences, and child nutrition outcomes respond to intensifying drought conditions in these locations. In the second part of our analysis, we estimate the drought-mitigating effects of the humanitarian response programme by interacting household-level reporting of receipt of transfers in areas targeted by the programme with the drought variable. We use panel fixed effects models with Conley (1999) standard errors to account for spatial correlation across observations.

¹ Household data were collected under the World Bank's LSMS-IHPS.

Our analysis shows that the 2015–16 drought has 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 an increase in relative dryness by one standard deviation leads to an average 8.5% decline in the FCS compared with its mean value. The effect is larger during the dry season, when the FCS drops by about 12% relative to its mean. However, the drought's effect on dietary quality disappears during the rainy season, when all households face a lean period. We find similar overall results when we use the 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 the drought-induced increase in consumption of cereals and the decrease in consumption of fish, vegetables, and fats and oils.

Furthermore, our analysis shows that the change in diet composition during the dry season is just a first response to the drought. We find evidence that as the year progresses and households exhaust food stocks, they resort 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 children aged under five years in the immediate aftermath of the drought. We estimate that, on average, an increase in relative dryness by one standard deviation during the 2015–16 farming season results in a 0.34 standard deviation decline in child weight-for-height Z scores (WHZ). Again, the effects are concentrated in the dry season, when the drought leads to a 0.36 standard deviation decline in WHZ scores while having an insignificant effect in the subsequent rainy season, when the usual lean period starts.

In our analysis of the effectiveness of the humanitarian response programme, our results show positive but statistically insignificant estimates for the effects of humanitarian transfers in mitigating the drought effects on dietary quality, food security responses, and acute child malnutrition.

The rest of the paper develops as follows. Section 2 provides a brief background to the 2015–16 drought in Malawi. Section 3 presents our conceptual framework and hypotheses, while section 4 outlines our methodology. We report our main results in section 5 and assess the robustness of our results in section 6. We give concluding remarks in section 7.

2 The 2015–16 drought in Malawi and the Food Insecurity Response Programme (FIRP)

In 2015, the Southern Africa region experienced the strongest El Niño event of the last 50 years (WFP 2016). El Niño caused intense drought in Botswana, Eswatini, Lesotho, Madagascar, Malawi, Mozambique, South Africa, Zambia, and Zimbabwe, resulting in food insecurity conditions in parts of these countries in 2016 and 2017 (FAO 2020). According to the 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 programmes aimed at saving the situation, with the Southern African Development Community estimating that US\$2.7 billion was needed to respond to the emergency.

The 2016–17 food insecurity was dire in Malawi, as it followed low agricultural production during the 2014–15 season due to late onset of rainfall, erratic rains in some parts of the country, and floods in others. About 2.8 million people were already in need of humanitarian aid in 2015. Therefore, the drought worsened an already precarious situation as it hit the country during the main farming months of November 2015 and March 2016, with the Southern and Central regions receiving 50% and 80% of normal rainfall respectively (Babu et al. 2018). This resulted in widespread food insecurity in 2016 and early 2017, with about 40% of the Malawian population in 24 of 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 food insecurity through a FIRP that targeted affected households with cash and food transfers between July 2016 and March 2017, shortly before the 2017 harvest.

At the time of its implementation, the FIRP was the largest humanitarian programme to be implemented in Malawi in terms of both financial resources used and number of beneficiaries targeted. The programme aimed to save lives, protect livelihoods, and build the resilience of about 6.7 million Malawians (about 40% of the population), at a cost of US\$300 million (in 2018 exchange rates), in 24 of Malawi's 28 districts (Babu et al. 2018). The FIRP was implemented through clusters with interventions in (1) agriculture, (2) nutrition, (3) health, (4) water, sanitation, and hygiene, (5) education, and (6) protection, on top of in-kind food distribution and cash transfers to reduce food insecurity.

Transfers started in July 2016 in Nsanje District, a district most affected by the hunger that followed the drought. Beneficiary targeting was at traditional authority (TA) level²: depending on TA, households received either cash or in-kind food assistance. The beneficiary households received transfers of either 50 kilos of maize, ten kilos of beans, and five litres of cooking oil per month, or its monetary equivalent at prevailing market prices, i.e. approximately US\$20 at February 2017 exchange rates, and the transfer value did not vary by household size (Duchoslav et al. 2023).

While beneficiary TAs were selected centrally by the programme, beneficiary households within TAs were selected by the community through community-based targeting criteria implemented by government officials during community meetings. To qualify for the programme, households needed to satisfy at least one of the following Joint Emergency Food Aid Programme (JEFAP) criteria: (1) be caring for orphaned children less than 18 years old; (2) be headed by a child; (3) be headed by an elderly person (over 65 years old); (4) have at least one member who was chronically ill or had HIV/AIDS; (5) be headed by a female member; (6) have experienced two or more years of successive crop failure; (7) have at least one malnourished child receiving supplementary or therapeutic feeding. Communities were required to select the most vulnerable households from a list of the households that met these JEFAP criteria. The number of beneficiaries per TA was predetermined by district-level government officials.

3 Conceptual framework and hypotheses

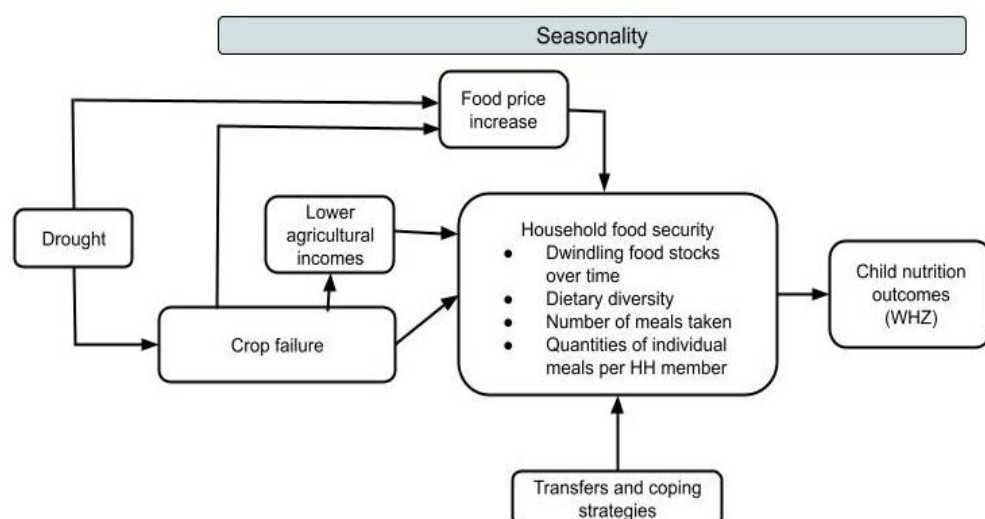
Figure 1 illustrates a conceptual framework outlining the main channels through which an agricultural drought such as that in Malawi in 2015–16 can affect food insecurity and child nutrition. In a context

² A TA area is a subdistrict unit falling under the jurisdiction of a local leader, who is also called a TA.

where household food security relies on both the household's own food production and food purchases, a drought can 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 their 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 harvest 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 may start hoarding stocks of food they would otherwise have sold during the growing season (Conte et al. 2023), and traders may hoard food to sell when prices are high after a failed harvest, thereby driving up food prices during the growing season, even before the failed harvest comes in (Osborne 2005). Additionally, droughts have negative effects on agricultural incomes through both reduced crop sales and lower employment opportunities and wages for agricultural workers, further lowering food consumption for households relying on market purchases.

Figure 1: Pathways through which the 2015–16 drought affected food security and child nutrition

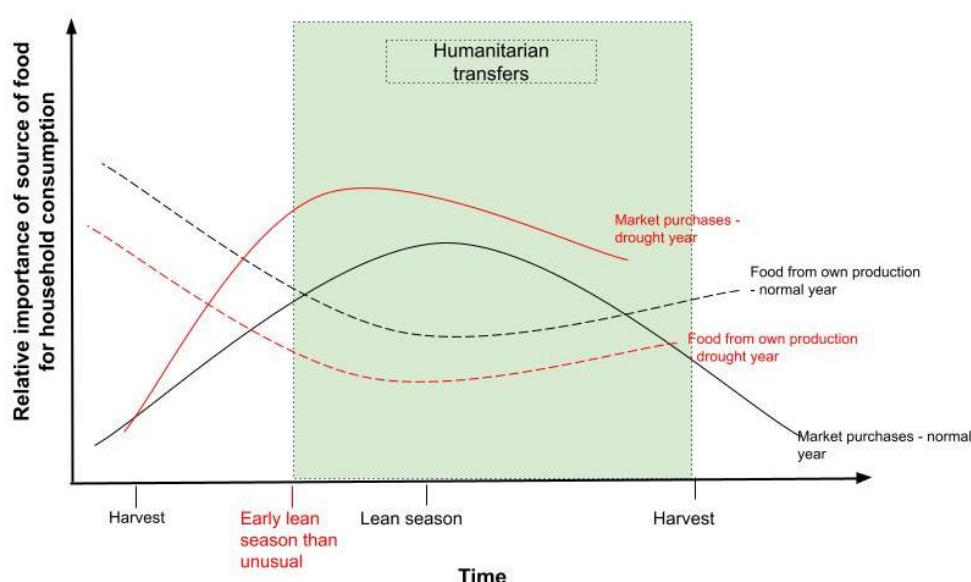


Source: authors' illustration.

Figure 2 illustrates (in black) the seasonal variation in food stocks, reliance on household-produced food, and dependence on food markets during a normal year. Typically, households have the highest food stocks immediately after the harvest (i.e. in the 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 to 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 2), resulting in prolonged periods of food insecurity. These households are forced to adopt negative coping strategies earlier and sustain them for longer compared with 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. Children aged under five years, depending on age, gender, 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 may experience wasting in the short run, and stunting if the food insecurity persists.

Figure 2: Seasonal variation in food stocks, reliance on household-produced food, and dependence on food markets



Source: authors' illustration.

We test these hypothesized outcomes following the 2015–16 drought in Malawi. Specifically, we examine the effect of the drought on dietary quality and household food security responses, and on acute child nutrition and wasting. We explore these effects during two different seasons, to empirically evaluate the timing of household responses and malnutrition outcomes over the year. Finally, we examine whether humanitarian transfers distributed through the FIRP play a role in moderating the negative drought effects.

4 Empirical strategy

4.1 Data

4.1.1 LSMS-IHPS

We use household- and child-level data from the 2013 and 2016 waves of Malawi's LSMS-IHPS. The IHPS is a ten-year-long nationally representative panel data set 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 the 2013 and 2016 IHPS rounds are based on listings from Malawi's 2008 decennial Population and Housing Census, include the three major regions of Malawi (Northern, Central, and Southern), 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) are randomly selected from the census, and 16 households are randomly selected within each EA. The initial 2010–11 round sampled 3,246 households in 204 EAs. A subsample of about 1,500 households from 102 EAs (out of the initial 204 EAs) was selected in 2010 for reinterview every three years to build a multiyear panel, with the sample size growing as the households split. For this study, we rely on this multiyear panel, which consists of 1,990 households in the 2013 wave and increases 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 children under five.

4.1.2 Seasonality and timing of IHPS data collection

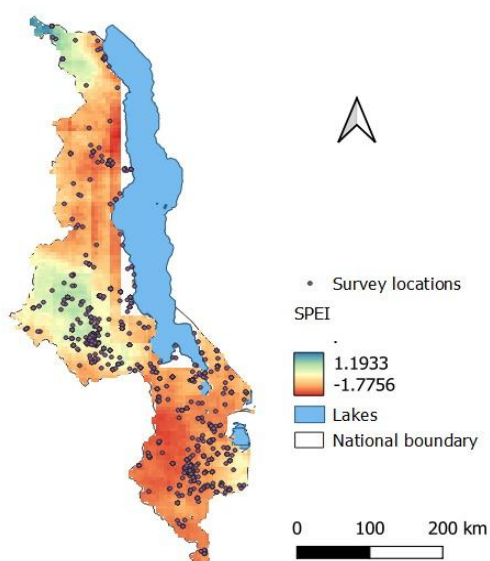
The IHPS data in Malawi are collected in such a way that they capture the seasonality of agricultural production and its implications for livelihoods. Malawi has two seasons. The rainy season starts mid-October and ends mid-April the next year, with the dry season spanning from April to early October (FEWSNET n.d.). The main harvest period spans from late March to July, while December to March represents the lean season, when the 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 households during the first, post-planting visit (the 'dry season sample') and to about half of households during the second, post-harvest visit (the 'rainy season sample'). The EAs were randomly assigned to either the dry or rainy subsamples at baseline (2010), so their assignment does not influence our results. Nonetheless, we conduct balancing tests to formally confirm the comparability of non-season-related characteristics across the two subsamples. We present the results of our balancing tests in Table 12 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 1% of households in the 2016 survey, the second interview was delayed due to difficulties in tracking them, resulting in their being interviewed between January and April 2017.

4.1.3 Climatic data and drought indicator

We use the SPEI to measure the intensity of the 2015–16 drought. The SPEI enables the calculation of the climatic water balance by taking the difference between precipitation and potential evapotranspiration covering periods between one and 48 months. The SPEI is expressed in standard deviations from a long-run mean for each grid (Vicente-Serrano et al. 2010). We use an SPEI data set for Africa constructed by Peng et al. (2019).³ The data set has a spatial resolution of 0.05 degrees across Africa and relies 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 a five-kilometre-by-five-kilometre-grid cell level and to reliably match it to the geographical locations of EAs in the IHPS survey data. Figure 3 is a map of Malawi summarizing the distribution of the SPEI during the main 2015–16 farming season. As we can see from the map, the whole country experienced drought conditions between December 2015 and March 2016. The main exceptions are some districts in the Central region and Chitipa District at the northern tip of the country.

Figure 3: Deviations in climatic water balance from the long-run mean in each location during the 2015–16 production season (December to March), measured using the SPEI



Note: dots are survey locations.

Source: authors' illustration.

³ The SPEI variable uses precipitation data from the Climate Hazards Group InfraRed Precipitation with Station data and potential evapotranspiration estimates from the Global Land Evaporation Amsterdam Model. The potential evapotranspiration estimates are calculated using the Priestley-Taylor equation.

The SPEI 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 at a specified point in time does not deviate from the grid's long-term average, while negative (positive) values imply water deficiencies (surpluses) compared with the grid cell's long-term average. Peng et al. (2019) categorize droughts as moderate if the 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.

To assess the impact of the 2015–16 drought, we construct an indicator of the intensity of drought for each EA. Following Hidrobo et al. (2024) and Hirvonen et al. (2023), after matching the SPEI grids with the locations of the EAs, we modify the SPEI variable by setting positive values equal to zero so that we only focus on areas that have negative water balances and hence experience 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 Humanitarian transfers

We use programme implementation data from the Malawi Vulnerability Assessment Committee's 2016 report to construct our indicator variable for exposure to the FIRP.⁴ The report identifies the affected TAs and proposes treatment with either cash or food transfers, depending on the availability of all-weather roads and active food markets during the lean season. We match the TAs listed in the Malawi Vulnerability Assessment Committee's report to the TAs in our survey data set. Approximately 75% of FIRP TAs receive in-kind food transfers. However, we do not disaggregate our analysis by transfer modality, instead focusing on whether or not a TA is treated. The FIRP variable thus captures whether or not households are located in a TA targeted by the FIRP, but it does not imply that the household itself is among the beneficiaries within the targeted TA.

To identify households that effectively receive transfers, we use a module on social safety nets in the LSMS data set that asks respondents about transfers they received in the previous 12 months, including the source (e.g., government, non-governmental organization), transfer modality, and timing of the last transfer. We use this information to create a dummy for household-level receipt of transfers, regardless of modality.

4.1.5 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 use indicators of dietary quality and household food insecurity response. We measure dietary quality using HDDS and FCS. The HDDS is the number of food groups (zero to 12) consumed by household members based on a seven-day recall (Kennedy et al. 2011). Being a simple sum of food groups consumed at the household level, HDDS gives equal importance to all 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 zero to 112, that

⁴ The Director of Disaster Response in the government of Malawi confirmed that transfers were implemented as proposed in the Malawi Vulnerability Assessment Committee's report.

accounts for dietary diversity, food frequency, and the relative nutritional value of food groups. It is calculated based on households' frequency of consuming eight food groups over a seven-day recall period (Wiesmann et al. 2009). To understand how diets shift in response to the drought, we also assess the effects of the drought on 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 seven days. These questions are based on the Household Food Insecurity Access Scale module (Coates et al. 2007). They are: (1) whether the household worries about not having enough food; (2) the number of days the household ate less preferred food in the past seven days; (3) the number of days the household limited meal portion sizes in the past seven days; (4) the number of days the household reduced the number of meals per day in the past seven days; (5) the number of days the household reduced adult consumption in the past seven days; (6) the number of days the household borrowed or was gifted food in the past seven days; (7) the number of meals taken by adults per day; (8) the number of meals taken by children (aged six months to 59 months); (9) whether the household has 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 six months and 59 months. We construct WHZ scores, a measure of acute undernourishment that captures how a child's weight-to-height ratio compares with that of a median child of the same sex and age. However, we restrict the WHZ scores to between -5 and five 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 capturing chronic malnutrition and child stunting is therefore not considered.

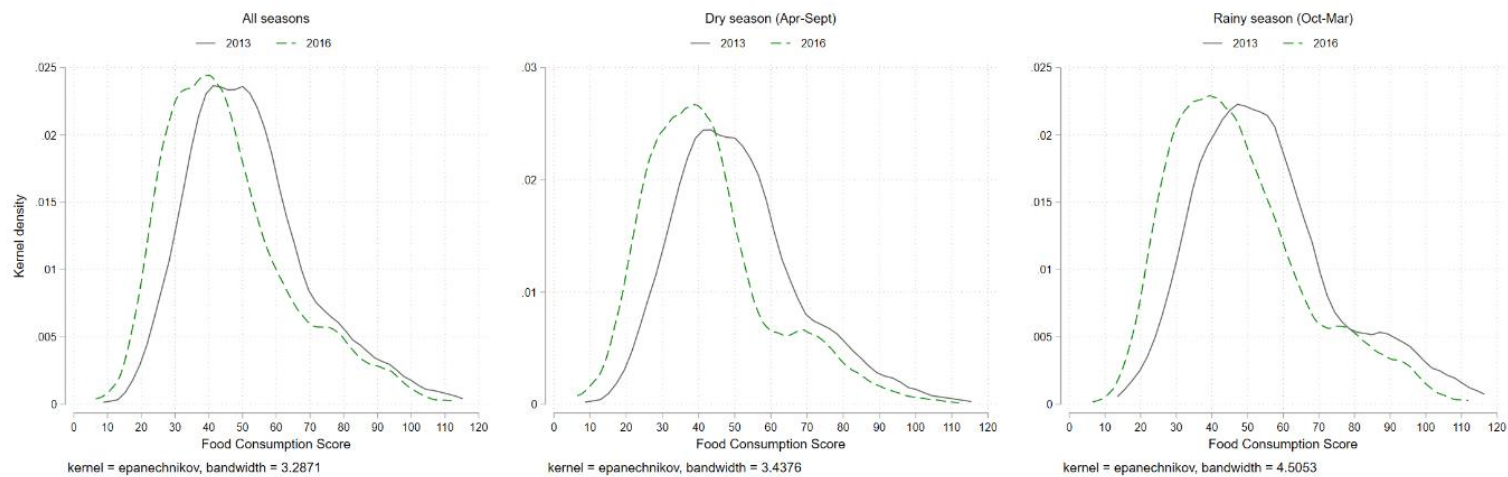
4.2 Descriptive statistics

In this section we describe the main characteristics of the sample and present a graphical descriptive analysis of our key outcome variables. Tables 10 and 11 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, and the average household is composed of five members, of whom one is child is under the age of five years. The average FCS is 51.9 in 2013 and 54.57 in 2016; on average 8.3 and 8.7 out of 12 food groups are consumed in 2013 and 2016 respectively.

Figure 4 shows the distribution of FCS by season between 2013 and 2016 and indicates that a large share of households have an FCS that is considered poor (< 21) or borderline (< 35). Generally, over all seasons, the graph shows that dietary quality is considerably better in 2013 than in 2016. A disaggregation of the analysis by season suggests that this holds similarly for both seasons. If we use HDDS as an alternative measure of dietary quality (Figure 5), the difference between 2013 and 2016 is less clear, with the density of households that report consuming over ten food groups being slightly higher in 2016.

Table 1 describes households' experiences of food insecurity: 34.2% in 2013 and 51.9% in 2016 report being worried about not having enough food. The number of days in the previous week when households ate less preferred food, limited portion sizes, reduced the number of meals in a day, restricted adults' consumption, or borrowed food from others is reported to be higher in 2016 than in 2013. The number of meals taken by adults and by children under five is lower in 2016 compared with 2013. The number of households who report having faced food insecurity situations in the previous year is similar for both years.

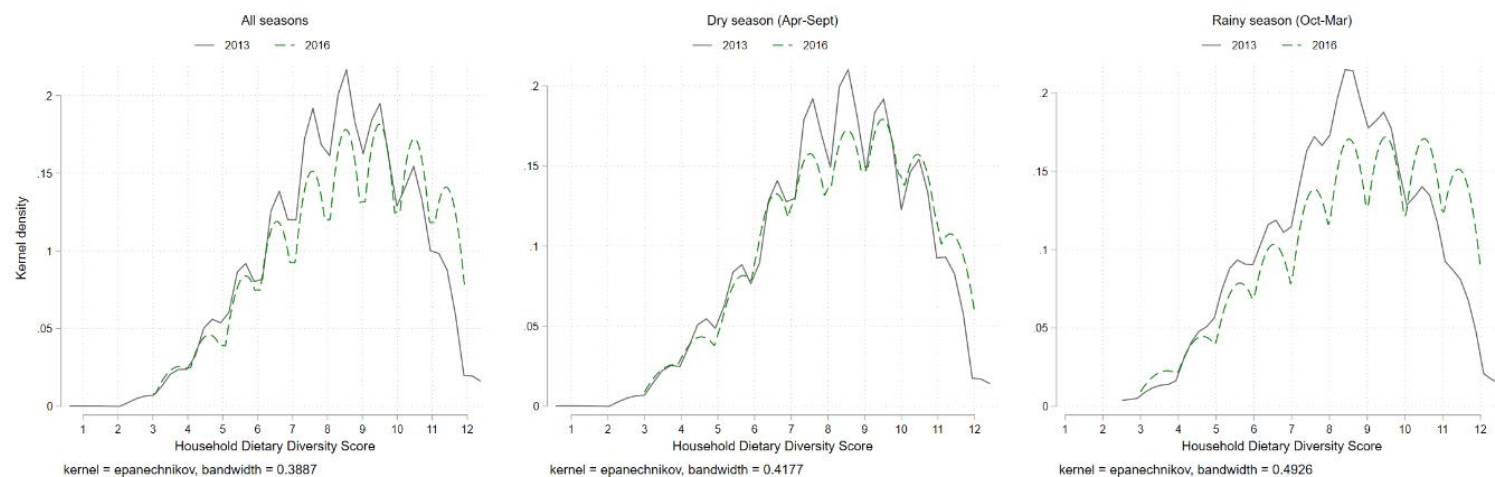
Figure 4: FCS distribution by survey round, disaggregated by season



Note: sample comprises 1,990 households in 2013 and 2,508 households in 2016. Analysis uses sampling weights.

Source: authors' illustration.

Figure 5: HDDS distribution by survey round, disaggregated by season



Note: sample comprises 1,990 households in 2013 and 2,508 households in 2016. Analysis uses sampling weights.

Source: authors' illustration.

Table 1: Household experiences of food insecurity by survey round

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

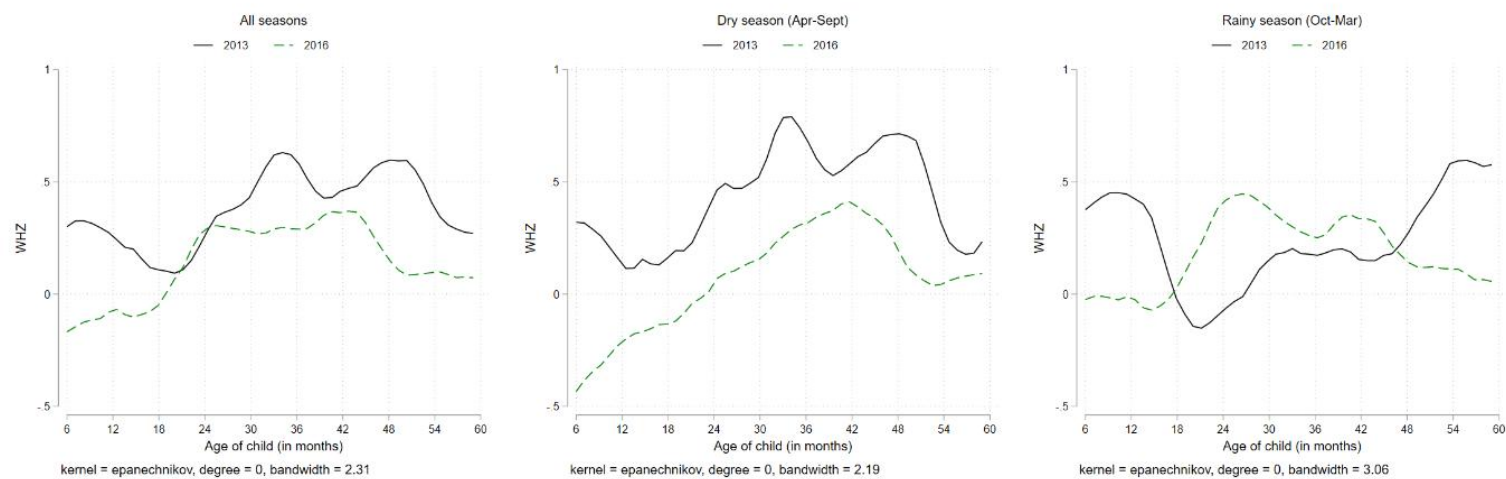
Source: authors' calculations

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

In Figure 7 we show the distribution of WHZ scores 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 8 plots the intensity of the drought by FIRP and non-FIRP locations. Generally, FIRP transfers seem to have been allocated to areas that were most severely affected by the drought, with the kernel density for FIRP areas having a peak above the one standard deviation relative dryness point. Overall, about 60% of households in our sample are in FIRP areas, and 6.5% of them report receiving transfers between October 2016 and January 2017, when IHPS data collection was completed.

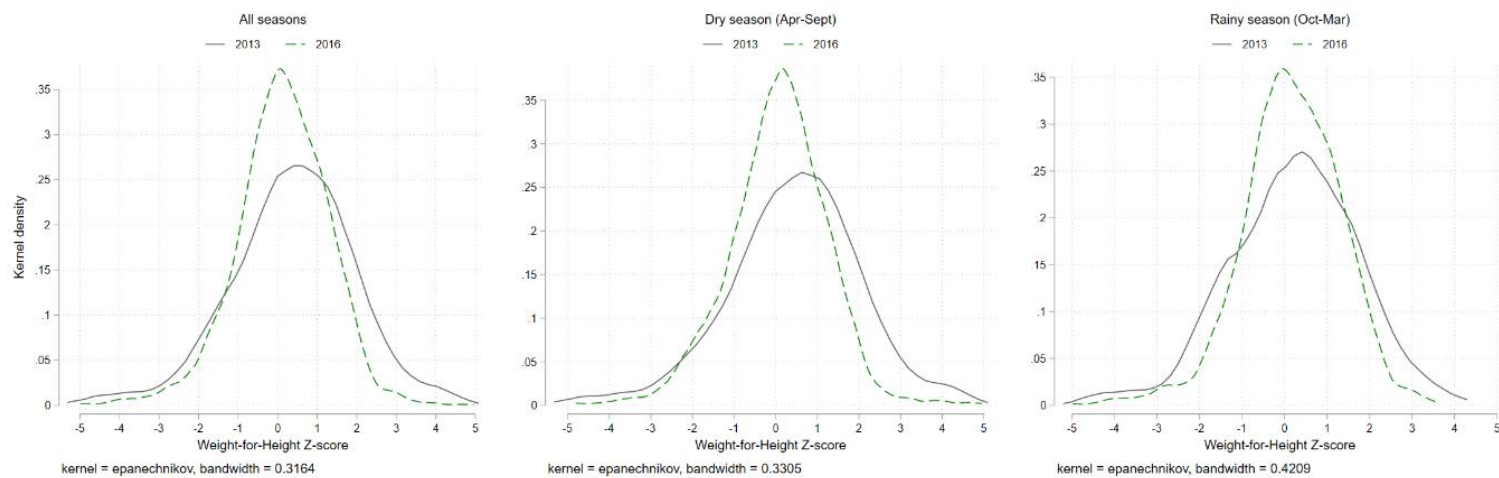
Figure 6: Local polynomial regression of WHZ scores by child age, disaggregated by season



Note: sample comprises 1,315 children in 2013 and 1,372 children in 2016. Analysis uses sampling weights.

Source: authors' illustration.

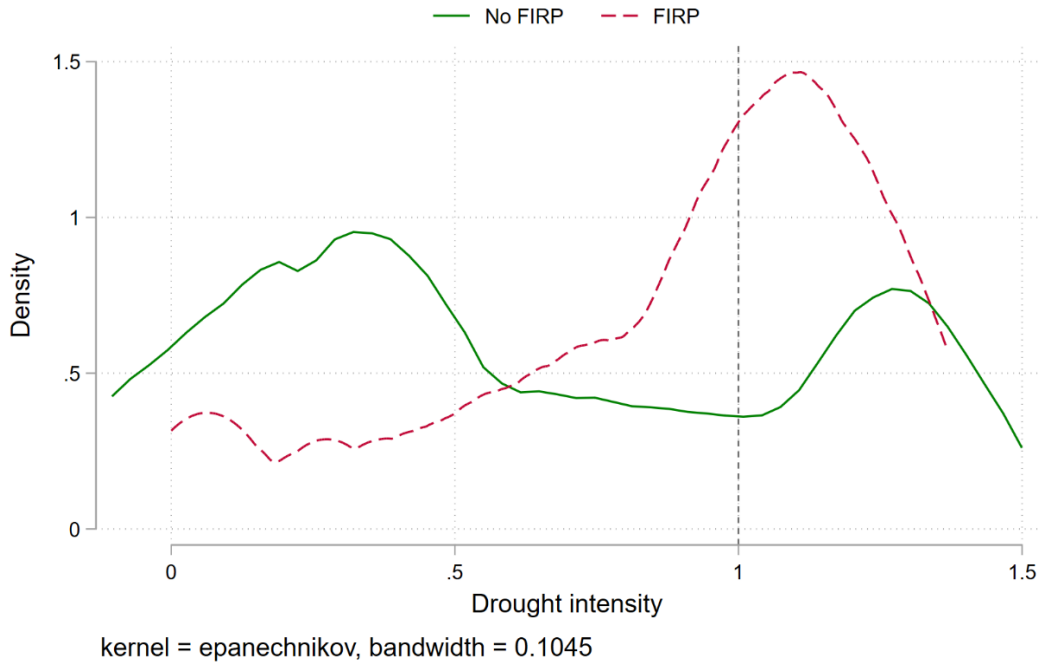
Figure 7: WHZ score distributions by survey round and season



Note: sample comprises 1,315 children in 2013 and 1,372 children in 2016. Analysis uses sampling weights.

Source: authors' illustration.

Figure 8: Drought intensity and FIRP targeting



Source: authors' illustration.

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 drought, humanitarian transfers, dietary quality, food insecurity responses, and child nutrition.

4.3 Econometric model

4.3.1 Estimating effects of the drought on food security

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

$$Y_{hct} = \alpha_f + \gamma_t + X_{hct}\delta + \beta_1 \text{drought}_c^{16} + u_{hct} \quad [1]$$

where Y_{hct} is the food security indicator for household h in EA c in year t ; α_f are fixed effects, with f referring to the household or EA, depending on the specification; γ_t is survey round fixed effects. u_{hct} is an error term, which we construct as explained in section 4.4. In this model, drought_c^{16} is our variable of interest as it measures the intensity of drought in EA c during the 2015–16 farming season. X_{hct} is factors that 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. β_1 is our parameter of interest. We test the null hypothesis that the 2015–16 drought does not affect household-level food security ($\beta_1 = 0$) against the alternative hypothesis that the drought impacts on consumption ($\beta_1 \neq 0$). We 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 experiences.

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

$$Y_{iht} = \alpha_f + \gamma_t + X_{hct}\delta + \tau_1 \text{drought}_c^{16} + u_{iht} \quad [2]$$

Here, Y_{iht} is the WHZ score or an indicator variable for wasting⁵ for child i in household h of EA c in year t , while the rest of the variables and parameters are as defined above. α_f again represents household- or EA-level fixed effects, depending on the specification. As anthropometric measurements are only taken for children up to the age of five years, 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 τ_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 does not affect short-term child nutrition ($\tau_1 = 0$) against the alternative hypothesis that the drought affects short-term child nutrition ($\tau_1 \neq 0$). Equation (2) controls for age of child in months, and its square; gender of child; age and gender of household head; number of years of education of most educated household member; whether the household uses a safe water source; whether the household resides in a rural area; region of residence of the household; distance to the nearest road; and distance to the district centre.

One of the main considerations for 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 might bias our estimates if weaker children die as a result of the drought such that we only observe outcomes of children who are strong enough to survive the drought. In such cases, the negative effects of the drought would be underestimated, or indeed positive estimates might be obtained, misleading our conclusions. The household data set that we use does not have data on child mortality. Therefore, we cannot directly test whether the 2015–16 drought causes excess child mortality. Instead, in line with equation (2), we regress variables for numbers of children aged under 24 months and under 60 months in the household on our drought indicator to test whether the drought changes the household composition.

4.3.2 Estimating potential drought-mitigating effects of humanitarian transfers

As discussed in section 2, Malawi responded to the drought by implementing a FIRP in which households in selected TA areas received food or cash transfers between July 2016 and March 2017. We assess the effect of the transfers on food consumption using the following model:

$$Y_{hct} = \alpha_f + \gamma_t + X_{hct}\delta + \beta_1 \text{drought}_c^{16} + \beta_2 \text{FIRP}_{ct} + \beta_3 \text{HT}_{hct} + \beta_4 (\text{drought}_c^{16} \times \text{FIRP}_{ct}) + \beta_5 (\text{HT}_{ht} \times \text{FIRP}_{ct}) + \beta_6 (\text{drought}_c^{16} \times \text{HT}_{hct}) + \beta_7 (\text{drought}_c^{16} \times \text{HT}_{hct} \times \text{FIRP}_{ct}) + u_{hct} \quad [3]$$

⁵ Coded one if a child has a WHZ of less than -2, and zero otherwise.

where Y_{hct} is food security outcome of household h in community c in year t ; HT_{hct} is a dummy variable equal to one if a household reports receiving cash or in-kind food transfers in year t and zero otherwise; $FIRP_{ct}$ is a dummy variable equal to one if a household is in a TA assigned to the FIRP. In this model, α_f is an EA fixed effect, while γ_t is a survey round fixed effect. β_7 captures the moderating effect of transfers for households exposed to the drought in FIRP areas. The rest of the variables and parameters are as defined in equation (1). On top of controlling for factors that affect food consumption as before, we also include components of the JEFAP targeting criteria used for beneficiary-targeting as independent variables in X_{hct} . These variables are: (1) whether the household experienced crop failure⁶; (2) whether the household is female-headed; (3) whether the household has a member who is chronically ill; (4) whether the household is child-headed; (5) whether the household is elder-headed; (6) whether the household has orphaned members; (7) whether children in the household are receiving nutrition therapy. The inclusion of the targeting criteria should minimize any selection bias emanating from the fact that the programme is not randomly assigned to households.

We use the same reasoning as above to estimate the potential drought-mitigating effects of the programme on child malnutrition. We estimate the association between humanitarian transfers and child nutritional outcomes using the following model:

$$Y_{ihct} = \alpha_f + \gamma_t + X_{ihct}\delta + \tau_1 drought_c^{16} + \tau_2 FIRP_{ct} + \tau_3 HT_{hct} + \tau_4(drought_c^{16} \times FIRP_{ct}) + \tau_5(HT_{hct} \times FIRP_{ct}) + \tau_6(drought_c^{16} \times HT_{hct}) + \tau_7(drought_c^{16} \times HT_{hct} \times FIRP_{ct}) + u_{ihct} \quad [4]$$

where Y_{ihct} is WHZ score of child i in household h of community c in year t . The rest of the parameters and variables are as defined in equation (2). In this specification, we evaluate the drought-mitigating effect of the FIRP on child malnutrition by testing the null hypothesis that $\tau_7 = 0$ against the alternative hypothesis that $\tau_7 \neq 0$. For this analysis, we focus only on WHZ as the outcome variable due to limited statistical power to estimate the drought-mitigating effect of the transfers on wasting. Only about 3% of the children in our sample are classified as wasted (WHZ < -2). As Headey and Venkat (2024) note, estimating effects with such small proportions—especially when interacted with other variables—can lead to unreliable results, including potential reversals in the direction of the estimated relationship. This limitation is particularly relevant to our analysis, as our parameter of interest involves a three-way interaction, with the third variable (HT_{hct}) also affecting only about 6% of the sample.

While we analyse the effects of the drought for the dry and rainy seasons separately, our analysis of the effects of humanitarian transfers focuses on the rainy season only, because the FIRP started in July 2016 in Nsanje District and only reached full coverage in October the same year.

By definition, our SPEI-based indicator of drought is an exogenous variable in our application, so the 2015–16 drought enters our models exogenously. Hence, our parameters of interest, β_1 and τ_1 in models (1) and (2), are given a causal interpretation. After the modification discussed in section 4.1.3,

⁶ Crop failure is defined as a maize yield of less than 500 kilos per hectare, following Duchoslav et al. (2023).

our drought variable has a median value of 0.8 standard deviation. Thus, we interpret the two parameters as the *average effect of being exposed to a moderate (-1 standard deviation) drought*.

We are more careful in the causal interpretation of our estimates from models (3) and (4) regarding the effects of the transfers because we do not explicitly account for non-random access to humanitarian transfers in such a drought setting. As the transfers aim to target the most vulnerable households, controlling for the observable targeting criteria may not be sufficient to capture all selection bias. If targeting is effective, more vulnerable households will have a higher chance of receiving the transfer. If the observable targeting criteria do not fully capture this, we anticipate that our estimates of the transfers may still be downwards biased and that the true causal effect of the transfer is larger than our estimates suggest. More sophisticated methods to control for selection into treatment are to be explored further. For now, we are therefore cautious when interpreting our estimates and rather present them as lower bounds.

4.4 Calculation of standard errors

Ordinarily, studies that use the LSMS data cluster standard errors at the EA level, which is the primary sampling unit for these data. Beyond being the primary sampling unit, 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 (Hirvonen et al. 2023). In practice, drought shocks in a farming season tend to cover a much larger geographical region than an EA, so effects may be spatially correlated across several EAs. We address this concern by using Conley spatial heteroskedastic and autocorrelation-consistent (HAC) standard errors with a 50-kilometre distance cut-off. The Conley standard errors use a weighting matrix to weight households that are close to each other compared with those far apart within a specified distance. The 50-kilometre distance cut-off in our application means that we assume the spatial correlation to extend up to 50 kilometres, so observations beyond 50 kilometres away from each other have zero spatial correlation. For further robustness-checking, we also cluster the standard errors at the EA 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 within households. Table 2 summarizes estimates of a one standard deviation increase in relative dryness for household FCS (panel A) and HDDS (panel B) using EA fixed effects. The results using household fixed effects are presented in Table 14 in the Appendix. Starting with FCS and focusing on column 3, which is our preferred specification, we find that, on average, exposure to a -1 standard deviation drought reduces 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% reduction in FCS. However, the effect of the drought on FCS is 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 drops by about 5.845 points or about 12% in the dry season.

Panel B of Table 2 summarizes the impact of the drought on 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% relative to mean HDDS. In line with our finding for FCS, the point estimates for HDDS are higher in the dry than in the rainy season, but they are measured with larger errors and not significantly different from zero.

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

Table 2: Effect of 2015–16 drought on food consumption, using 2013 and 2016 data

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
		All seasons			Dry season (Apr–Sep)			Rainy season (Oct–Mar)	
<i>Panel A: outcome variable is FCS</i>									
Drought (β_1)	-5.853** (2.289)	-3.827*** (1.216)	-4.289*** (1.145)	-9.139*** (2.116)	-6.311*** (1.617)	-5.845*** (1.533)	-4.548 (2.927)	0.677 (2.057)	0.690 (1.652)
EA 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
<i>Panel B: outcome variable is HDDS</i>									
Drought (β_1)	0.306 (0.215)	-0.273* (0.164)	-0.296* (0.160)	0.230 (0.240)	-0.260 (0.214)	-0.169 (0.204)	0.261 (0.278)	-0.141 (0.245)	-0.182 (0.218)
EA 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 gender of household head; age of household head; education level of most educated household member; household size; whether household resides in a rural area; region of residence; distance in kilometres to the nearest road; distance in kilometres to the district centre. Numbers in parentheses are Conley spatial HAC standard errors with Bartlett kernel decay weights and a 50 km distance cut-off. *** indicates 1% significance level; ** indicates 5% significance level; * indicates 10% significance level.

Source: authors' calculations.

Table 3: Effect of 2015–16 drought on consumption of foods from various groups, using 2013 and 2016 data

<i>Outcome variables</i>	(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 (β_1)	0.00478* (0.00259)	-0.0160 (0.0228)	-0.00858** (0.00355)	-0.0513 (0.0375)	-0.0326 (0.0347)	-0.0101 (0.0185)	0.0255 (0.0278)	-0.0689* (0.0353)	-0.0286 (0.0264)	-0.0742*** (0.0209)	-0.0300 (0.0205)	-0.00571 (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 gender of household head; age of household head; education level of most educated household member; household size; whether household resides in a rural area; region of residence; distance in kilometres to the nearest road; distance in kilometres to the district centre. Numbers in parentheses refer to Conley spatial HAC standard errors with Bartlett kernel decay weights and a 50 km distance cut-off. *** indicates 1% significance level; ** indicates 5% significance level; * indicates 10% significance level.

Source: authors' calculations.

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 EA fixed effects. The results using household fixed effects are presented in Table 16 in the Appendix. We find that, on average, exposure to a moderate (-1 standard deviation) drought in the 2015–16 farming season results in a 0.179 increase in the number of days per week that adult household members restrict food consumption so that children in the household can eat ($p < 0.05$) (column 5). Given a mean value of 0.371, our estimate means that the drought results in a 48% increase in the number of days adults restrict their 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 results in adults in the household reducing the number of meals they eat per day by 0.141 or 5.39% ($p < 0.01$).

Considering the importance of seasonality of consumption in Malawi, we disaggregate our analysis by season to estimate how the effect of the drought varies in dry and rainy seasons. We summarize our results in Figure 9. We do not find significant effects of the drought on most of our nine indicators of household food insecurity responses during the dry season immediately following the failed harvest. However, the aggregate effect 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 five months after the failed 2016 harvest. Moreover, we find that during the rainy season, households borrow food and/or rely on food gifts more (6), and for households with children aged under five the number of meals the children eat per day increases (8) as a result of the drought.

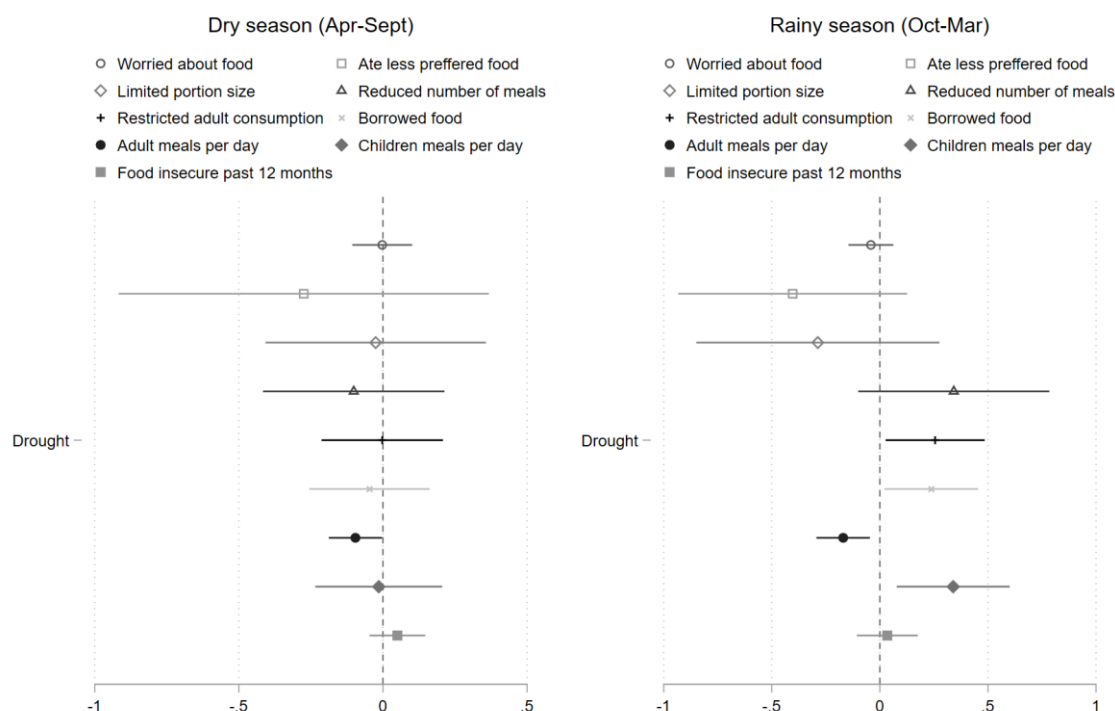
Table 4: Effect of 2015–16 drought on household food security, using 2013 and 2016 data

Outcome variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Worried about not having enough food (0/1)	Number of days household ate less preferred food in the past 7 days	Number of days limited meal portion size in past 7 days	Number of days household reduced number of meals per day in the past 7 days	Number of days household reduced adult consumption in the past 7 days	Number of days household 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)	Household faced food insecurity issues in the past 12 months (0/1)
Drought (β_1)	-0.00659 (0.0488)	-0.283 (0.242)	-0.0865 (0.170)	0.0283 (0.131)	0.179** (0.0845)	0.0230 (0.0641)	-0.141*** (0.0310)	-0.0323 (0.100)	0.0217 (0.0481)
EA 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 gender of household head; age of household head; education level of most educated household member; household size; whether household resides in a rural area; region of residence; distance in kilometres to the nearest road; distance in kilometres to the district centre. Numbers in parentheses are Conley spatial HAC standard errors with a 50 km distance cut-off. *** indicates 1% significance level; ** indicates 5% significance level; * indicates 10% significance level.

Source: authors' calculations.

Figure 9: Coefficient plots summarizing the 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 gender of household head; age of household head; education level of most educated household member; household size; whether household resides in a rural area; region of residence; distance in kilometres to the nearest road; distance in kilometres to the district centre. Analysis uses Conley spatial HAC standard errors with a 50 km distance cut-off.

Source: authors' illustration.

5.3 Effect of the drought on child malnutrition

5.3.1 Testing for potential survivorship bias

We now assess the effect of a one standard deviation 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 the 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 17 in the Appendix.

Table 5: Potential presence of survivorship bias in our estimations of drought impacts on child nutrition, using 2013 and 2016 data

Variables	Number of children less than 24 months old	Number of children less than 60 months old
Drought (τ_1)	-0.0237 (0.0328)	-0.00344 (0.0586)
EA 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 gender (male = 1); gender of household head (female = 1); age of household head; education level of most educated household member; household size; whether household uses safe water sources; whether household resides in a rural area; region of residence; distance in kilometres to the nearest road; distance in kilometres to the district centre. Numbers in parentheses are Conley spatial HAC standard errors with a 50 km cut-off. *** indicates 1% significance level; ** indicates 5% significance level; * indicates 10% significance level.

Source: authors' calculations.

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 model (2) using EA 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 18 in the Appendix. Columns 1 to 3 of panel A summarize the impacts of the drought on WHZ scores, where we start by assessing the association between a moderate (-1 standard deviation) drought and short-term malnutrition by pooling 2013 and 2016 survey waves as cross-sections. We find a negative and significant association between 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 gender, and education in the household (column 3). On average, we find that exposure to a moderate drought reduces child weight for height by about 0.344 standard deviation ($p < 0.01$).

Similarly to the drought's impact on food consumption, we hypothesize that the effects of the drought on child nutritional outcomes 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 0.364 standard deviation reduction in WHZ score ($p < 0.05$). In the rainy season the effect is negative and not statistically different from zero. We hypothesize that household coping mechanisms in response to the drought—for example, adults prioritizing children in the distribution when the lean season (rainy season) approaches—contribute to reducing the gap in WHZ between more and less drought-affected regions. At the same time, including in 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 the drought.

Panel B of Table 6 summarizes linear probability model estimates of exposure to a -1 standard deviation 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 children under five. The negative association between wasting and the drought in column 1 disappears when we introduce community and survey round fixed effects, and it 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 suggests that exposure to the drought reduces a child's probability of being wasted during the rainy season by about 8% ($p < 0.01$). A possible explanation is that coping strategies used by households with children in the rainy season (estimated in Figure 9) may have been effective in protecting the children against the negative nutritional impacts of the drought. As wasting is defined by an extremely low WHZ score, we hypothesize that drought-affected regions' catching-up in children's WHZ scores by the time of the rainy season (through adults prioritizing children, humanitarian support, or community-level measures) is especially strong for the weakest children, bringing them above the -2 score. On the other hand, the share of children being wasted in our sample is very low (about 3%), and the estimates of such small proportions may not be fully robust to outliers or potential misspecification. The small sample size also does not allow further heterogeneity analysis to investigate this in more detail. We are therefore careful in the conclusions derived from the estimates on wasting.

Table 6: Impact of the 2015–16 drought on acute malnutrition, using 2013 and 2016 data

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
		All seasons			Dry season (Apr–Sep)			Rainy season (Oct–Mar)	
<i>Panel A: outcome variable is WHZ</i>									
Drought (τ_1)	-0.211*** (0.0759)	-0.432*** (0.116)	-0.344*** (0.117)	-0.294*** (0.112)	-0.365** (0.159)	-0.364** (0.160)	-0.0860 (0.0936)	-0.121 (0.214)	-0.0768 (0.229)
EA 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
<i>Panel B: outcome variable is wasting (0/1)</i>									
Drought (τ_1)	-0.0199** (0.00883)	0.00626 (0.0147)	0.00715 (0.0148)	-0.0219 (0.0147)	0.0155 (0.0204)	0.0162 (0.0204)	-0.0106 (0.0130)	-0.0755*** (0.0220)	-0.0760*** (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
EA 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 gender (male = 1); gender of household head (female = 1); age of household head; education level of most educated household member; household size; whether household uses safe water sources; whether household resides in a rural area; region of residence; distance in kilometres to the nearest road; distance in kilometres to the district centre. Numbers in parentheses are Conley spatial HAC standard errors with a 50 km distance cut-off. *** indicates 1% significance level; ** indicates 5% significance level; * indicates 10% significance level.

Source: authors' calculations.

5.4 Role of humanitarian transfers

Table 7 summarizes our estimates of effects of transfers on FCS and HDDS during the rainy season. We focus on the rainy season sample (October to March) only, because the FIRP started in July 2016 in Nsanje District but initially took off slowly. It only reached peak coverage in October of the same year. As per our parameter of interest (β_7), we find positive but insignificant effects of transfers on both FCS and HDDS for drought-affected households that report receiving transfers in FIRP beneficiary areas. We present estimates for humanitarian transfers and consumption of specific food groups in Table 13 in the Appendix.

Table 7: Drought-mitigating effect of humanitarian transfers on food security, using 2013 and 2016 data: rainy season

Variables	(1) FCS	(2) HDDS
Drought (β_1)	2.425 (1.852)	-0.278 (0.232)
FIRP area (β_2)	0.0755 (5.536)	-0.318 (0.388)
Received transfers (β_3)	-1.761 (2.421)	0.176 (0.207)
Drought * FIRP area (β_4)	-0.614 (5.334)	0.183 (0.428)
Received transfers * FIRP area (β_5)	10.17* (5.854)	0.616 (0.525)
Drought * Received transfers (β_6)	-5.167 (8.662)	-0.348 (0.571)
Drought * Received transfers* FIRP area (β_7)	3.413 (10.10)	0.151 (0.748)
Observations	1,980	1,980
R-squared	0.129	0.147
EA fixed effects?	Yes	Yes
Survey fixed effects?	Yes	Yes
Control variables?	Yes	Yes
Mean of outcome variable	51.07	8.761
Std dev. of outcome variable	20.11	2.194

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 gender of household head; age of household head; education level of most educated household member; household size; whether household resides in a rural area; region of residence; whether household experienced crop failure; whether household has a member who is chronically ill; whether household is child-headed; whether household is elder-headed; whether household has orphaned members; whether children in the household are receiving nutrition therapy; distance in kilometres to the nearest road; distance in kilometres to the district centre. Numbers in parentheses are Conley standard errors with 50 km distance cut-off. *** indicates 1% significance level; ** indicates 5% significance level; * indicates 10% significance level.

Source: authors' calculations.

In Table 8, we assess the effects of the transfers on household food insecurity responses. Overall, we find that our estimates of the drought-mitigating effects of receipt of transfers in FIRP areas have the a priori expected signs but are not significantly different from zero on all outcomes.

Table 9 summarizes the effects of transfers in mitigating the adverse effects of the drought on acute child nutrition. As explained in section 4.3.2, we estimate the drought mitigation effect of humanitarian transfers on WHZ only. We find a positive and statistically insignificant effect of transfers in mitigating effects of a -1 standard deviation drought in FIRP areas on children's weight-for-height scores (τ_7). While the estimate has an a priori correct sign, exposure to the transfers does not seem to have a statistically significant effect on child weights in this setting.

Table 8: Drought-mitigating effect of safety nets on food security, using 2013 and 2016 data

Variables	(1) Worried about not having enough food (0/1)	(2) Number of days household ate less preferred food in the past 7 days	(3) Number of days limited meal portion size in the 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
Drought (β_1)	-0.0245 (0.0944)	-0.298 (0.453)	-0.313 (0.284)	0.192 (0.251)	0.182 (0.159)	0.227 (0.179)	-0.102 (0.0626)	0.208* (0.116)
FIRP area (β_2)	0.133 (0.104)	0.331 (0.431)	1.054** (0.437)	0.995** (0.397)	0.0438 (0.188)	0.347** (0.172)	0.0974 (0.119)	-0.0794 (0.264)
Received transfers (β_3)	0.257*** (0.0709)	0.223 (0.342)	1.097** (0.460)	0.204 (0.259)	0.207* (0.110)	0.260 (0.202)	-0.0338 (0.0801)	0.343*** (0.125)
Drought * FIRP area (β_4)	0.0384 (0.117)	-0.0314 (0.480)	-0.301 (0.477)	-0.340 (0.456)	0.139 (0.205)	0.0104 (0.207)	-0.228* (0.138)	0.263 (0.269)
Received transfers * FIRP area (β_5)	-0.497*** (0.166)	0.0722 (0.562)	-1.175* (0.629)	-0.727 (0.525)	0.197 (0.626)	-0.179 (0.314)	0.158 (0.215)	0.369 (0.387)
Drought * Received transfers (β_6)	-0.0664 (0.145)	0.102 (0.553)	0.643 (0.624)	1.461* (0.796)	-0.359** (0.140)	0.786 (0.974)	0.358*** (0.123)	-0.588 (0.593)
Drought * Received transfers* FIRP area (β_7)	0.179 (0.215)	-0.446 (0.750)	-0.0266 (0.699)	-0.863 (0.871)	0.180 (0.528)	-0.936 (1.016)	-0.247 (0.237)	0.0783 (0.743)
Observations	1,980	1,979	1,979	1,979	1,979	1,979	1,980	1,275
R-squared	0.072	0.049	0.064	0.048	0.053	0.051	0.089	0.143
EA fixed effects?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Survey fixed effects?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control variables?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean of outcome variable	0.490	1.619	1.223	1.049	0.385	0.441	2.557	2.528
Std dev. of outcome variable	0.500	2.090	1.982	1.869	1.082	1.046	0.659	1.213

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 gender of household head; age of household head; education level of most educated household member; household size; whether household resides in a rural area; region of residence; distance in kilometres to the nearest road; distance in kilometres to the district centre. Numbers in parentheses are Conley standard errors with 50 km distance cut-off. *** indicates 1% significance level; ** indicates 5% significance level; * indicates 10% significance level.

Source: authors' calculations.

Table 9: Effect of the 2015–16 drought and humanitarian transfers on child acute malnutrition, using 2013 and 2016 data

Variables	(1) WHZ
Drought (τ_1)	-0.0885 (0.196)
FIRP area (τ_2)	-0.314* (0.182)
Received transfers (τ_3)	-0.205 (0.317)
Drought * FIRP area (τ_4)	0.0561 (0.373)
Received transfers * FIRP area (τ_5)	0.0388 (0.237)
Drought * Received transfers (τ_6)	0.0300 (0.467)
Drought * Received transfers* FIRP area (τ_7)	0.0825 (0.451)
Observations	1,105
R-squared	0.037
EA fixed effects?	Yes
Survey fixed effects?	Yes
Control variables?	Yes
Mean of outcome variable	0.166
Std dev. of outcome variable	1.256

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 gender of household head; age of household head; education level of most educated household member; household size; whether household resides in a rural area; whether household has a member who is chronically ill; whether household is child-headed; whether household is elder-headed; whether household has orphaned members; whether children in the household are receiving nutrition therapy; region of residence; distance in kilometres to the nearest road; distance in kilometres to the district centre. Numbers in parentheses are Conley standard errors with 50 km cut-off. *** indicates 1% significance level; ** indicate 5% significance level; * indicates 10% significance level.

Source: authors' calculations.

6 Robustness

We conduct a number of robustness checks to assess the sensitivity of our findings. First, given that exposure to the drought in our data set is at the 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 14 and 16 in the Appendix show that regardless of the fixed effects we use, the drought has negative effects on food security. Table 17 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 types of question using similar data sets ordinarily cluster standard errors at the EA level, we follow Hirvonen et al. (2023) in using Conley 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 construct our standard errors by using cluster robust standard errors. As summarized in Tables 15, 19, and 23 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 the 2013 and 2016 waves of the IHPS 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 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 (Figure 10; Figure 11 in the Appendix) and child nutrition outcomes (Figure 12 in the Appendix).

Additionally, we estimate effects of the drought on short-term child nutrition outcomes separately for girls and boys and report the results in Table 20 in the Appendix. We still find a 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 to be generally stronger for boys than girls. Due to the small numbers of children in our sample, we cannot disaggregate this analysis by season.

Lastly, we estimate the potential drought-mitigating effects of humanitarian transfers using cluster standard errors instead of Conley standard errors (Tables 23 and 25 in the Appendix) as well as using household fixed effects instead of EA fixed effects (Tables 21, 22, and 24 in the Appendix). Our results for all outcome variables generally replicate.

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 they 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 they are unable to provide insights into pathways, coping strategies, and short-term effects during or in the immediate aftermath of the event.

This paper has evaluated the food consumption and child nutrition effects of an El Niño-induced drought that hit nine Southern African countries and affected about 30 million people during the 2015–16 farming season. Using two rounds of a nationally representative panel survey data set 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 (-1 standard deviation) drought in the 2015–16 farming season. Capitalizing on variation in the timing of data collection for the household survey over the two seasons in which the effects of the drought were most strongly experienced, we are able to measure household food consumption, food insecurity responses, and child malnutrition as the consequences of the drought unfolded. We find that the effects of the drought are 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, the period when—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 with non-drought-affected areas is 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 find households to prioritize children over adults in the allocation of food.

Furthermore, we have assessed the potential drought-mitigating effects of humanitarian transfers in the aftermath of the drought. While the sign of our estimates has the expected effects across outcome variables, we do not find significant effects of the safety nets on the quality or diversity of diets, or on households' food insecurity responses. Additionally, we find positive but statistically insignificant effects of the transfers in mitigating drought-related weight loss in children aged under five.

We have conducted a number of checks to ascertain the robustness of our results and find that our results are robust to: (1) using clustered standard errors instead of Conley standard errors; (2) using household fixed effects instead of EA fixed effects; (3) disaggregating short-term nutrition effects by child gender; (4) pooling together all four waves of the panel data set 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, and that those consequences vary according to season. Our analysis is not able to identify significant drought-mitigating effects of humanitarian transfers, and the estimated effects need to be interpreted with caution due to selection concerns that may bias our estimates downwards. Nevertheless, we believe that the insights from our analysis help in pointing out how the effects of weather shocks interfere with the seasonal pattern of consumption, and the need to optimize the timing of interventions during humanitarian emergencies. However, 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 contexts 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 for 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.

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Appendix

Table 10: Household-level summary statistics by survey round

	N	All	2013	2016	Difference	Prob>F
Food Consumption Score	4,489	48.340 (18.588)	51.929 (17.965)	45.576 (18.591)	-6.356	0.000
Household Dietary Diversity Score (0-12)	4,489	8.494 (2.110)	8.258 (1.973)	8.676 (2.194)	0.435	0.000
Household worried about not having enough food (0/1)	4,489	0.442 (0.497)	0.342 (0.475)	0.519 (0.500)	0.179	0.000
Number of days ate less preferred food in the past 7 days	4,488	1.570 (2.128)	1.271 (2.059)	1.801 (2.151)	0.554	0.000
Number of days household limited portion sizes at mealtimes in the past 7 days	4,488	1.122 (1.899)	0.860 (1.684)	1.323 (2.027)	0.515	0.000
Number of days household reduced number of meals eaten in day in the past 7 days	4,488	0.977 (1.814)	0.588 (1.385)	1.277 (2.036)	0.736	0.000
Number of days household restricted consumption for adults in the past 7 days	4,487	0.383 (1.078)	0.243 (0.772)	0.492 (1.253)	0.296	0.000
Number of days household borrowed food or help from others in the past 7 days	4,488	0.440 (1.049)	0.355 (0.868)	0.506 (1.164)	0.183	0.001
Number of meals taken by adults per day in the household	4,486	2.529 (0.630)	2.613 (0.526)	2.465 (0.693)	-0.134	0.000
Number of meals taken by children (5-17 years old) per day in household	3,026	2.409 (1.223)	2.601 (1.003)	2.266 (1.347)	-0.259	0.000
Household faced food insecurity situations in the past 12 months (0/1)	4,489	0.638 (0.481)	0.624 (0.484)	0.648 (0.478)	0.037	0.271
Household consumed cereal2 in the past week (0/1)	4,489	0.998 (0.048)	0.999 (0.025)	0.996 (0.060)	-0.003	0.139
Household consumed root2 in the past week (0/1)	4,489	0.750 (0.433)	0.789 (0.408)	0.721 (0.449)	-0.074	0.001
Household consumed egg2 in the past week (0/1)	4,489	0.404 (0.491)	0.397 (0.489)	0.410 (0.492)	0.008	0.483

Household consumed fish2 in the past week (0/1)	4,489	0.486 (0.500)	0.093 (0.291)	0.788 (0.409)	0.719	0.000
Household consumed veg2 in the past week (0/1)	4,489	0.997 (0.055)	0.996 (0.061)	0.997 (0.050)	0.000	0.618
Household consumed fruit2 in the past week (0/1)	4,489	0.635 (0.481)	0.666 (0.472)	0.612 (0.487)	-0.039	0.029
Household consumed meatpo2 in the past week (0/1)	4,489	0.514 (0.500)	0.556 (0.497)	0.482 (0.500)	-0.067	0.000
Household consumed pulse2 in the past week (0/1)	4,489	0.886 (0.318)	0.946 (0.226)	0.839 (0.367)	-0.105	0.000
Household consumed dairy2 in the past week (0/1)	4,489	0.231 (0.421)	0.214 (0.411)	0.243 (0.429)	0.026	0.076
Household consumed oilfat2 in the past week (0/1)	4,489	0.815 (0.389)	0.795 (0.404)	0.830 (0.376)	0.024	0.019
Household consumed sugar2 in the past week (0/1)	4,489	0.780 (0.414)	0.808 (0.394)	0.758 (0.428)	-0.055	0.000
Household consumed miscbev2 in the past week (0/1)	4,489	0.998 (0.039)	0.998 (0.047)	0.999 (0.032)	0.001	0.534
Number of under 5 children in the HH	4,489	0.725 (0.772)	0.808 (0.807)	0.661 (0.739)	-0.137	0.000
Number of under 2 children in the HH	4,489	0.288 (0.479)	0.334 (0.508)	0.253 (0.452)	-0.079	0.000
Received cash or food transfer (0/1)	4,489	0.081 (0.273)	0.089 (0.284)	0.075 (0.264)	-0.009	0.451
Residence in FIRP-targeted area (0/1)	4,455	0.355 (0.478)	0.000 (0.000)	0.629 (0.483)	0.555	0.000
Female HH head (0/1)	4,489	0.255 (0.436)	0.241 (0.428)	0.266 (0.442)	0.022	0.007
Age of household head	4,324	42.260 (14.708)	42.037 (14.636)	42.441 (14.766)	0.605	0.155
Maximum HH education (years)	4,489	8.150 (3.573)	7.979 (3.601)	8.282 (3.547)	0.223	0.001
Education level of household head (years)	3,832	6.099 (4.207)	5.904 (4.228)	6.210 (4.192)	0.203	0.003

Household size	4,489	4.903 (2.261)	4.959 (2.264)	4.860 (2.258)	-0.066	0.115
Household uses a safe source of drinking water (0/1)	4,489	0.858 (0.349)	0.855 (0.352)	0.860 (0.347)	0.011	0.759
Children on supplementary/therapeutic feeding (0/1)	4,489	0.016 (0.125)	0.005 (0.072)	0.024 (0.153)	0.017	0.001
Household has a chronically ill member (0/1)	4,489	0.259 (0.438)	0.254 (0.436)	0.262 (0.440)	-0.003	0.663
Child-headed household (HH head <18 years old)	4,489	0.405 (0.491)	0.001 (0.024)	0.717 (0.451)	0.704	0.000
Elderly-headed household (HH head >60 years old)	4,489	0.136 (0.342)	0.151 (0.358)	0.124 (0.329)	-0.016	0.041
Household has orphans (0/1)	4,489	0.150 (0.357)	0.168 (0.374)	0.137 (0.344)	-0.033	0.002
Low maize yield (0/1)	4,489	0.375 (0.484)	0.440 (0.496)	0.326 (0.469)	-0.075	0.000
Household owns agricultural land (0/1)	4,489	0.836 (0.370)	0.866 (0.340)	0.813 (0.390)	-0.039	0.000
Rainy season (0/1)	4,489	0.464 (0.499)	0.246 (0.431)	0.632 (0.482)	0.351	0.000
Distance (km) to nearest road	4,489	7.713 (9.226)	7.850 (9.290)	7.608 (9.176)	-0.115	0.116
HH Distance in (KMs) to Nearest ADMARC Outlet	4,489	7.263 (5.290)	7.217 (5.235)	7.298 (5.333)	0.116	0.457
Distance (km) to district centre	4,489	22.057 (17.065)	21.923 (16.806)	22.161 (17.264)	0.553	0.497
Residence in a rural area (0/1)	4,489	0.811 (0.392)	0.810 (0.393)	0.812 (0.391)	0.013	0.850
Northern region (0/1)	4,489	0.109 (0.311)	0.111 (0.314)	0.107 (0.310)	-0.005	0.401
Central region (0/1)	4,489	0.412 (0.492)	0.399 (0.490)	0.422 (0.494)	0.034	0.008
Southern region (0/1)	4,489	0.479 (0.500)	0.491 (0.500)	0.471 (0.499)	-0.029	0.011

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

Table 11: Child-level summary statistics by survey round

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

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

Table 12: 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

Note: standard deviations are in parentheses. Analysis uses sampling weights.

Table 13: Drought-mitigating effect of humanitarian effects on food consumption (using 2013 and 2016 data)

VARIABLES	(1) Cereals	(2) Roots/tuber	(3) vegetables	(4) Fruits	(5) Meats/poultry	(6) eggs	(7) fish	(8) Pulses/nuts	(9) Dairy	(10) Oils & fats	(11) Sugars	(12) Condiments
Drought (β_1)	0.0121	-0.0424	-1.96e-05	0.0246	-0.0655	-0.0614	-0.0606	0.0301	-	0.0676	-0.0220	-0.0170
	(0.0110)	(0.0571)	(0.00128)	(0.0428)	(0.0771)	(0.0516)	(0.0503)	(0.0378)	0.144***	(0.0455)	(0.0423)	(0.0411)
FIRP area (β_2)	0.00133	-0.0798	-0.0203**	0.0335	0.0417	-0.101	0.0188	-0.0223	0.0274	-0.0156	-	-0.0339*
	(0.00339)	(0.0719)	(0.00966)	(0.121)	(0.0908)	(0.130)	(0.0706)	(0.0710)	(0.120)	(0.0616)	(0.0647)	(0.0177)
Received transfers (β_3)	0.00263	0.0948	0.00704*	-0.0684	0.0764	-0.0361	0.0825	0.00557	-0.0357	-0.0203	0.0654	0.00202
	(0.00282)	(0.0672)	(0.00394)	(0.0829)	(0.107)	(0.0769)	(0.0541)	(0.0869)	(0.0434)	(0.0554)	(0.0814)	(0.00202)
Drought * FIRP area (β_4)	-0.0133	0.0851	0.0168*	-0.0953	-0.0116	0.0306	0.00235	0.0792	0.0764	-0.0336	0.0168	0.0293*
	(0.0121)	(0.101)	(0.00925)	(0.128)	(0.109)	(0.136)	(0.0883)	(0.0690)	(0.123)	(0.0687)	(0.0765)	(0.0155)
Received transfers * FIRP area (β_5)	-0.00242	-0.0280	-0.00928	0.0954	0.182	-0.0333	0.00161	0.109	0.0828	0.204*	0.00423	0.0105
	(0.00373)	(0.150)	(0.0272)	(0.204)	(0.143)	(0.157)	(0.110)	(0.114)	(0.138)	(0.118)	(0.137)	(0.00895)
Drought * Received transfers (β_6)	-0.00797	0.162	-0.00554	0.175*	-0.136	0.0655	-0.466	0.0897	-0.206	0.142	-0.161	-5.80e-05
	(0.00532)	(0.139)	(0.00444)	(0.0975)	(0.253)	(0.212)	(0.319)	(0.0986)	(0.179)	(0.128)	(0.149)	(0.00247)
Drought * Received transfers* FIRP area (β_7)	0.00765	-0.195	-0.00210	-0.149	0.0115	0.0722	0.455	-0.112	0.157	-0.213	0.129	-0.00960
	(0.00576)	(0.205)	(0.0279)	(0.210)	(0.261)	(0.226)	(0.324)	(0.118)	(0.229)	(0.140)	(0.183)	(0.00999)
Observations	1,980	1,980	1,980	1,980	1,980	1,980	1,980	1,980	1,980	1,980	1,980	1,980
R-squared	0.009	0.038	0.013	0.032	0.063	0.080	0.050	0.025	0.079	0.063	0.090	0.008
Enumeration area fixed effects?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Survey fixed 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
Mean of outcome variable	0.996	0.714	0.997	0.697	0.536	0.452	0.615	0.867	0.277	0.833	0.779	0.998
Std. dev. of outcome variable	0.0644	0.452	0.0568	0.460	0.499	0.498	0.487	0.339	0.448	0.373	0.415	0.0430

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; whether household experienced crop failure; whether households has a member who is chronically ill; whether household is child-headed; whether household is elderly-headed; whether household has orphaned members; whether children in the household are receiving nutrition therapy; distance in kilometres to the nearest road; and distance in kilometres to the district centre. Numbers in parentheses are Conley (1999), standard errors with 50km distance cutoff. *** indicates 1% significance level; ** indicates 5% significance level; and * indicates 10% significance level.

Table 14: Replicating Table 2, but using HH fixed effects instead of enumeration area fixed effects

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	All seasons			Dry season (Oct - Mar)			Rainy season (Apr - Sept)		
<i>Panel B – Outcome variable is FCS</i>									
Drought (β_1)	-5.853** (2.289)	-4.190*** (0.939)	-4.644*** (1.014)	-9.139*** (2.116)	-6.670*** (1.371)	-6.755*** (1.352)	-4.548 (2.927)	0.300 (1.587)	-0.0479 (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
<i>Panel B – Outcome variable is HDDS</i>									
Drought (β_1)	0.306 (0.215)	-0.312** (0.145)	-0.337** (0.151)	0.230 (0.240)	-0.235 (0.205)	-0.178 (0.206)	0.261 (0.278)	-0.146 (0.221)	-0.303 (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 15: 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)		
<i>Panel A – Outcome variable is FCS</i>									
Drought (β_1)	-5.853*** (1.101)	-3.827** (1.511)	-4.289*** (1.553)	-9.139*** (1.298)	-6.311*** (2.177)	-5.845*** (2.102)	-4.548** (1.773)	0.677 (2.411)	0.690 (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
<i>Panel B – Outcome variable is HDDS</i>									
Drought (β_1)	0.306** (0.128)	-0.273 (0.175)	-0.296* (0.178)	0.230 (0.171)	-0.260 (0.258)	-0.169 (0.261)	0.261 (0.197)	-0.141 (0.255)	-0.182 (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.

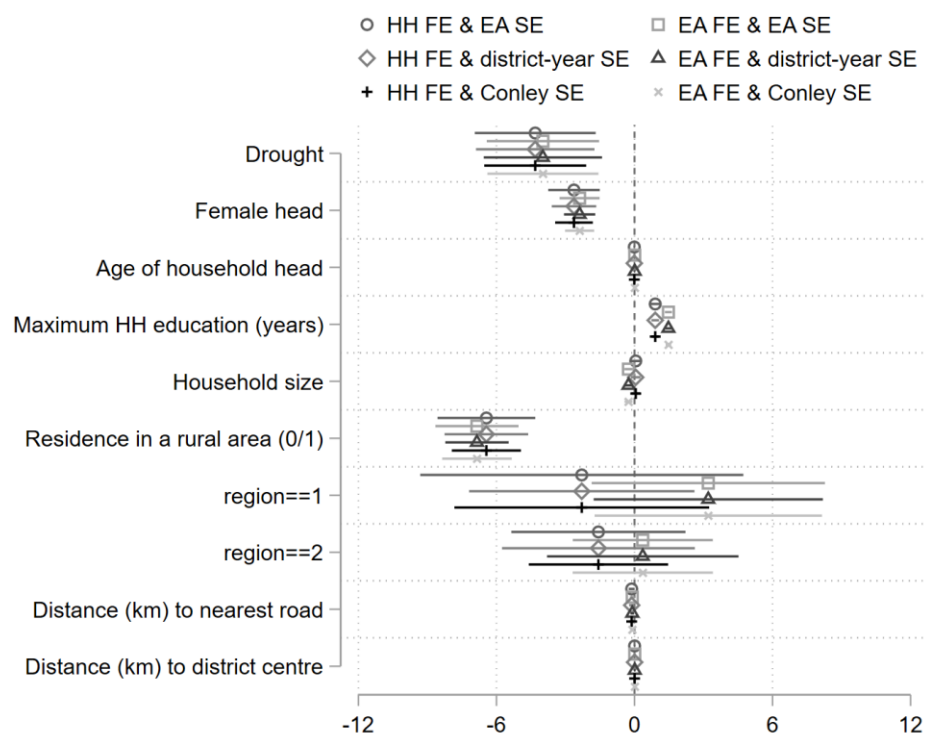
Table 16: Replicating Table 4, but using household fixed effects instead of EA fixed effects (using 2013 and 2016 data)

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	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 size in the 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 (β_1)	-0.0146 (0.0462)	-0.278 (0.241)	-0.0861 (0.167)	0.0771 (0.121)	0.202** (0.0857)	0.0258 (0.0640)	-0.128*** (0.0286)	-0.00653 (0.0866)	0.0438 (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.

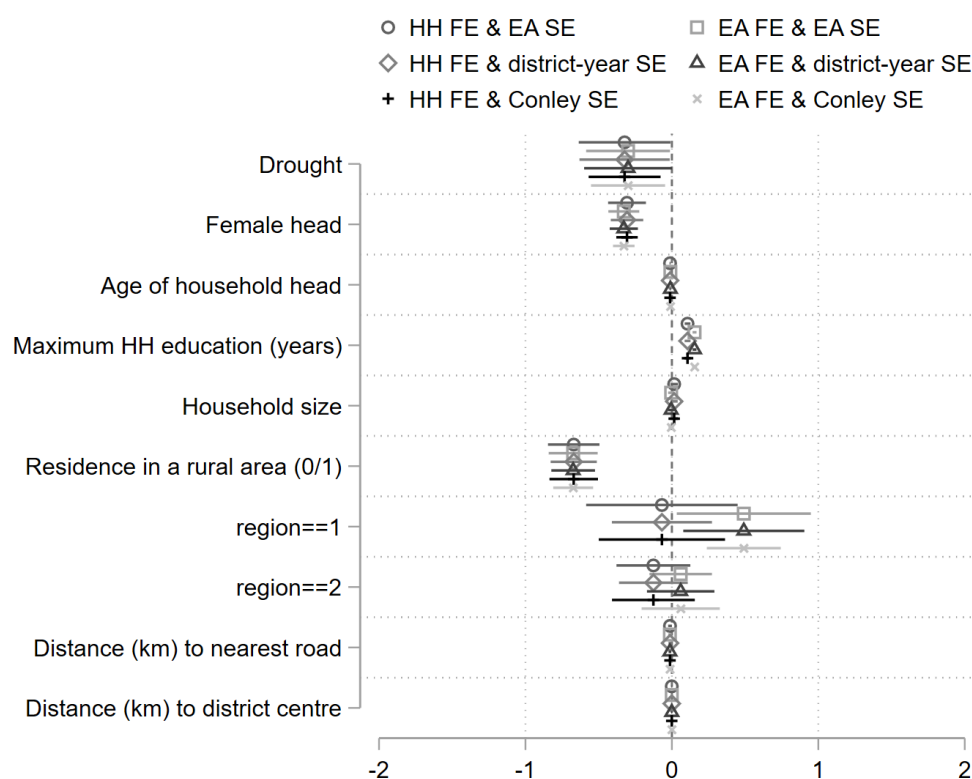
Figure 10: Coefficient plot replicating Table 2 - Panel A (FCS), but pooling all data from 2010 to 2020 and using different fixed effects and standard errors instead of 2013 and 2016 data



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.

Source: authors' illustration.

Figure 11: 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.

Source: authors' illustration.

Table 17: Replicating Table 5, but using household fixed effects instead of enumeration area fixed effects (using 2013 and 2016 data)

VARIABLES	(1) Number of children less than 24 months old	(1) Number of children less than 60 months old
Drought (τ_1)	-0.0166 (0.0259)	-0.0107 (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 18: Replicating Table 6, but using household fixed effects instead of enumeration area fixed effects

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
<i>Panel A: Outcome variable is WHZ</i>	All seasons			Dry season (Apr - Sept)			Rainy season (Oct - Mar)		
Drought (τ_1)	-0.211*** (0.0759)	-0.360*** (0.111)	-0.344*** (0.117)	-0.294*** (0.112)	-0.209 (0.197)	-0.225 (0.193)	-0.0860 (0.0936)	-0.0714 (0.224)	-0.0122 (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
<i>Panel B: Outcome variable is wasting (0/1)</i>									
Drought (τ_1)	-0.0199** (0.00842)	0.0241* (0.0140)	0.0207 (0.0140)	-0.0219 (0.0146)	0.0403 (0.0261)	0.0366 (0.0253)	-0.0106 (0.0125)	-0.0444 (0.0271)	-0.0477 (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 19: 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)
<i>Panel A: Outcome variable is WHZ</i>	All seasons			Dry season (Apr - Sept)			Rainy season (Oct - Mar)		
Drought (τ_1)	-0.211*** (0.0708)	-0.432** (0.169)	-0.425** (0.179)	-0.294*** (0.0984)	-0.365 (0.235)	-0.364 (0.249)	-0.0860 (0.0911)	-0.121 (0.250)	-0.0768 (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
<i>Panel B: Outcome variable is wasting (0/1)</i>									
Drought (τ_1)	-0.0199** (0.00954)	0.00626 (0.0195)	0.00715 (0.0200)	-0.0219 (0.0149)	0.0155 (0.0299)	0.0162 (0.0308)	-0.0106 (0.0108)	-0.0755** (0.0310)	-0.0760** (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
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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.

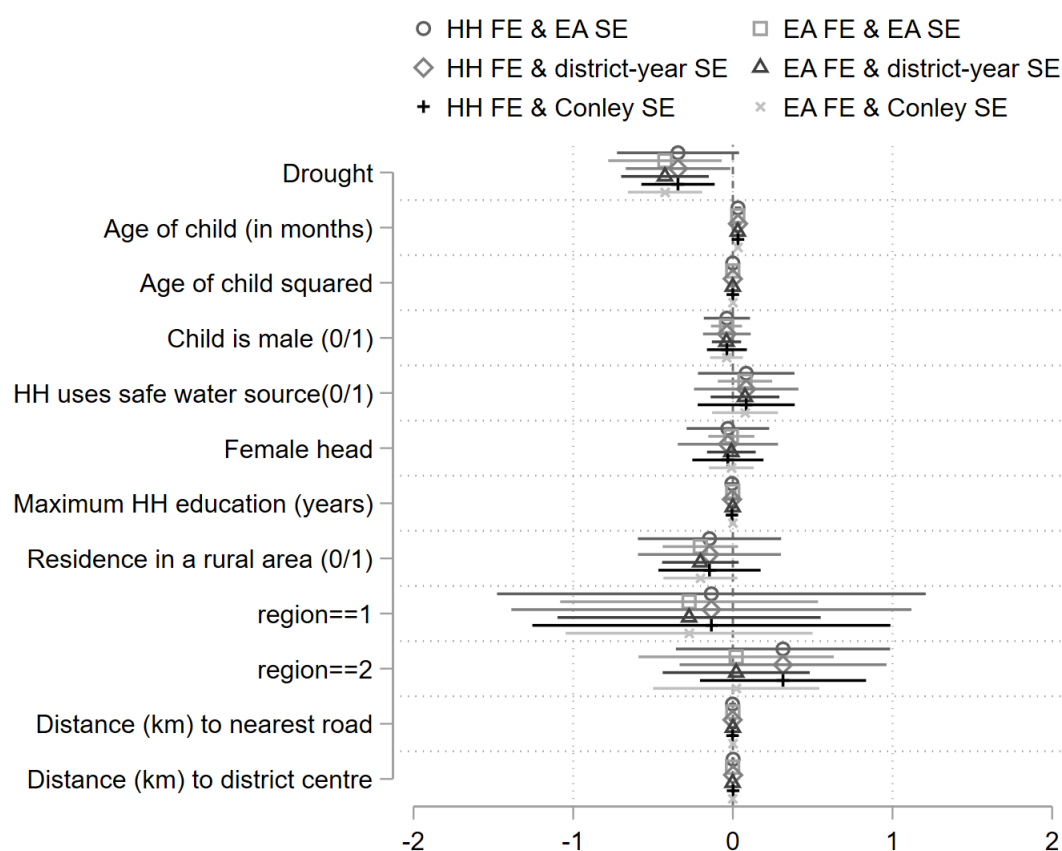
Table 20: Replicating Table 6, but disaggregating by sex of child instead of seasons

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
<i>Panel A: Outcome variable is WHZ</i>	All children			Female children only			Male children only		
Drought (τ_1)	-0.211*** (0.0752)	-0.432*** (0.114)	-0.427*** (0.116)	-0.238** (0.0939)	-0.393*** (0.131)	-0.341** (0.136)	-0.183** (0.0905)	-0.415** (0.178)	-0.424** (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
<i>Panel B: Outcome variable is wasting (0/1)</i>									
Drought (τ_1)	-0.0199** (0.00882)	0.00626 (0.0149)	0.00796 (0.0150)	-0.0181* (0.0102)	0.00755 (0.0162)	-0.000131 (0.0170)	-0.0218 (0.0138)	0.00496 (0.0264)	0.0114 (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 12: 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



Source: authors' illustration.

Table 21: Replicating Table 7, but using household fixed effects instead of enumeration area fixed effects

VARIABLES	(1) FCS	(2) HDDS
Drought (β_1)	2.667 (1.719)	-0.328 (0.200)
FIRP area (β_2)	2.615 (3.712)	-0.490 (0.432)
Received transfers (β_3)	-4.467 (3.016)	0.00499 (0.309)
Drought * FIRP area (β_4)	-3.886 (3.858)	0.335 (0.483)
Received transfers * FIRP area (β_5)	4.946 (4.932)	1.088 (0.760)
Drought * Received transfers (β_6)	-8.716 (5.902)	-0.608* (0.323)
Drought * Received transfers* FIRP area (β_7)	13.13* (7.058)	-0.0238 (0.870)
Observations	1,980	1,980
R-squared	0.092	0.110
Household fixed effects?	Yes	Yes
Survey fixed effects?	Yes	Yes
Control variables?	Yes	Yes
Mean of outcome variable	51.07	8.761
Std. dev. of outcome variable	20.11	2.194

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; whether households has a member who is chronically ill; whether household is child-headed; whether household is elderly-headed; whether household has orphaned members; whether children in the household are receiving nutrition therapy; 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 TA level. *** indicates 1% significance level; ** indicates 5% significance level; and * indicates 10% significance level.

Table 22: Replicating Table 8, but using household fixed effects instead of enumeration area fixed effects

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
Drought (β_1)	0.00264 (0.0950)	-0.214 (0.456)	-0.252 (0.291)	0.439* (0.225)	0.238 (0.171)	0.222 (0.185)	0.0277 (0.0375)	0.260** (0.112)
FIRP area (β_2)	0.292*** (0.0912)	0.761 (0.483)	1.444*** (0.543)	1.092** (0.434)	0.0960 (0.184)	0.214 (0.198)	0.204** (0.0925)	0.181 (0.342)
Received transfers (β_3)	0.274*** (0.0828)	-0.432 (0.320)	1.113*** (0.377)	0.115 (0.247)	0.295** (0.124)	-0.165 (0.286)	-0.0405 (0.106)	0.394* (0.221)
Drought * FIRP area (β_4)	-0.0970 (0.116)	-0.607 (0.514)	-0.734 (0.583)	-0.641 (0.451)	0.148 (0.188)	0.144 (0.244)	-0.393*** (0.0991)	-0.165 (0.312)
Received transfers * FIRP area (β_5)	-0.704*** (0.209)	-0.347 (0.673)	-2.403*** (0.774)	-1.520* (0.849)	-0.719* (0.404)	0.272 (0.434)	-0.102 (0.242)	-0.375 (0.499)
Drought * Received transfers (β_6)	-0.0698 (0.202)	0.453 (0.661)	0.559 (0.444)	0.919 (0.812)	-0.647*** (0.190)	0.0543 (0.359)	0.191 (0.163)	0.972** (0.398)
Drought * Received transfers* FIRP area (β_7)	0.335 (0.348)	0.0669 (1.141)	1.115 (0.799)	1.165 (0.966)	1.173*** (0.349)	-0.111 (0.511)	0.215 (0.280)	-0.816 (0.657)
Observations	1,980	1,979	1,979	1,979	1,979	1,979	1,980	1,275
R-squared	0.069	0.039	0.062	0.069	0.051	0.030	0.102	0.130
Enumeration area fixed effects?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Survey fixed effects?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control variables?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean of outcome variable	0.490	1.619	1.223	1.049	0.385	0.441	2.557	2.528
Std. dev. of outcome variable	0.500	2.090	1.982	1.869	1.082	1.046	0.659	1.213

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; whether households has a member who is chronically ill; whether household is child-headed; whether household is elderly-headed; whether household has orphaned members; whether children in the household are receiving nutrition therapy; 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 TA level. *** indicates 1% significance level; ** indicates 5% significance level; and * indicates 10% significance level.

Table 23: Replicating Table 7, but clustering standard errors at TA level instead of using Conley (2009) standard errors

VARIABLES	(1) FCS	(2) HDDS
Drought (β_1)	4.131 (2.560)	-0.343 (0.295)
FIRP area (β_2)	-1.558 (6.579)	-0.553 (0.463)
Received transfers (β_3)	-1.734 (2.502)	0.180 (0.225)
Drought * FIRP area (β_4)	-1.316 (6.561)	0.379 (0.560)
Received transfers * FIRP area (β_5)	10.31 (6.460)	0.631 (0.501)
Drought * Received transfers (β_6)	-5.712 (9.888)	-0.389 (0.501)
Drought * Received transfers* FIRP area (β_7)	3.714 (11.57)	0.169 (0.643)
Observations	1,881	1,881
R-squared	0.342	0.382
Enumeration area fixed effects?	Yes	Yes
Survey fixed effects?	Yes	Yes
Control variables?	Yes	Yes
Mean of outcome variable	48.63	8.660
Std. dev. of outcome variable	19.03	2.169

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; whether households has a member who is chronically ill; whether household is child-headed; whether household is elderly-headed; whether household has orphaned members; whether children in the household are receiving nutrition therapy; region of residence; distance in kilometres to the nearest road; and distance in kilometres to the district centre. Numbers in parentheses are Conley (1999) standard errors with 50km cutoff. *** indicates 1% significance level; ** indicates 5% significance level; and * indicates 10% significance level.

Table 24: Replicating Table 9, but using household fixed effects instead of enumeration area fixed effects

VARIABLES	(1) WHZ
Drought (τ_1)	-0.0512 (0.240)
FIRP area (τ_2)	-0.456 (0.356)
Received transfers (τ_3)	-0.233 (0.570)
Drought * FIRP area (τ_4)	0.144 (0.559)
Received transfers * FIRP area (τ_5)	0.690 (0.652)
Drought * Received transfers (τ_6)	0.0603 (0.718)
Drought * Received transfers* FIRP area (τ_7)	-0.580 (0.868)
Observations	1,105
R-squared	0.063
Enumeration area fixed effects?	Yes
Survey fixed effects?	Yes
Control variables?	Yes
Mean of outcome variable	0.166
Std. dev. of outcome variable	1.256

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 age of child in months; square of child age; sex of child; whether household uses safe water source; 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; whether households has a member who is chronically ill; whether household is child-headed; whether household is elderly-headed; whether household has orphaned members; whether children in the household are receiving nutrition therapy; region of residence; distance in kilometres to the nearest road; and distance in kilometres to the district centre. Numbers in parentheses are Conley (1999) standard errors with 50km cutoff. *** indicates 1% significance level; ** indicates 5% significance level; and * indicates 10% significance level.

Table 25: Replicating Table 9, but clustering standard errors at TA level instead of using Conley (2009) standard errors

VARIABLES	(1) WHZ
Drought (τ_1)	-0.148 (0.218)
FIRP area (τ_2)	-0.293 (0.239)
Received transfers (τ_3)	0.0817 (0.297)
Drought * FIRP area (τ_4)	-0.111 (0.367)
Received transfers * FIRP area (τ_5)	-0.199 (0.378)
Drought * Received transfers (τ_6)	-0.159 (0.522)
Drought * Received transfers* FIRP area (τ_7)	0.482 (0.553)
Observations	1,105
R-squared	0.091
Enumeration area fixed effects?	Yes
Survey fixed effects?	Yes
Control variables?	Yes
Mean of outcome variable	0.181
Std. dev. of outcome variable	1.237

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 age of child in months; square of child age; sex of child; whether household uses safe water source; 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; whether households has a member who is chronically ill; whether household is child-headed; whether household is elderly-headed; whether household has orphaned members; whether children in the household are receiving nutrition therapy; region of residence; distance in kilometres to the nearest road; and distance in kilometres to the district centre. Numbers in parentheses are Conley (1999) standard errors with 50km cutoff. *** indicates 1% significance level; ** indicates 5% significance level; and * indicates 10% significance level.