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Vulnerability to Poverty Following Extreme Weather Events in Malawi

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Abstract

Severe weather shocks recurrently hit Malawi, and they adversely affect the incomes of many farm households as well as small businesses. With climate change, the frequency of extreme weather events is expected to increase further. A clear understanding of households' vulnerability to shock-induced poverty is critical for disaster risk management and the design of scalable social safety net programs. Standard poverty measures rely on static snapshots that are suitable for quantifying structural poverty but not for assessing the vulnerability of non-poor households to fall below the poverty line when they experience shocks. This study uses a nationally representative household survey and exogenously measured weather shocks to assess households' vulnerability to poverty in Malawi. To accurately estimate the impacts of shocks on consumption and vulnerability, the study excludes any kind of assistance (aid and food or cash transfers) that households might have received after major disasters. The key findings of the study are as follows: (1) drought during the growing season decreases non-assistance consumption per capita by 5–12 percent, depending on its intensity; (2) excess rainfall at the onset of the growing season reduces food consumption by 1.8 percent, while excess rainfall later in the growing season appears to increase consumption; (3) vulnerability to poverty is generally higher than static poverty, especially compared to static poverty measured during a good weather year; and (4) in years of extreme droughts, such as 2016, recorded poverty rates are higher than vulnerability, which indicates that the magnitude of drought in 2016 was so large that the chance of falling below the poverty line as a result of an even higher magnitude shock was low. These results suggest that identifying vulnerable households is key in designing adaptive social safety net programs that can be scaled up to cover those who become eligible for such programs after experiencing shocks.

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1 Introduction

Idiosyncratic and community-level shocks have serious implications for poor households' income and overall well-being. Job loss, disease, and death of a family member are considered to be idiosyncratic in nature, while crop disease and extreme weather events are examples of common shocks. Despite the existence of some risk-coping strategies and institutional safety net programs, household consumption is adversely affected in the aftermath of such shocks. This uncertainty is at the crux of improving welfare of households with limited opportunities to smooth their consumption, whether it stems from low access to credit or absence of insurance against shocks to their incomes. Addressing the problem of risk and uncertainty is also crucial in poverty reduction efforts in countries where idiosyncratic and community shocks are common. With climate change exacerbating the probability of extreme weather events (Monirul Qader, 2003), food insecurity (FAO, 2016; Wheeler and von Braun, 2013), and price volatility (Zenghelis, 2006), assessing vulnerability to poverty has become vital (Ahmed, Diffenbaugh, and Hertel, 2009).

Traditional poverty measures provide a static snapshot of living conditions at the time of surveying. A household with consumption per capita above the national poverty line is not identified as poor. Nevertheless, if the variance of this household's consumption over time is high, the household may be at risk of becoming poor when shocks strike. Therefore, households' current consumption is not very informative of their vulnerability to poverty. This study aims at bridging this gap by analyzing households' vulnerability to poverty following exposure to shocks in Malawi.

Identifying the structural causes of chronic poverty and shocks that trigger transitional poverty is a key first step in designing an effective poverty reduction strategy. On the one hand, structural measures and social assistance such as cash transfers and aid could be effective instruments to reduce chronic poverty. On the other, insurance schemes are better suited to tackle shock-induced poverty and vulnerability (Skoufias and Quisumbing, 2004). For these reasons, risk management has been at the core of development policies in the last decade, as explained in the 2014 World Development Report (World Bank, 2014). Social protection interventions such as cash transfer programs should be designed such that the programs could be scaled up after natural disasters to support more households, which become eligible as their incomes decline due to shocks. Assessing vulnerability to poverty is the first step toward the implementation of such adaptive risk-based safety net programs (de Janvry, del Valle, and Sadoulet, 2018).

There are extensive studies on the welfare impacts of weather shocks (Anttila-Hughes and Hsiang, 2013). Some of them rely on the analysis of a single extreme weather event

(Carter et al., 2007; Little et al., 2006). Although this approach facilitates causal identification, the choice of an extraordinary phenomenon undermines the external validity of the findings. Such studies are informative only of the impact of the dramatic weather event and not of recurring droughts or floods. Our analysis focuses on droughts and excess rainfall during the main growing season in Malawi (November to April) and evaluates the implications of weather shocks on households' vulnerability to poverty. This vulnerability analysis first identifies the impact of extreme weather events during the growing season on the consumption per capita in the months following the harvest time. The study uses the spatial and temporal variation in droughts and excess rainfall experienced by the 35,627 households surveyed in the three rounds of the Integrated Households Survey (IHS) (2004–2016).[1]

The Self-calibrating Palmer Drought Severity Index (SC-PDSI) is used as a measure of drought at the second lowest administrative division in Malawi (traditional authority [TA]). SCPDSI is calculated from temperature, precipitation, and locally available soil water content (Barichivich, Osborn, and Jones, 2018; van der Schrier et al., 2013). To measure floods, we use raw precipitation data to calculate the number of days with rainfall above the 98th percentile in each TA (NASA GES DISC, 2019). This is a rough approximation of flooding. In reality, flooding is a function of topography, rainfall amount and intensity, soil moisture, and vegetation. The use of SC-PDSI and extremely high rainfall enables us to address the endogeneity in the measurement of weather shocks. Self-reported shocks, quick post-disaster assessment of damages, and the Normalized Difference Vegetation Index (NDVI) are all potentially endogenous. For instance, the amount of losses could be higher in relatively wealthier areas that have more physical assets that could be damaged, but the households may as well be more resilient. Farmers may also delay planting due to a late onset of rainy season, which in turn lowers the NDVI. The latter index is indeed used to measure the onset and end of growing seasons (Yu, Luedeling, and Xu, 2010). In addition to these community-level shocks, we include idiosyncratic shocks, which are self-reported and likely to be endogenous, in our model.

Another major empirical challenge in identifying the welfare effects of natural disasters is the difficulty of disentangling private and public assistance to the affected households from the change in their non-transfer consumption. Previous studies (Chaudhuri, Jalan, and Suryahadi, 2002; Gunther and Harttgen, 2009; Hill and Porter, 2017; Suryahadi and Sumarto, 2003) compare households' total consumption, which includes transfers received from the government, nongovernmental organizations, relatives, and migrant family members.

[1] Not only is the assessment of vulnerability critical in the context of climate change, but it is even more relevant as 51.5 percent of Malawians lived in poverty in 2016. This rate is even higher (59.5 percent) among rural households who tend to be the most affected by weather shocks (Malawi NSSO and World Bank 2018).

However, it is likely that the amount of such transfers will increase following the realization of shocks. For instance, in the Philippines, households with overseas migrants received higher remittances in the aftermath of floods (Yang and Choi, 2007). In this study, we improve on previous welfare impact studies by excluding food aid or in-kind and cash transfers received by households from the consumption per capita.

Various definitions and theoretical frameworks of vulnerability to poverty have been suggested in the literature (Calvo and Dercon, 2013; Hoddinott and Quisumbing, 2003; Pritchett, Suryahadi, and Sumarto, 2000). Even though there is no consensus as to which one is a superior approach, they all rely on the estimation of expected consumption per capita and variance of consumption per capita. Some vulnerability studies use panel data to assess insurance of consumption in the aftermath of shocks (Townsend 1994; Udry 1995). The main challenge with adopting this approach is the lack of nationally representative panel data, which is rare in developing countries where vulnerability and resilience matter the most. Indeed, most nationally representative data sets are cross-sectional, and some vulnerability studies utilize these rich data sets. For example, Chaudhuri (2003) interprets the residuals from a regression of consumption per capita on household characteristics as the variance of welfare due to shocks. The distribution of consumption is then assumed to be lognormal with variance being the one that was imputed to the shocks (Chaudhuri, 2003). An alternative to rigorously used cross-sectional data is to build a pseudo-panel before conducting the vulnerability estimation (Christiaensen and Subbarao, 2004). Other authors have designed methodologies bridging the gap between these two approaches. On the one hand, Gunther and Harttgen (2009) improve on Chaudhuri's method by using a multilevel model that decomposes the error term into idiosyncratic and community shocks. This method relies on interpreting the residuals and may, therefore, be particularly sensitive to measurement errors (Gunther and Harttgen, 2009). On the other, Hill and Porter (2017) include both covariate and idiosyncratic shocks in the estimates of vulnerability to poverty. In this study, we improve on Hill and Porter's paper by excluding transfers from the welfare measures. Similar to Hill and Porter (2017), using nationally representative data allows us to calculate estimates of vulnerability to poverty along different dimensions (such as rurality and regions).

Malawi suffers from recurrent weather shocks that are detrimental to poverty reduction effort. The latest shock is tropical cyclone *Idai* that hit Malawi and neighboring countries in March 2019 and led to devastating floods. The post-disaster needs assessment (PDNA) estimated that 500,000 farmers or small businesses had their income affected by this event (Malawi Government, 2019). Three years earlier, in 2016, a severe drought resulted in poor harvests and prompted humanitarian emergency. This historical drought followed the 1 in 500 years flood of January 2015. The country was also affected by floods in January 2016. On the contrary, the weather during the 2009/10 growing season was relatively good while the one in 2003/04 was comparable to the average. The later growing season was preceded by the severe 2002 drought and followed by the dramatic 2005 drought and flooding.

The analysis conducted in this study to examine the impact of droughts and excess rainfall on the welfare of Malawian households shows that exposure to these shocks decreases households' consumption and elevates their vulnerability to poverty. Weather shocks have severe impacts on welfare of households and push non-poor households into poverty. Drought during crop growing season decreases consumption per capita without aid by significant margin, by 5–12 percent. Similarly, flooding during the first two months of growing season has an adverse effect on consumption per capita. As a result, households' vulnerability to poverty is generally higher than static poverty. In other words, even if poverty rate is already very high in Malawi, the non-poor households are likely to fall into poverty when exposed to these shocks. Design of safety net programs, such as social cash transfer, need to take into account vulnerability to poverty and such programs can be scaled up during disaster periods to benefit households that become poor as a result.

The rest of this paper is organized as follows: Section 2 describes the data and methodology. Sections 3 and 4 present the results and robustness checks. Finally, we conclude in Section 5 by highlighting policy implications of the main results and acknowledging the study's limitations.

2 Data and Methods

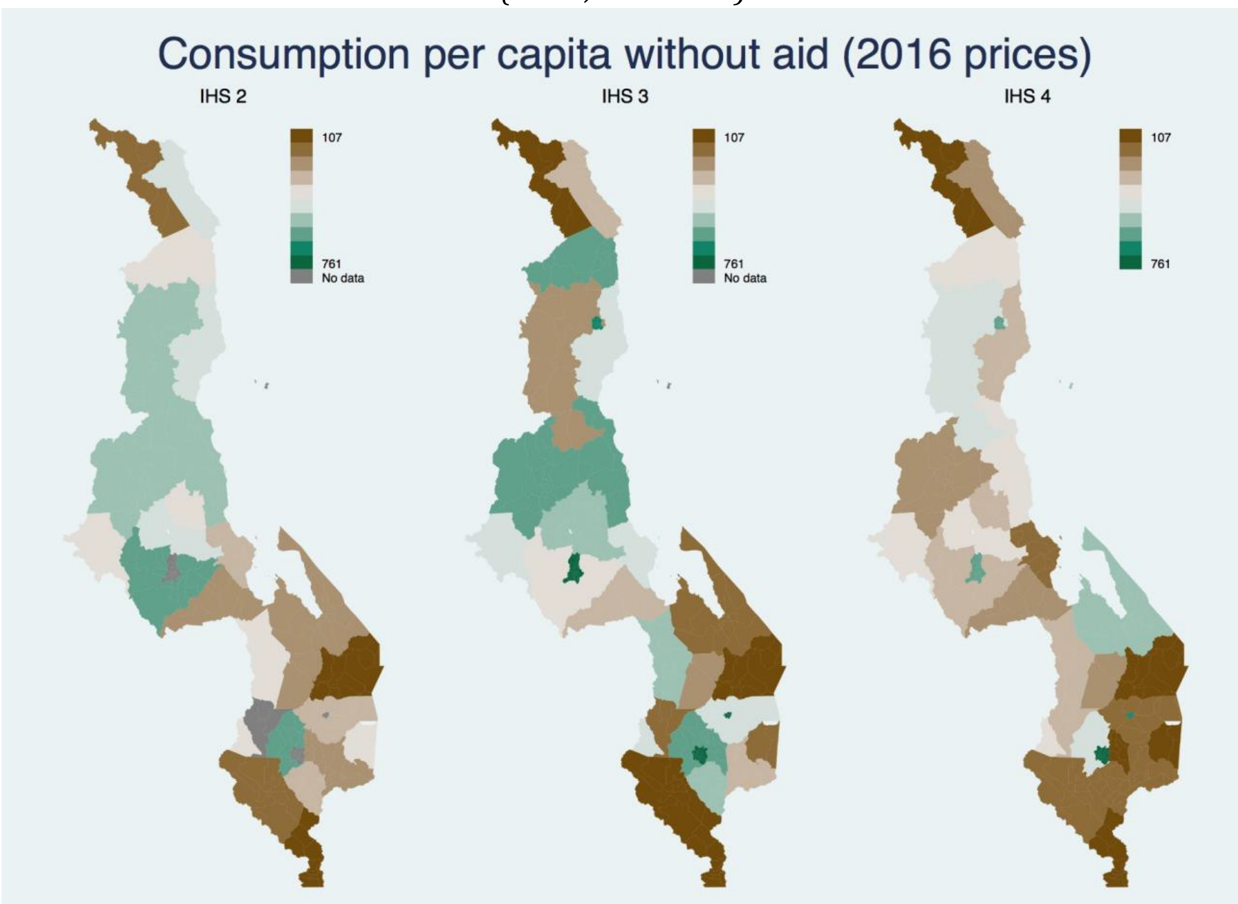
2.1 Data and Descriptive Statistics

To analyze vulnerability of households to poverty, we used the three rounds of the IHS, which is nationally representative, comparable over time, and used to produce the official poverty statistics. The second round (IHS 2) was conducted from March 2004 to March 2005, and a total of 11,281 households were interviewed. The third round (IHS 3) was implemented from March 2010 to March 2011 and covered 12,271 households. The fourth round (IHS 4) was carried out from April 2016 to May 2017 and included 12,447 households. As mentioned in the introduction, 2010/11 is considered to be a good weather year while 2016/17 is a dire one.

The key dependent variable for the vulnerability analysis is consumption per capita. To ensure comparability and capture changes in real consumption per capita, all consumption expenditures are expressed in 2016 prices, thousands of Malawian Kwachas [MWK]. In addition, to account for the fact that public and private support to households increases during periods of extreme shocks, the analysis excludes in-kind and cash support from the total consumption basket. The amount of assistance is estimated from self-reported cash and food aid received by the household. Figure 1 shows the district-level average consumption per capita during the three IHS rounds.

Figure 1: Average District-level Consumption per Capita, Excluding Food and Cash Aid

(MWK, thousands)



Note: Consumption is expressed in 2016 prices.

The Central region has the highest consumption per capita, while the Southern and Northern regions have lower consumption levels and higher variance in consumption over time. Residents in major city centers enjoy the highest welfare: Blantyre and Zomba in the South, Lilongwe in the Center, and Mzuzu in the North. When comparing consumption per capita over time, several districts had smaller levels of consumption in 2016, likely due to the severe drought recorded in that year. Table 1 presents summary statistics of all the variables used in our analysis when pooling all survey rounds. Table A.1 in the annex presents similar statistics for each of the three survey rounds.

Table 1: Summary Statistics

	Median	Mean	Std. Error	Minimum	Maximum
1. Consumption per capita (2016 MWK, thousands)					
Total consumption without aid	133.1	192.3	4.46	0	113562
Total consumption without food aid	133.3	192.5	4.46	0	113562
Total food consumption without transfers	77.0	99.4	0.56	0	2952
Total food transfers	1.6	8.3	0.10	0	544
2. Weather shocks					
Drought in growing season		0.4	0.01	0	4
Days with excess rainfall (Nov-Dec)		1.8	0.01	0	8
Days with excess rainfall (Jan-Feb)		4.6	0.01	0	13
Days with excess rainfall (Mar-Apr)		1.8	0.01	0	8
TA's median Palmer Index		-0.2	0.00	-2	1
TA's 98th percentile of rainfall		37.8	0.07	20	94
3. Self-reported shocks					
Job loss (dummy expressed in %)		2.5	0.08	0	100
Food price shock (dummy expressed in %)		43.0	0.26	0	100
Death (dummy expressed in %)		11.7	0.17	0	100
Death of breadwinner [a] (dummy expressed in %)		2.7	0.09	0	100
Death of another member [a] (dummy expressed in %)		9.8	0.16	0	100
4. Household head					
Age		42.9	0.08	13	110
Female (Dummy expressed in %)		21.6	0.22	0	100
Years of education		5.0	0.02	0	17
5. Household					
% its members in services		12.7	0.14	0	100
% its members in agriculture		53.5	0.23	0	100
% its members in industry		3.7	0.08	0	100
No one employed (Dummy expressed in %)		2.3	0.08	0	100
Household size		5.5	0.01	1	27
Dependency ratio		1.3	0.01	0	11
Has electricity (Dummy expressed in %)		8.5	0.15	0	100
Owns toilets (Dummy expressed in %)		3.0	0.09	0	100
Own more than 2 plots (Dummy expressed in %)		35.3	0.25	0	100
6. Aid received in the last year					
Food aid [a] (dummy expressed in %)		22.5	0.22	0	100
MASAF aid [a] (dummy expressed in %)		4.5	0.11	0	100
Education aid [a] (dummy expressed in %)		0.5	0.04	0	100
MASAF or Education aid (dummy expressed in %)		4.9	0.11	0	100
7. Geography					
Rural Household (dummy expressed in %)		84.2	0.19	0	100
Distance to town (km)		51.3	0.29	0	860
Observations	35998				

Note: [a] These variables are not included in the main regression but summarized for the reader's information. Some indicator variables take values of 0 or 1 but are expressed as percentage terms. The summary statistics are generated by pooling the three IHS rounds.

The analysis is based on the consumption aggregates used for official poverty estimation. However, to allow estimation of vulnerability in the absence of assistance, we exclude self-reported food aid and cash transfer in the first consumption estimate ('without aid') and exclude food aid only in the second estimate ('without food aid').[2] The food aid and cash transfer information in these estimations are taken from the assistance module of the survey questionnaires. In addition, households report that the part of food consumed comes from in-kind transfers and food aid. This item-level in-kind transfer is aggregated to quantify the total amount of food transfers received by the household. By excluding the transfers, as reported in the food consumption module of the questionnaires, from the total consumption, we built an alternative index of food consumption ('without transfers').[3]

Part 2 of Table 1 presents the measures of weather shocks. To select the appropriate drought and rainfall indexes, we mapped several indicators over multiple years. Existing empirical evidence and expert knowledge of which districts were hit most by dramatic weather events and the years extreme weather events guided the selection of indicators. The measure of drought used in this study is based on CRU's Global SC-PDSI during the growing season. It is calculated from temperature, precipitation, and locally available soil water content (Barichivich and Jones, 2018; van der Schrier et al., 2013). We averaged this index (for each month) at the TA level to merge it with the IHS. The Palmer index varies from −10 to 10 with values lower than −2 indicating droughts. For TAs with Palmer index above −2, that is, those that did not experience drought, a value of zero is assigned. For those with index below −2, the absolute value of the index is used such that higher positive values correspond with severe droughts. This definition makes the interpretation of the drought coefficient easier. To generate a rough indicator of floods, we aggregated raw precipitation data from NASA's MERRA-2 model and we calculated the number of days with rainfall above the 98th percentile in each TA (NASA GES DISC, 2019).[4] All the weather indexes are defined for the growing season preceding the household surveys. Since maize growing season is from November to April in Malawi, households interviewed in March or April 2004 are matched to shocks occurring in the 2002/03 growing season. Those households that were interviewed in May 2004 to March 2005 (84% of IHS2) are linked to the preceding 2003/04 growing season. Similarly, 85% of IHS3 observations are associated with weather indicators in the 2010/11 growing season, and 97% of IHS4 data corresponds to shocks that occurred

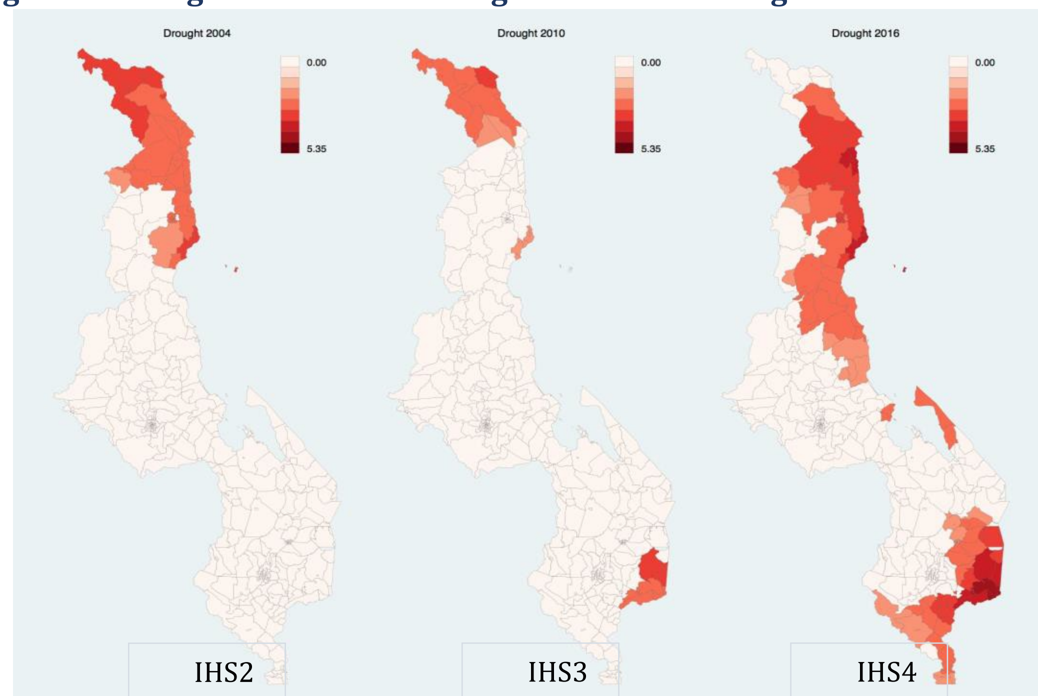
[2] Some extremely poor households have zero consumption per capita when food aid and cash transfers are excluded.

[3] This could only be created for IHS 3 and IHS 4 due to unavailability of documentation and do-file for IHS 2 consumption aggregate. Even if it is likely to be more accurate than the self-reported food aid, we found it difficult to reconstruct this in a consistent manner for IHS 2.

[4] Constructing a precise indicator of flooding requires extensive analysis of rainfall, topography, and plant coverage. This is beyond the scope of this study.

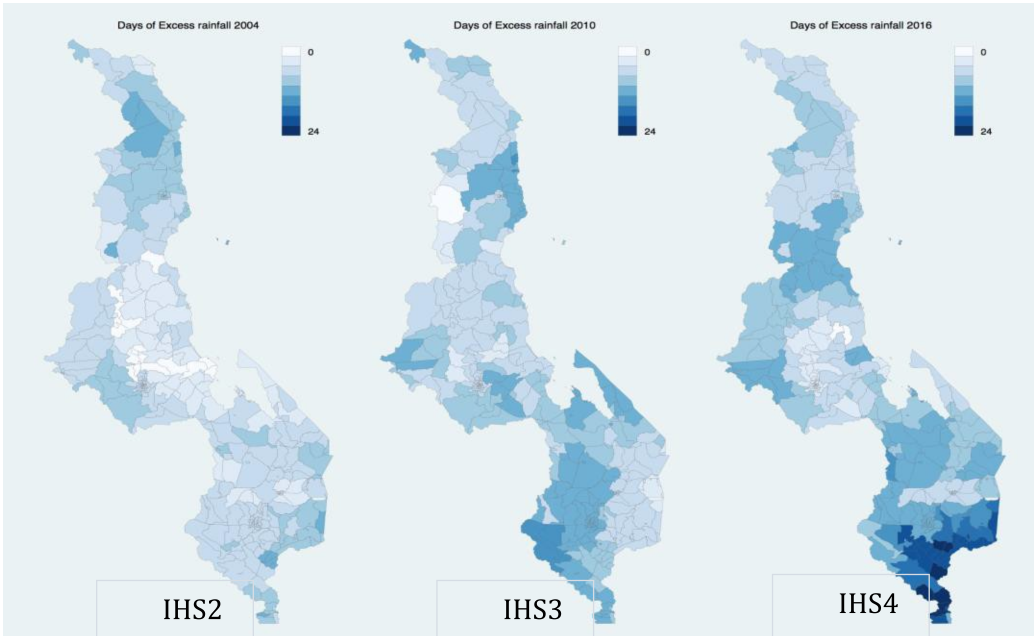
in the 2015/16 growing season. Figures 2 and 3 show these indicators over the main preceding growing season in all IHS rounds. For the three main growing seasons corresponding to the IHS waves, parts of the Northern region have experienced more droughts than other regions. The 2016 drought threatened both the Northern and the Southern regions. In terms of rainfall, IHS 2 and IHS 3 had relatively good rainfall. In 2016, the Southern region had extreme precipitations following the severe drought.

Figure 2: Drought Index for Growing Seasons Preceding each IHS Round



Note: The drought index is defined as the absolute value of the Palmer index if the latter is below −2. No drought is indicated by 0 on the map.

Figure 3: Total Number of Days with Excess Rainfall in Growing Seasons Preceding each IHS Round



Note: Excess rainfall is defined as rainfall above the 98th percentile of the distribution of the TA. No excess rainfall is indicated by 0 on the map.

As described earlier, weather shocks are exogenous given their probability distribution. To control for this probability, we use the historical distribution (1980–2018) of droughts and excess rainfall. We control for the median Palmer index of each TA and the 98th percentile of its rainfall. We show the geographical variation of these weather shock indicators in the supplemental annex.[5] For most of the IHS survey years, the Northern region happened to be drier, while the Southern region had more excess rainfall days. However, the 2016 drought was severe and affected a large portion of the country, both in the Southern and Northern regions as well as parts of the Central region.

Part 3 of Table 1 details the idiosyncratic shocks used in our analysis. All of these subjective shock indicators are created from the self-reported idiosyncratic shocks experienced by the household in the last 12 months. One may argue that self-reported shocks are not a good measure of exposure. Therefore, we focus on prominent traumas that the household has experienced: the death of a household member, job losses, and unusually high prices for food. Due to concern of their likely endogeneity, we exclude job losses that may be a consequence of the weather shocks, which could cause the collapse of agricultural

[5] See maps A1 and A2 in the supplemental annex. Results are available upon request.

businesses. Therefore, we define the job loss shock as the loss of employment of previously salaried household members. Only 2.5 percent of households experience this kind of job loss.

On average, 43 percent of households report unusually high food prices. Approximately 26 percent of households did so in IHS 2 and IHS 3 and 71 percent in IHS 4, most likely reflecting the adverse weather conditions observed in 2016. The correlation between drought and self-reported inflation for food is 12.3 percent. Delays in passing the cost on to consumers and potential changes in importations or transportation costs all matter to this weak correlation.

About 18 percent of households suffer the death of a member. The deceased was a breadwinner in around 20 percent of cases. Parts 4 to 7 of Table 1 present household characteristics. The average family is headed by a male with low education and has half of its working-age members employed in agriculture. Moreover, around 22 percent of households receive food aid. We remove food aid from consumption per capita when constructing our dependent variable. However, we do not include it as a control in our regression as it is responsive to weather conditions and would therefore bias our coefficients on weather shocks.[6] Instead, we control for receiving aid unrelated to weather conditions (Malawi Social Action Fund [MASAF] program and educational aid). Finally, note that 84.2 percent of the households reside in rural areas.

2.2 Impacts of Weather and Idiosyncratic Shocks on Consumption

As a first step in the analysis of vulnerability to poverty following a household's exposure to common and idiosyncratic shocks, we assess the impact of these shocks on per capita consumption. To do so, the following consumption model is estimated:

$$ln(C_{ict}) = \alpha + \beta S_{ct} + \gamma S_{ict} + \sum_k \delta_k x^k_{ict} + \mu_t + \nu_d + \epsilon_{ict} \quad , \tag{1}$$

where C_{ict} is per capita consumption without aid of household i in TA c at time t.[7] S_{ct} is a vector of weather shock indicators and their historical geographic distribution: drought and excess rainfall in the growing season preceding the survey time in TA c at time t. We also include controls of the historical trends in droughts (median Palmer index for the TA) and excess rainfalls (98th percentile of rainfall in the TA) for exogeneity of the shocks. S_{ict} are self-reported idiosyncratic shocks: job loss, death of a household member, or food price inflation. The additional k control variables, x^k_{ic}, are household-specific controls:

[6] Angrist and Pischke (2008) refer to theses variables as "bad controls".

[7] Adding one to the consumption per capita to account for households that have zero consumption when food aid and cash transfers are excluded from the consumption basket.

characteristics of the household head; employment status of working-age members; household size and dependency ratio; ownership of toilets, electricity, or farm plots; recipient of MASAF or education aid; rural-urban indicator; and distance to the closest town, while μ_t are time fixed effects (season and year), ν_d are district fixed effects, and $_{ict}$ is the error term. Standard errors are clustered by districts.

The main identification challenge in assessing the impact of shocks is endogeneity. When shocks are self-reported, one may argue that poor households with limited coping mechanisms are more likely to report them than the non-poor households, who tend to have good mitigation and coping strategies in place. The use of weather shock indicators derived by exogenously measured temperature and precipitation addresses this endogeneity problem. These indicators are aggregated at the TA level, the lowest administrative division in Malawi.[8] As shown in the annex, there is low correlation between self-reported weather shocks and exogenously measured shocks at the TA level.[9] This discrepancy may stem from the endogeneity of self-reporting and/or the difference in spatial coverage of the shock indicators, that is, TA average versus specific location of individual household.

Even when measured exogenously, the probability of occurrence of a shock is not exogenous to consumption per capita across households. Indeed, arid areas are more likely to be poor and hit by frequent droughts due to their geography. We use the fact that the timing of a shock is exogenous to welfare status conditional on the likelihood of its occurrence (Anttila-Hughes and Hsiang, 2013). We account for the probability distribution of weather events by including variables related to the TA-specific historical distribution of these shocks.

It is difficult to measure idiosyncratic shocks exogenously. In the annex, we present the correlation between self-reported shocks and household characteristics. [10] Households planting crops are more likely to report droughts or floods, and they are less likely to report food price shocks. These correlations can be explained by a real difference in exposure and/or by the fact that households report more on what matters most to them. We partially address this caveat of endogeneity by including a set of household and community observables that could correlate with differences in reporting.

[8] This restricts the geographic fixed effects of the regression analysis at the district level, instead of the TA level.

[9] See table A1 in the annex. Results are available upon request.

[10] See Table 2. Results are available upon request.

2.3 Estimating Vulnerability to Poverty

The second step in the vulnerability analysis extends the assessment of welfare impact of weather shocks by estimating vulnerability to poverty. After introducing measures of vulnerability, we explain how we assess the probability distribution of future consumption to estimate households' vulnerability.

This analysis aims at quantifying vulnerability to poverty and comparing it with static measures of poverty. To facilitate direct comparison, both the static poverty and vulnerability measures refer to consumption per capita without aid. We also choose to use the expected value of Foster Greer Thorbecke (FGT) indexes to quantify vulnerability. Indeed, the static counterparts of these indexes are widely used in national poverty assessments (Foster, Greer, and Thorbecke 1984). The formula for static FGT indexes is as follows:

$$Poverty_a = \frac{1}{N}\sum_{i=1}^{N}(max(0, \frac{z - c_i}{z}))^a, \qquad (2)$$

where c_i is the consumption of individual i, which corresponds to each person in the considered population (N), and z is the poverty line. In the static ex post case, a household is counted as poor if its per capita consumption is below this poverty line, which is defined to represent the cost to meet basic nutritional needs (2,400 calories per person per day) and the allowance for other nonfood basic needs. The 2016 poverty line is MWK 137,000. The ultra-poverty line, which is the cost of meeting the nutritional needs, is MWK 87,000.[11] We focus on three measures: the poverty headcount (a = 0), the poverty gap (a = 1), and the severity of poverty (a = 2).

Vulnerability is measured by taking the *ex-ante* expectation of the abovementioned measures conditional on the probability distribution of shocks (Christiaensen and Subbarao, 2004). With parameter a ranging from 0 to 2, the formulas are as follows:

$$Vulnerability_a = \frac{1}{N}\sum_{i=1}^{N} E[(max(0, \frac{z - c_i}{z}))^a \mid ShocksProbabilityDistribution] \qquad (3)$$

The parallel between the static and dynamic formulas allows direct comparison of these measures. The difference between the two calculations is that we do not take ex post

[11] Poverty measure using the national poverty line is used to generate moderate poverty rate, and the ultra-poverty line is for ultra-poverty rate.

consumption per capita but ex ante potential consumption per capita that we average given the probability distributions for the shocks.

Another intuitive measure of vulnerability uses the probability that a household falls below the poverty line (Chaudhuri, Jalan, and Suryahadi, 2002):

$$Vulnerability = \frac{1}{N}\sum_{i=1}^{N}\mathbb{1}(Pr[c_i \leq z \mid ShocksProbabilityDistribution] \geq 0.5) \quad (4)$$

Here, only households with a probability of falling into poverty above 50 percent are counted as vulnerable. We also present a similar measure with a threshold of 29 percent as defined by Gunther and Harttgen (Gunther and Harttgen, 2009). If one considers that the probability to fall into poverty in the next two years is 0.5, than it is equivalent to a probability to fall into poverty in any given year of 29%.[12] The overall measure is the proportion of households counted as vulnerable in the considered group of the population. Other vulnerability measures in the literature focus on the expected utility to consider preferences and risk aversion (Ligon and Schechter, 2002).

At the crux of calculating vulnerability to poverty is the estimation of probability distribution of consumption per capita. To reconstruct the distribution of consumption under different realization of shocks, we use equation 1 and calculate the predicted consumption per capita without aid from a given set of shocks (aggregate and idiosyncratic). Several papers in the literature assume that consumption per capita is lognormal and only assess its mean and variance. We are cautious about this assumption and prefer to use a bootstrap approach that relies on the empirical distribution of the shocks. The idea is to randomly draw 'states of the world', that is, vectors of all shocks from their joint probability distribution, as suggested in Hill and Porter (2017).

We assume that the community and idiosyncratic shocks are independent, and drought is independent of excess rainfall. Then, we randomly draw drought and excess rainfall from their respective TA-specific historical distributions. For robustness, we test an alternative process (i.e. simultaneously drawing drought and excess rainfall from their TA-specific joint historical distribution) and find similar results. We categorize households in groups according to the gender of their head, his/her education, and age as well as ownership of

[12] The idea is from the formula: $threshold_{t+k}=1-P[(\ln c > \ln z)]^k$ where $threshold_{t+k}$ is the vulnerability threshold to fall into poverty at least once in the next k years. $P[(\ln c > \ln z)]$ is the probability to have a consumption above the poverty line in any given year (Gunther and Harttgen 2009).

farm plot. We assume that idiosyncratic shocks have a Bernoulli distribution with a probability equal to the proportion of households hit by this shock in a given group. Based on these assumptions, we define the joint distribution of shocks.

We draw 'states of the world' from this joint distribution and calculate the predicted consumption per capita for each household. We run 4,000 simulations to have an accurate probability distribution of each household's consumption, given the shocks' joint distribution. This allows us to apply the vulnerability measures presented earlier.

3 Results

3.1 Impacts of Weather and Idiosyncratic Shocks on Consumption

As a first step in the vulnerability analysis, we estimate the impact of shocks on consumption per capita without aid and present the results in Table 2 under different specifications. We find that both drought and excessive rainfall at the onset of the preceding growing season decrease welfare. These estimates can be interpreted as causal since the shocks are exogenous once we control for the probability of their occurrence. It is confirmed by the fact that the coefficients on the exogenously measured weather shocks do not change when we include additional controls progressively. On the other hand, self-reported shocks are likely to be endogenous. We account for household characteristics to partially address this issue. Hence, the fact that the sign and magnitude remain similar when adding household-specific controls is somehow reassuring.

Table 2: Association between Shocks and Consumption per Capita

	% change consumption per capita, excluding aid					
1. Weather shocks						
Drought in growing season	-3.4***	(1.2)	-3.4***	(1.2)	-3.0***	(0.9)
Days with excess rainfall (Nov-Dec)	-1.4*	(0.8)	-1.4*	(0.8)	-1.0	(0.7)
Days with excess rainfall (Jan-Feb)	0.9*	(0.5)	0.9*	(0.5)	1.1**	(0.5)
Days with excess rainfall (Mar-Apr)	1.6*	(0.8)	1.6*	(0.8)	1.3	(0.8)
TA's median Palmer Index	-4.0	(4.7)	-4.1	(4.7)	-7.4*	(3.7)
TA's 98th percentile of rainfall	0.2**	(0.1)	0.2**	(0.1)	0.1	(0.1)
2. Self-reported shocks						
Job loss			4.4	(2.8)	2.7	(1.7)
Food price shock			-3.9**	(1.5)	-1.9	(1.4)
Death			1.7	(1.5)	3.8**	(1.5)
3. Household head						
Age					0.6***	(0.1)
Age, squared					-0.0**	(0.0)
Female					-2.5*	(1.3)

Years of education					3.4***	
(0.2)						
3.2 4. Household						
% its members in services					0.3***	
(0.0)						
% its members in agriculture					-0.0*	(0.0)
% its members in industry					0.2***	(0.0)
No one employed					19.7***	(1.9)
Household size					-11.6***	(0.3)
Dependency ratio					-10.4***	(0.5)
Has electricity					55.1***	(2.6)
Owns toilets					43.9***	(5.7)
Own more than 2 plots					10.6***	(1.7)
5. Aid received in the last year						
MASAF or Education aid					3.7**	(1.7)
6. Geography						
Rural Household	-53.6***	(3.7)	-53.5***	(3.7)	-9.8***	(3.4)
Distance to town (km)	0.0	(0.0)	0.0	(0.0)	0.0	(0.0)
District FE	Yes		Yes		Yes	
IHS round FE and Season FE	Yes		Yes		Yes	
Observations	35755		35755		35627	

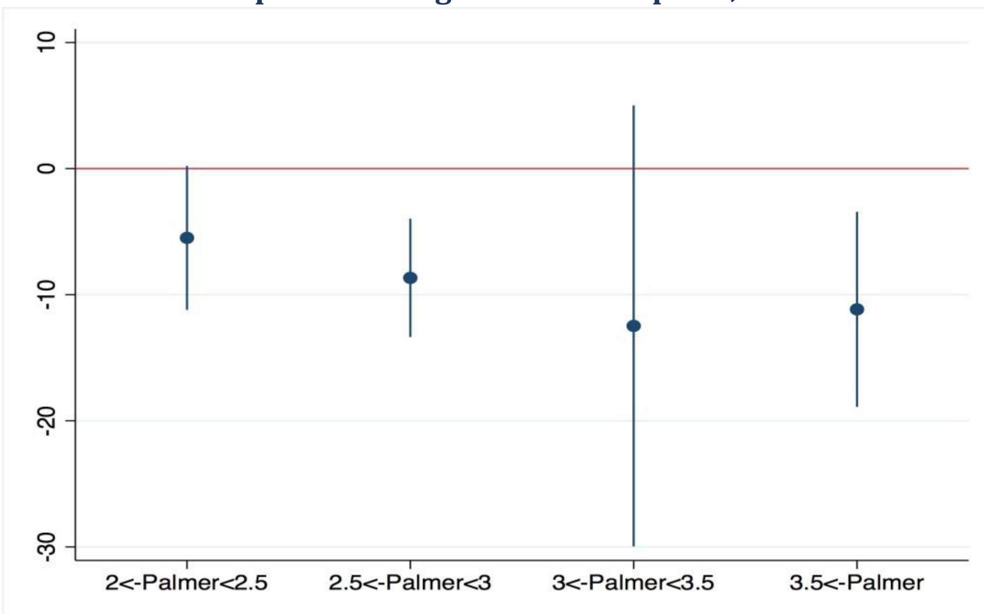
Note: The coefficients capture the percentage change in per capita consumption without aid (food and cash). Standard errors are clustered at the district level. Standard errors in parentheses: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Households' exposure to droughts decreases their consumption per capita, after accounting for any increase in food aid and cash support in response to such a disaster (Table 2). Drought reduces the consumption of households, on average, by 3 percentage points, compared to those that are not exposed to drought. Of course, the magnitude of the impact varies based on the severity of drought (as measured in the Palmer index ranging from 2 to 4). The extent of this decline in per capita consumption increases from 5 percent to 12 percent as the intensity of drought increases. This range of impact magnitude is what we find when considering the coefficient in Table 2 and the Palmer Index ranging from a minimum of 2 to a maximum of 4 (as in Table 1).[13] Excess rainfall in the first two months of the growing season does not decrease consumption per capita after harvest, while excess rainfall in the following months of the growing season appears to increase consumption by 1 percent. When we exclude transfers from the food consumption basket, the negative coefficients on weather shocks decrease further and the positive ones become insignificant (see Table 3). Therefore, the coefficients on excess rainfall in Table 2 seem to be upward biased due to

[13] We find similar conclusions and impact magnitudes as the ones drawn from the linear model. In the primary regression, we opted to use the drought intensity indicator, instead of a dummy variable for drought, to be able to leverage this variation in drought intensity in the simulations.

transfers not being fully accounted for. When addressing this bias, excess rainfall at the onset of the growing season significantly reduces consumption per capita by 1–2 percent for each day of excess rainfall in that period (see Table 3).

Figure 4: Nonlinear Impact of Drought on Consumption, without Transfers



Note: Coefficients in the regression of the percentage change in per capita consumption without aid (food and cash) as a function of weather and idiosyncratic shocks, household characteristics, and geography variables. The specification of drought includes values of the standardized average Palmer index during the previous growing season within fixed bins (below −2 as the reference, between −2 and −2.5, between −2.5 and −3, between −3 and −3.5, below −3.5). Standard errors are clustered at the district level.

Loss of job does not seem to be strongly associated with welfare. This is not surprising in that the majority of households are self-employed and would not be affected by the loss of salaried employment. On the other hand, food price inflation, which was experienced by a significant share of the population during the 2016 drought, is the most adverse idiosyncratic shock. It decreases food consumption per capita by 6 percent (Table 3). However, its impact on total consumption is low and statistically insignificant. Finally, the death of a household member is associated with an increase in consumption per capita likely due to the associated decrease in household size.

Households with female or less-educated heads are poorer on average. As expected, large households and those with a large share of dependents (the elderly and children) tend to be poor. Residing in rural areas is also associated with a high poverty rate as seen on the maps of consumption per capita (Figure 1). Employment in the services or industrial sector and asset ownerships—farm plots, houses with toilets, access to services such as electricity—all correlate with higher welfare. Surprisingly, households in which no one works have a higher consumption per capita. Our interpretation of this surprising finding is that these households rely entirely on aid and in-kind transfers. This coefficient is upward biased due to the transfers per capita that remain after self-reported cash and food aid are removed from consumption. It decreases when focusing on food consumption without transfers (Table 3). Similarly, the coefficient on receiving MASAF or education aid is upward biased and is insignificant in Table 3.

Table 3: Association between Shocks and Consumption per Capita, without Transfers and Aid

	% change in total consumption, excluding aid				% change in food consumption, excluding transfers	
	IHS2-4		*IHS3-4*		*IHS3-4*	
1. Weather shocks						
Drought in growing season	-3.0***	(0.9)	-3.5***	(1.2)	-4.3***	(1.3)
Days with excess rainfall (Nov-Dec)	-1.0	(0.7)	-1.6**	(0.7)	-1.8**	(0.8)
Days with excess rainfall (Jan-Feb)	1.1**	(0.5)	1.0*	(0.5)	0.7	(0.5)
Days with excess rainfall (Mar-Apr)	1.3	(0.8)	0.8	(1.0)	1.3	(1.2)
TA's median Palmer Index	-7.4*	(3.7)	-4.3	(3.9)	-7.9*	(4.3)
TA's 98th percentile of rainfall	0.1	(0.1)	0.2*	(0.1)	0.2	(0.2)
2. Self-reported shocks						
Job loss	2.7	(1.7)	1.2	(3.4)	0.7	(3.6)
Food price shock	-1.9	(1.4)	-5.1***	(1.6)	-6.1***	(1.9)
Death	3.8**	(1.5)	1.0	(2.1)	-0.2	(3.3)
3. Household head						
Age	0.6***	(0.1)	0.8***	(0.2)	1.5***	(0.2)
Age, squared	-0.0**	(0.0)	-0.0***	(0.0)	-0.0***	(0.0)
Female	-2.5*	(1.3)	-1.3	(1.5)	-5.6***	(1.7)
Years of education	3.4***	(0.2)	3.9***	(0.2)	3.5***	(0.2)
4. Household						
% its members in services	0.3***	(0.0)	0.4***	(0.0)	0.4***	(0.0)
% its members in agriculture	-0.0*	(0.0)	-0.0	(0.0)	0.0*	(0.0)
% its members in industry	0.2***	(0.0)	0.3***	(0.0)	0.4***	(0.0)
No one employed	19.7***	(1.9)	21.7***	(2.5)	11.8***	(4.0)
Household size	-11.6***	(0.3)	-11.3***	(0.4)	-9.6***	(0.4)
Dependency ratio	-10.4***	(0.5)	-10.4***	(0.7)	-9.2***	(0.7)
Has electricity	55.1***	(2.6)	51.9***	(2.8)	41.6***	(2.9)
Owns toilets	43.9***	(5.7)	45.3***	(5.4)	24.6***	(2.9)
Own more than 2 plots	10.6***	(1.7)	7.9***	(1.8)	11.4***	(1.8)
5. Aid received in the last year						
MASAF or education aid	3.7**	(1.7)	3.9**	(1.7)	1.9	(2.0)
6. Geography						
Rural Household	-9.8***	(3.4)	-14.0***	(3.0)	-14.4***	(3.0)
Distance to town (km)	0.0	(0.0)	-0.0	(0.0)	0.0	(0.1)
District FE	Yes		Yes		Yes	
IHS round FE and Season FE	Yes		Yes		Yes	
Observations	35627		24643		24643	

Note: FE stands for fixed effects. The dependent variables are per capita consumption without aid (food and cash) in columns 1 and 2 and per capita food consumption (without transfers) in column 3. In Column 2, we restrict the sample to households included IHS 3 and 4 so that we could measure food consumption without transfers in a similar way. Due to lack of access to Stata dofile used to construct consumption aggregates in IHS2, we could not reconstruct food consumption without transfers. Standard errors are clustered at the district level. Standard errors in parentheses: ∗ $p < 0.10$, ∗∗ $p < 0.05$, ∗∗∗ $p < 0.01$.

As mentioned earlier, removing self-reported aggregate food aid, as reported in the social safety net module of the IHS, from consumption per capita does not fully account for the total amount of support received by households. Instead of relying on this aggregate estimate of in-kind transfer, we create an alternative measure of food consumption per capita without transfers by excluding transfer of individual food items in the consumption module of IHS 3 and IHS 4. The aggregate transfer constructed from individual food items is a more accurate measure of food transfer than the aggregated aid reported by households for all food items. A downside is that we were able to build this measure only for IHS 3 and IHS 4 but not for IHS 2. Column (2) of Table 3 displays results from model (3) of Table 2 applied to IHS 3 and IHS 4 (excluding IHS 2) and the same model used on food consumption when transfers are removed.[14]

Table 4 shows food consumption per capita in columns (1) and (2) and the same model in column (3). Thus, the difference between columns (2) and (3) is related to the removal of food transfers only. It confirms that the coefficients of excess rain later in the growing season, lack of employment, and MASAF or education aid are all likely to pick up assistance that is unaccounted for in Table 2.

Table 4: Association between Shocks and Consumption per capita, without Transfers and Aid

	% change in total consumption, excluding aid				% change in food consumption, excluding transfers	
	IHS2-4		*IHS3-4*		*IHS3-4*	
1. Weather hocks						
Drought in growing season	-2.7**	(1.0)	-3.2**	(1.3)	-4.3***	(1.3)
Days with excess rainfall (Nov-Dec)	-0.7	(0.7)	-1.2	(0.8)	-1.8**	(0.8)
Days with excess rainfall (Jan-Feb)	1.4**	(0.5)	1.5**	(0.6)	0.7	(0.5)
Days with excess rainfall (Mar-Apr)	1.5*	(0.8)	1.0	(1.1)	1.3	(1.2)
TA's median Palmer Index	-6.4*	(3.7)	-2.7	(3.6)	-7.9*	(4.3)
TA's 98th percentile of rainfall	0.1	(0.1)	0.2*	(0.1)	0.2	(0.2)
2. Self-reported shocks						
Job loss	2.9*	(1.7)	0.5	(3.3)	0.7	(3.6)
Food price shock	-2.0	(1.4)	-5.5***	(1.6)	-6.1***	(1.9)
Death	3.4**	(1.4)	0.4	(2.1)	-0.2	(3.3)
3. Household Head						

[14] The difference between columns (1) and (2) is only due to the exclusion of IHS 2. The difference between columns (2) and (3) is due to the new dependent variable, which accounts better for transfers. As explained earlier, the coefficients on excess rainfall, as well as the one on job loss, death, and no employment, become smaller.

Age	0.6***	(0.2)	0.8***	(0.1)	1.5***	(0.2)
Age, squared	-0.0**	(0.0)	-0.0***	(0.0)	-0.0***	(0.0)
Female	-2.1*	(1.2)	-0.7	(1.4)	-5.6***	(1.7)
Years of education	3.4***	(0.2)	3.9***	(0.2)	3.5***	(0.2)
4. Household						
% its members in services	0.3***	(0.0)	0.4***	(0.0)	0.4***	(0.0)
% its members in agriculture	-0.0	(0.0)	0.0	(0.0)	0.0*	(0.0)
% its members in industry	0.2***	(0.0)	0.3***	(0.0)	0.4***	(0.0)
No one employed	22.6***	(1.7)	25.4***	(2.5)	11.8***	(4.0)
Household size	-11.8***	(0.3)	-11.6***	(0.4)	-9.6***	(0.4)
Dependency ratio	-10.4***	(0.5)	-10.4***	(0.7)	-9.2***	(0.7)
Has electricity	54.7***	(2.6)	51.5***	(2.7)	41.6***	(2.9)
Owns toilets	44.3***	(5.7)	45.5***	(5.3)	24.6***	(2.9)
Own more than 2 plots	10.7***	(1.7)	7.9***	(1.9)	11.4***	(1.8)
5. Aid received in the last year						
MASAF or Education aid	4.0**	(1.5)	4.3**	(1.6)	1.9	(2.0)
6. Geography						
Rural household	-9.4***	(3.4)	-13.2***	(3.2)	-14.4***	(3.0)
Distance to town (km)	0.0	(0.0)	-0.0	(0.0)	0.0	(0.1)
Year and season FE	Yes		Yes		Yes	
District FE	Yes		Yes		Yes	
Observations	35627		24643		24643	

Note: FE stands for fixed effects. The dependent variables are per capita consumption without aid (food and cash) in columns 1 and 2 and per capita food consumption (without transfers) in column 3. In Column 2, we restrict the sample to households included IHS 3 and 4 so that we could measure food consumption without transfers in a similar way. Due to lack of access to Stata dofile used to construct consumption aggregates in IHS2, we could not reconstruct food consumption without transfers. Standard errors are clustered at the district level. Standard errors in parentheses: ∗ $p < 0.10$, ∗∗ $p < 0.05$, ∗∗∗ $p < 0.01$

In conclusion, the welfare analyses conducted in this study show that drought in the growing season reduces consumption per capita (without aid) in the months following harvest by 5 to 12 percentage points. The amount of welfare loss depends on the intensity of the drought. Excess rainfall in the first two months of the growing season (November–December) decreases food consumption per capita by 1.8 percent for each day of excess rainfall in that period, while excess rain in later months of the growing season has less impact on consumption.

Self-reported food price inflation is also negatively associated with consumption per capita. Although model (3) of Table 2 does not fully remove transfers from consumption per capita, we choose to use this specification for the simulations to benefit from the use of the three rounds of the IHS.

3.2 Vulnerability Estimates

Building on the consumption model presented in Table 2, we predict consumption in 4,000 states of the world. This simulation is then used to calculate the vulnerability measures discussed earlier. The vulnerability estimates, along with the static poverty indicators, are presented in Table 5.[15] The static poverty figures are not identical to the official poverty statistics since the underlying consumption aggregate does not include cash transfer and food aid. They are relatively close to the official statistics in 2010/11 (IHS 3) since households received less assistance in that relatively affluent year but are higher in 2016/17 (IHS 4) when several households experienced drought.[16]

Malawi experienced a severe drought before the 2016/17 survey. Therefore, it is expected that the recorded poverty in this year would likely be higher than the vulnerability to poverty. The 2004/05 round was preceded by a growing season comparable to the historical average. As expected, the recorded moderate headcount poverty is comparable to the share of the population with more than 50 percent chance of falling below the moderate poverty line. After the major drought in 2016, the vulnerability rate (52 percent) was lower than the moderate poverty rate (53.7 percent) recorded in IHS 4. In other words, the magnitude of drought in 2016 was so large that the chance of falling below the poverty line as a result of an even higher magnitude shock was low. On the other hand, during a good weather year such as 2010/11, the vulnerability rate (53.8 percent) was higher than the static poverty rates recorded in that year (51 percent).

The expected poverty gap and severity of poverty are always higher than their static counterparts. The poverty gap accounts for the number of poor as well as how far their consumption is from the poverty line. The severity of poverty gives more weight to the households who are the furthest from the poverty line. In our simulations, the predicted consumption of the poor and ultra-poor individuals is consistently lower than the actual/static consumption, likely due to their higher probability to suffer from idiosyncratic shocks. Therefore, expected poverty gap and expected severity of poverty are overall higher

[15] We also present results disaggregated by region and urban/rural characteristics in the annex. Results are available upon request.

[16] In 2010/11, the official moderate poverty headcount was 50.7 percent (17.3 percent for urban and 56.6 percent for rural), while the poverty rate in 2016/17 was 51.5 percent (17.7 percent for urban and 59.5 percent for rural).

than their static counterparts. This effect of the idiosyncratic shocks is mitigated by the year-on-year differences in weather shocks explained earlier. As a result, the expected poverty gap is closer to the poverty gap in 2016 (IHS 4) than it is in 2010 (IHS 3).[17] Figure 5 shows vulnerability to poverty and static poverty at the district level in 2016/17. In some districts, vulnerability is higher than static poverty. The reverse is true in other districts.[18]

Table 5: Vulnerability to Poverty and Static Poverty

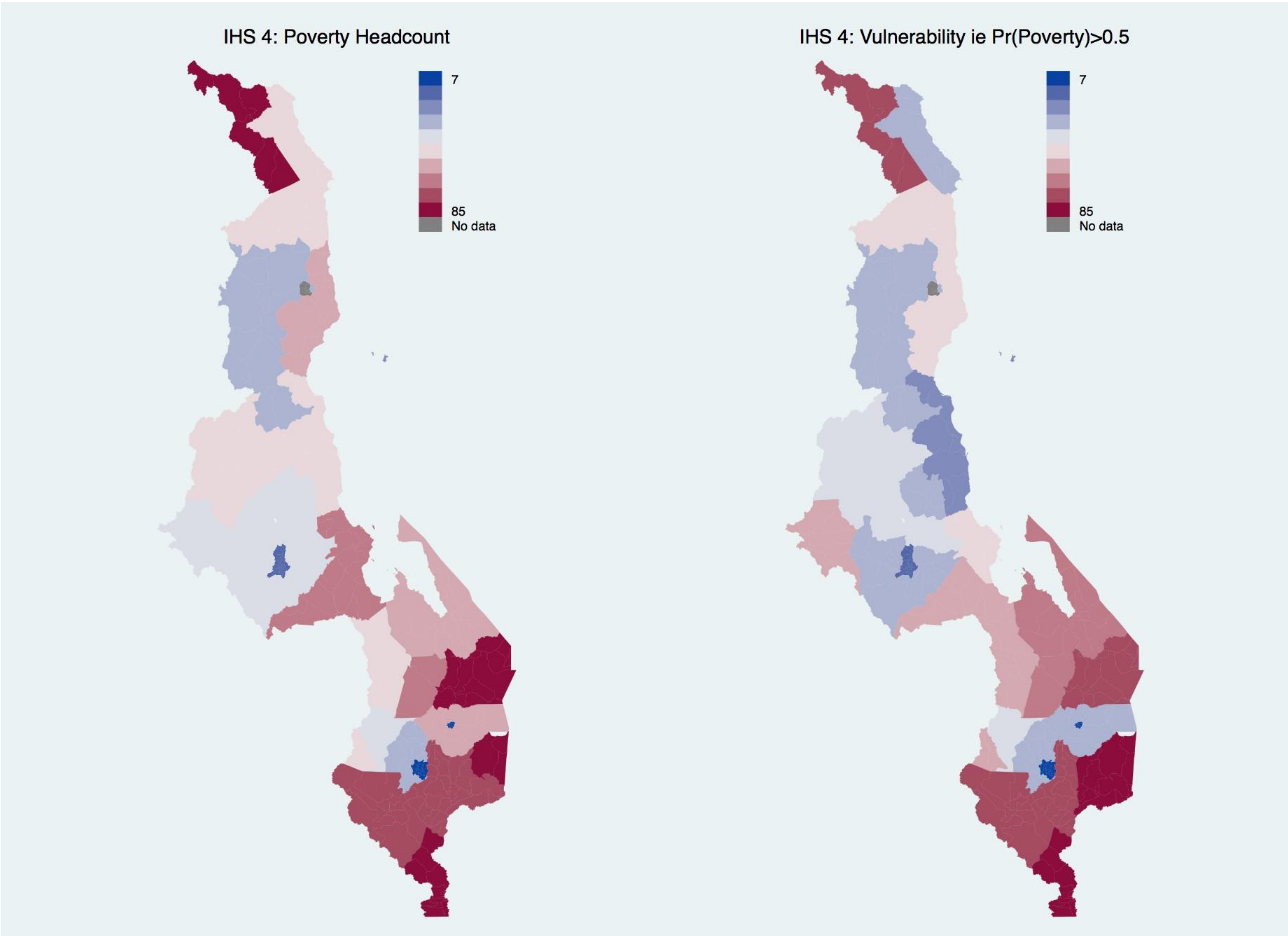
	2004/05 (IHS 2)	2010/11 (IHS 3)	2015/16 (IHS 4)
Static Moderate-Poverty			
Headcount poverty	52.9	51.0	53.7
	(0.5)	(0.5)	(0.5)
Poverty gap	18.1	19.1	18.3
	(0.2)	(0.2)	(0.2)
Severity of poverty	8.2	9.4	8.3
	(0.1)	(0.1)	(0.1)
Dynamic Moderate-Poverty			
Expected headcount of poverty	52.5	53.8	52.0
	(0.4)	(0.4)	(0.4)
Pr(Moderate poverty)>0.5	53.1	54.8	52.8
	(0.5)	(0.5)	(0.5)
Pr(Moderate poverty)>0.29	58.6	59.3	58.5
	(0.5)	(0.5)	(0.5)
Expected poverty gap	20.9	23.6	20.6
	(0.2)	(0.2)	(0.2)
Expected severity of poverty	11.5	14.0	11.5
	(0.2)	(0.2)	(0.2)
Observations	11,281	12,271	12,447

Note: The poverty measures displayed on this table are based on the authors' calculation. They rely on consumption without food and cash aid. Therefore, they are not the official statistics. The vulnerability results are based on 4000 simulations in which weather and idiosyncratic shocks were randomly drawn. Drought and excess rainfall were drawn independently.

[17] We present ultra-poverty results and their decomposition by regions and rural/urban in the annex. The results are available upon request.

[18] District-level maps for the other years are also presented in the annex and are available upon request.

Figure 5: Share of vulnerable and poor households, 2016/17



In sum, generally a higher proportion of Malawians are vulnerable to falling below the poverty line than the static poverty headcount. However, in a relatively bad year with extreme droughts and flooding such as 2016, observed poverty tends to be slightly higher than vulnerability. In 2010/11, when relatively good weather was observed, vulnerability headcount is higher than the observed poverty headcount by about 3.5 percentage points. On the contrary, during IHS 4, which was conducted after the 2016 extreme drought and the 2015 flooding, vulnerability estimates are slightly lower than the static poverty snapshot. In IHS 2, vulnerability rates are more or less equal to the static poverty. When the 29 percent threshold probability suggested by Gunther and Harttgen (2009) is used, vulnerability rate is higher. More than two-thirds of Malawians are vulnerable to falling below the poverty line. In the drought years of 2004/5 and 2016/17, about 58.5 percent of Malawians were vulnerable to poverty. Similarly, in 2010/11 some 59.3 percent of Malawians were vulnerable (Table 5).

4 Robustness

This section details the alternative specifications used to test the robustness of our analysis. We describe how the quantification of the impact of shocks on consumption per capita depends on the choice of specification. Then, we come back to some of the assumptions behind the calculation of vulnerability and test the robustness of the results to changes in these assumptions.

We first assess the robustness of the results when only drought or only excess rainfall is considered at a time.[19] The results show that drought effect remains strong and significant when flooding is not accounted for. The impacts of excess rainfall become slightly weaker if drought is controlled for (Table A.2 and Table 6). We also check if exclusion of indicator for households' access to MASAF makes a difference. The limited coverage of MASAF means, however, exclusion of the indicator did not make much difference.

Table 6: Vulnerability to Poverty when randomly drawing weather and idiosyncratic shocks as well as residuals

	2004/05 (IHS 2)	2010/11 (IHS 3)	2015/16 (IHS 4)
Static Moderate-Poverty			
Headcount poverty	52.9	51.0	53.7
	(0.5)	(0.5)	(0.5)
Poverty gap	18.1	19.1	18.3
	(0.2)	(0.2)	(0.2)
Severity of poverty	8.2	9.4	8.3
	(0.1)	(0.1)	(0.1)
Dynamic Moderate-Poverty			
Expected headcount of poverty	49.3	46.1	49.2
	(0.3)	(0.3)	(0.3)
Pr(Moderate poverty)>0.5	51.5	47.4	52.3
	(0.5)	(0.5)	(0.5)
Pr(Moderate poverty)>0.29	69.8	65.4	69.8
	(0.4)	(0.4)	(0.4)
Expected poverty gap	32.5	30.0	32.6
	(0.2)	(0.2)	(0.2)
Expected severity of poverty	27.2	25.0	27.3
	(0.2)	(0.2)	(0.2)

[19] It should, however, be noted that in some years both drought and excess rainfall can occur. For example, in the 2015/16 growing season, even if there was excess rainfall at the onset of growing seasons, extended dry spells were recorded later in the season.

Observations	11,281	12,271	12,447

Note: The poverty measures displayed on this table are based on the authors' calculation. They rely on consumption without food and cash aid. Therefore, they are not the official statistics. The vulnerability results are based on 4000 simulations in which weather, idiosyncratic shocks and residuals were randomly drawn. Drought and excess rainfall were drawn independently.

We test the robustness of our results to several alternative specifications of the main regression model.[20] Removing only food aid from consumption per capita does not change the coefficients significantly. It stems from the fact that food aid is received by 22.5 percent of the population, whereas only 1.7 percent of households receive cash aid. When we remove historical trends in climate that ensure exogeneity of the weather shocks, coefficients are also similar even though the magnitude of the effects of the weather shocks is slightly smaller. When fully interacting, district, year, and season fixed effects coefficients stay similar, but the significance of excess rain in the first two months is lost while the benefits of excess rainfall over the last two months of the growing seasons are reinforced. The negative effect of food price inflation is strengthened as well. Adding interactions to our main specification shows that drought more adversely affects welfare of rural households with numerous plots. Similarly, loss of salaried employment is mainly an issue for urban educated households as expected. These results are also reassuring as the interactions between exogenous weather shocks and idiosyncratic shocks all have insignificant coefficients. We also use the least absolute shrinkage and selection operator (LASSO) with data-dependent penalization for the estimation.[21] The LASSO coefficients are similar to those of the main regression. Finally, the coefficients remain quite similar when we take into account the sampling weights. We do not use the weights in the regression used to predict consumption for the simulations as they enter in the calculation of poverty measures. Accounting for them in the prediction stage would double-count weights and give a disproportionate importance to observations with high weights.

We also run the primary regression for the indicators displaying enough variation over these years. The number of days with rainfall below 1 ml in the growing season seems to capture geographical variation more than the temporal one. The longest dry spell in the growing season is a noisy measure in terms of intensity: the 2016 drought appears as less severe as the drought mentioned in IHS 2 for some districts. The number of dry spells during the growing season when counting them with pentads is also not capturing very well the

[20] The robustness check results are available upon request. They have been redacted for conciseness.

[21] The estimation is implemented in Stata using pdslasso with rlasso option.

temporal variation and the 2016 drought. Dummy variable for standard precipitation index below −1 is a common measure of drought that does not work well in our case. The likely reason is that the precipitation distribution has a long right tail driving the standard deviation upward. Accumulated excess rainfall is correlated to the total number of days with excess rainfall and gives similar results. Finally, we already explained why the NDVI may be endogenous, but we run the corresponding specification for completeness. It captures both floods and droughts as well as anything else that can affect greenness.

As a robustness check, we relax some of the assumptions behind the simulations. We present national statistics when drawing only the weather shock; the weather and idiosyncratic shocks jointly (as in the main results); residuals inside groups of households with similar characteristics; and residuals. In general, drawing residuals leads to noisier measures as they might exceed the effects of the shocks. This discrepancy worsens when drawing residuals inside groups. Our main simulation is directly conducted on consumption per capita to keep all variations. In the annex, we present the ones based on the prediction of percentage change in consumption per capita. Results are similar when drawing shocks but vary when adding residuals' draw since the residuals from the log regression behave better. We also present simulations based on IHS3 and IHS4 only. Then, we relax the assumption of independence between drought and rainfall. We make them perfectly correlated by drawing them simultaneously. Results are very similar. Finally, we also present matrices of the number of vulnerable versus poor households for each IHS year in the annex.

5 Conclusion and Policy Implications

This study examines the impact of droughts and excess rainfall on the welfare of Malawian households using a nationally representative household survey and exogenously measured weather shock indicators. After taking into account household characteristics as well as idiosyncratic shocks and carefully dealing with transfers and aid in response to drought, we quantify vulnerability to poverty during 2004–2016. The results indicate that weather shocks have severe impacts on the welfare of households and push non-poor households into poverty. In particular, drought during the growing season decreases consumption per capita without aid by 5–12 percent. Excess rainfall during the first two months also has an adverse effect on consumption per capita. Leveraging this link between consumption and weather shocks, we conducted 4,000 simulations to estimate vulnerability to poverty following extreme weather events. Households' vulnerability to poverty is generally higher than static poverty. This is particularly true during a good weather year when the static poverty measures are lower than the share the population that has a more than 50 percent chance of falling into poverty. In years of extreme droughts such as 2016, recorded poverty rates tend to be higher than vulnerability, which indicates that the magnitude of drought these years is so large that the chance of falling below the poverty line as a result of an even higher magnitude shock was low.

These results have several policy implications and provide insight during the preparation of disaster response plans as well as the design of shock-responsive safety net programs. For example, social protection programs target people who are identified as poor or ultra-poor. The beneficiary is identified based on a snapshot of household characteristics and welfare condition in a given year. However, the results from this study show that households who are not poor during a good harvest year are vulnerable to falling below the poverty line when they experience shocks. Therefore, the timing of beneficiary identification in traditional safety net programs alters the selection significantly. There are two ways to modify traditional social protection programs into adaptive safety nets. One possibility is to have a vertical expansion that increases the amount of benefits received by the beneficiaries to reduce structural poverty. On the other hand, a horizontal expansion includes vulnerable people as beneficiaries. The latter has the potential to tackle risk-induced poverty by providing support to the vulnerable households when disaster strikes. It also requires an ex ante identification of vulnerable households to trigger disaster responses promptly. The empirical method and analysis presented in this paper could be used for such ex ante identification.

Finally, we would like to point out some of the limitations and underlying assumptions of the analysis presented in this study. First, the measures of poverty and vulnerability are all expenditure based. The analysis could be extended to other aspects of poverty, such as asset-based poverty and multidimensional poverty. Second, the simulations assume that weather events are distributed according to their historical probability distribution. With climate change increasing the probability of extreme events, it might be better to draw weather shocks from climate models' predictions to account for future high probability of extreme weather events. In the absence of adequate risk mitigation measures, we expect the difference between the static measures of poverty and vulnerability to increase dramatically as extreme shocks become more frequent.

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Annex

Table A.1: Summary Statistics for each IHS round

	IHS2		HIS3		IHS4	
	Mean	Std. Error	Mean	Std. Error	Mean	Std. Error
1. Consumption per capita (2016 MWK, thousands)						
Total consumption without aid	180.1	1.86	204.4	2.59	191	11.95
Total consumption without food aid	180.1	1.86	204.4	2.59	191.5	11.95
Total food consumption without transfers			107	0.89	92.7	0.69
Total food transfers			6	0.14	10.2	0.15
2. Weather shocks						
Drought in growing season	0.2	0.01	0.2	0.01	0.7	0.01
Days with excess rainfall (Nov-Dec)	1.9	0.01	1.9	0.01	1.7	0.01
Days with excess rainfall (Jan-Feb)	3.0	0.02	4.4	0.01	6	0.02
Days with excess rainfall (Mar-Apr)	1.8	0.01	1.8	0.01	1.8	0.02
TA's median Palmer Index	-0.2	0.01	-0.2	0.01	-0.2	0.01
TA's 98th percentile of rainfall	37.5	0.13	37.9	0.12	38.1	0.12
3. Self-reported shocks						
Job loss (dummy expressed in %)	5.9	0.22	0.7	0.08	1.3	0.1
Food price shock (dummy expressed in %)	28.2	0.42	24.9	0.39	69.8	0.41
Death (dummy expressed in %)	26.5	0.42	4.1	0.18	7.1	0.23
Death of breadwinner [a] (dummy expressed in %)	4.3	0.20	1	0.09	2.9	0.15
Death of another member [a] (dummy expressed in %)	24.5	0.40	3.2	0.16	4.3	0.18
4. Household head						
Age	43.1	0.14	42.5	0.13	43.1	0.13
Female (Dummy expressed in %)	19.1	0.37	19.6	0.36	25.2	0.39
Years of education	3.3	0.04	5.5	0.04	5.9	0.04
5. Household						
% its members in services	11.7	0.23	12.4	0.24	13.7	0.24
% its members in agriculture	59.5	0.39	54.9	0.39	47.8	0.39
% its members in industry	5.5	0.16	3.6	0.13	2.5	0.11
No one employed (Dummy expressed in %)	2.0	0.13	2.4	0.14	2.5	0.14
Household size	5.7	0.02	5.6	0.02	5.2	0.02
Dependency ratio	1.3	0.01	1.3	0.01	1.3	0.01
Has electricity (Dummy expressed in %)	6.5	0.23	7.5	0.24	10.9	0.28
Owns toilets (Dummy expressed in %)	3.2	0.16	2.9	0.15	3	0.15
Own more than 2 plots (Dummy expressed in %)	30.5	0.43	38.6	0.44	36	0.43
6. Aid received in the last year						
Food aid [a] (dummy expressed in %)	15.4	0.34	17.2	0.34	32.3	0.42
MASAF aid [a] (dummy expressed in %)	3.9	0.18	0	0	8.9	0.25
Education aid [a] (dummy expressed in %)	0.5	0.07	0.3	0.05	0.7	0.07
MASAF or Education aid (dummy expressed in %)	4.3	0.19	0.3	0.05	9.5	0.26
7. Geography						
Rural Household (dummy expressed in %)	87.7	0.31	84.6	0.33	81	0.35
Distance to town (km)	96.4	0.77	33.2	0.19	32.9	0.19
Observations	11281		12,271		12,447	

Note: [a] These variables are not included in the main regression but summarized for the reader's information. Some indicator variables take values of 0 or 1 but are expressed as percentage terms. The summary statistics are generated by pooling the three IHS rounds.

Table A.2: Alternative specifications and association between shocks and consumption per capita (% change)

	Only drought		Only excess rainfall		Without control for aid	
1. Weather shocks						
Drought in growing season	-2.7***	(1.0)			-3.0***	(0.9)
Days with excess rainfall (Nov-Dec)			-1.2	(0.8)	-1.0	(0.8)
Days with excess rainfall (Jan-Feb)			0.9*	(0.5)	1.1**	(0.5)
Days with excess rainfall (Mar-Apr)			1.1	(0.7)	1.3	(0.8)
TA's median Palmer Index	-7.0*	(3.6)	-5.0	(3.9)	-7.3*	(3.7)
TA's 98th percentile of rainfall	0.1	(0.1)	0.1	(0.1)	0.1	(0.1)
2. Self-reported shocks						
Job loss	2.5	(1.7)	2.7	(1.7)	2.8	(1.7)
Food price shock	-1.9	(1.4)	-1.8	(1.4)	-1.8	(1.4)
Death	3.9**	(1.5)	3.9**	(1.6)	3.8**	(1.5)
3. Household head						
Age	0.6***	(0.1)	0.6***	(0.1)	0.6***	(0.1)
Age, squared	-0.0**	(0.0)	-0.0***	(0.0)	-0.0***	(0.0)
Female	-2.4*	(1.3)	-2.6*	(1.3)	-2.5*	(1.3)
Years of education	3.4***	(0.1)	3.4***	(0.2)	3.4***	(0.2)
4. Household						
% its members in services	0.3***	(0.0)	0.3***	(0.0)	0.3***	(0.0)
% its members in agriculture	-0.0*	(0.0)	-0.0*	(0.0)	-0.0*	(0.0)
% its members in industry	0.2***	(0.0)	0.2***	(0.0)	0.2***	(0.0)
No one employed	19.5***	(1.9)	19.7***	(2.0)	19.6***	(1.9)
Household size	-11.5***	(0.3)	-11.6***	(0.3)	-11.5***	(0.3)
Dependency ratio	-10.4***	(0.5)	-10.4***	(0.5)	-10.4***	(0.5)
Has electricity	55.1***	(2.6)	55.0***	(2.7)	55.0***	(2.6)
Owns toilets	44.0***	(5.7)	43.9***	(5.7)	43.8***	(5.7)
Own more than 2 plots	10.4***	(1.7)	10.4***	(1.7)	10.6***	(1.7)
5. Aid received in the last year						
MASAF or education aid	3.6**	(1.7)	3.2*	(1.7)		
6. Geography						
Rural Household	-9.7***	(3.4)	-9.2**	(3.4)	-9.8***	(3.4)
Distance to town (km)	0.0	(0.0)	0.0	(0.0)	0.0	(0.0)
District FE	Yes		Yes		Yes	
IHS round FE and Season FE	Yes		Yes		Yes	
Observations	35627		35627		35627	

Note: FE stands for fixed effects. The dependent variable is per capita consumption without aid (food and cash). In column 1, only drought is included as a weather shock. In column 2 only excess rainfall is considered. In column 3, we do not control for education and MASAF aid. Note that MASAF aid's correlation with drought in the growing season is 14% and it is 8% with excess rainfall in January-February. The correlation with excess rainfall in other months is below 2% in absolute value. Standard errors are clustered at the district level. Standard errors in parentheses: $*$ $p < 0.10$, $**$ $p < 0.05$, $***$ $p < 0.01$