Droughts, Measurement and Impact: The Case of Ethiopia in 2015.

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1. Introduction

Weather variation is key to livelihoods in Ethiopia, where 98 percent of the rural households report agricultural activity and only 7 percent have anyone working in any kind of employment outside the household. This is also reflected in its history of severe droughts with catastrophic human outcomes. The drought in 2015 was reported as the worst in decades with more than 10 million estimated to be in need of food aid (UNICEF 2015).

Though the link between drought and dire human outcomes is very intuitive, drought in itself is defined in so many ways that in a review of drought reviews, Bachmair et al. (2016) conclude that "A comprehensive synopsis of existing drought indicators is impractical given the vast (and growing) number of available indicators". Yet, despite the large number of drought indicators, the ground impact of these is rarely well-understood either, nor systematically assessed, and there is little consensus on which are most meaningful for impact on the society (Bachmair et al. 2016).

This paper contributes to an improved understanding of the link between drought measurement and drought impact by analyzing the impact of drought, defined in multiple ways, on household well-being measured by consumption. Past assessments of impact of drought in Ethiopia on consumption or vulnerability, measured by consumption, have used hydrological droughts based on rainfall from ground measuring stations (Demeke et al. 2011; Dercon 2004; Porter 2012); self-reported exposure to rain and drought (Calvo and Dercon 2013; Demeke et al. 2011; Dercon et al. 2005; Dercon and Krishnan 2000; Fuje 2018; Lei Pan 2009; Little et al. 2006); as well as predicted agricultural losses (Hill and Porter 2016). Unlike past assessments, this analysis includes more recent drought indicators, such as satellite-based vegetation (NDVI) and rain(CHIRPS), that are now standard use in analysis of weather and drought patterns in Ethiopia (Lewis 2017; Zewdie et al. 2017). However, until their inclusion in this paper, satellite-based indicators have never, to the author's knowledge, been used to measure impact of drought on households' consumption in Ethiopia.

2. Data

2.1 Survey and Consumption Data

The main sources of data for this impact assessment are the two rounds of Ethiopia Socioeconomic Survey (ESS) data from 2014 and 2016 (Ethiopia - Socioeconomic Survey 2017). The Survey is a national representative panel of households observed before and after the 2015 drought. For this analysis, the data has been restricted to rural households that were observed in both rounds of data.

Consumption data was collected in February through April in 2014 and again in same months in 2016, which is a minimum of three months after completion of the last harvest. Hence, the timing of the consumption expenditures is such that they should capture both primary and some secondary economic effects from the 2015 minor (belg) and main (meher) harvests, while not be influenced by the 2016 harvest starting with the belg harvest in May 2016. Descriptive statistics shows that consumption on average fell between 2014 and 2016, while durable assets and livestock did not change significantly over time. The pattern is consistent with a negative shock impacting consumption, though it hasn't resulted in changes in saving yet. The analysis will show if the drought could explain this pattern.

2.2 Drought indicators

The analysis uses four types of drought indicators: 1) rainfall based on satellite images (CHIRPS), 2) predicted crop losses (LEAP), 3) vegetation based on satellites (NDVI), 4) households' self-reported exposure to drought.

Rain anomalies is based on the Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS) (Funk et al. 2015). Mean monthly rainfall is merged with the survey data based on households' GPS locations. The value for each household is set to be the weighted value of the four nearest grid areas, with weights being the inverse distance from the households' GPS locations and the center point of the grid. In Ethiopia's Upper Blue Nile Basin, the monthly CHIRPS data have been shown to be highly correlated with rainfall from weather stations (Bayissa et al. 2017). Following Bayissa et al. (2017), rain anomalies are defined by a z-score for accumulated rain during the meher growing season (June to August) based on values for each household between 2000 and 2016.

Predicted crop losses are from the Livelihoods, Early Assessment and Protection Project (LEAP) system, developed in 2006 by the Government of Ethiopia in collaboration with the World Food Programme. LEAP uses crop-modeling approaches to estimate the likely rainfall-induced crop losses in woredas throughout Ethiopia based on water balance (Hill and Porter 2016). The data is estimated percentage crop loss in the meher season at woreda level. Woreda is the third administrative level, below district, and there are 670 rural woredas in Ethiopia, of which 238 are found in ESS.

Self-reported drought exposure is found in both the community and the household questionnaire in ESS surveys. Here, 21 percent of households live in communities that report a drought in 2015 as one of maximum of four negative events. In the household questionnaire, 28 percent of households report a drought within the last year, leaving 46 percent of households as having been exposed to drought according to either the community or household question. The community reporting includes an estimate of how many households were hit by the drought. Here, 39 percent of communities report that 50 percent or less of households were hit by the drought. In a country where almost all households rely on rain-fed agriculture, it is unlikely that meteorological drought will expose households within same community vastly differently, indicating that the reported drought exposure also reflects socio-economic drought, and not just meteorological drought.

Vegetation anomalies is measured through the Vegetation Condition Index (VCI) (Kogan 1995), based on the Normalized Difference Vegetation Index (NDVI) from the MODIS Terra satellite. VCI values are expressed as a percentage reflecting the historical best and worst vegetation for each location. VCI is used in two different ways. VCI is included based on its values in the growing season (June to August) and for the harvest period of the meher season (August to October). The former is the value when VCI is used as a monitoring tool (Eshetie et al. 2016; Tagel Gebrehiwot 2016), while the latter is the actual vegetation outcome, reflecting agricultural production. The index is merged with the household survey data based on households' GPS locations, using inverse distance to center points as weights.

All drought indicators are included as they are used for assessment of socio-economic impact of droughts, but they differ in key aspects. Rain anomalies is a meteorological drought indicator and is usually the first and primary source of drought monitoring. Predicted crop losses builds on the rain data and transfers it into an agricultural indicator, while vegetation anomalies in the growing season is also used to predict agricultural outcomes. Common for all three indicators is that they are predictors as opposed to self-reported drought exposure and vegetation anomalies for the harvest season, which can be seen outcome measures.

Self-reported drought exposure is included as much past drought impact work has used this indicator (for lack of better alternatives). However, self-reported drought has some drawbacks. First, it is not clearly defined as a type of drought, as households could report lack of rains (meteorological drought), lack of vegetation (agricultural drought), or even the direct loss of consumption (a socio-economic drought), and the reported value might differ by each household. Second, self-reported drought exposure is likely endogenous to consumption, as households that fared worse are more likely to report a drought than households that suffered less for same drought exposure. The 39 percent of communities that report 50 percent or less of households were hit by the drought support self-reported droughts exposures endogeneity. Such endogeneity would give an upward-biased impact analysis using regression analysis.

3. Method

The key interest is the impact from drought on households' well-being, where well-being is measured by consumption. Agricultural production is a key transition mechanism between drought and households' well-being, as around 98 percent of the rural households report agricultural activity and only 7 percent have anyone working in any kind of employment outside the household. However, the net impact from crop or pasture failures is not necessarily negative for those most dependent on agriculture. For instance, crop failures can lead to higher prices, which can benefit farmers despite the lower harvest; a few farmers are even insured against such losses, and losses can give access to external assistance. Further, there are likely to be secondary effects as households and markets adjust to the supply and demand shocks, while some households are not directly exposed to drought (Ya et al. 2011).

Drought impact is estimated via a first difference regression with households being the unit of observation as in Equation 1.

Equation 1

$$\Delta \ lnY = \delta D + \theta \Delta H$$

Where $\Delta \ \mathrm{lnY}$ is change in log consumption between the two survey rounds, D is the drought indicator for drought exposure in the 2015 season, and the impact of drought is captured in δ. Following the discussion above, the Equation 1 is estimated with D being: 1) z-scores for rainfall during the meher season, 2) estimated crop losses as a percentage of expected, 3) vegetation anomalies measured through VCI in the meher growing season, 4) self-reported drought exposure at household level, and 5) vegetation anomalies in the 2015 harvest season. $\Delta\mathrm{H}$ is time-variant household characteristics. The control variables include household size, household size squared, highest education level in household, and change in gender of household head. The first-difference regression analysis controls for all unobserved time-invariant factors. All regressions are done in stata using the svy commands taking survey designs into effect and using the household weights from the 2014 round of the data.

4. Analysis

4.1 The 2015 drought

Household self-reported data from ESS indicate that the 2015 season was worse than previous years. This is true for the 28 percent of households that reported a drought, compared to only 9 and 14 percent in the 2013 and 2011 seasons, as well as for the 21 percent of households that lived in communities that reported a drought in 2015, compared to the little more than one percent reporting it in 2011 and 2013 (Figure 1.B). Similarly, the share of households that reported to be food insecure in the months immediately following the end of the meher season (November through January) increased to more than 5 percent in 2015/16, compared to around 2 percent in 2011/12 and 2013/14 (Figure 1.B).

Meteorologically, rain anomalies also show 2015 to be a drought year with low rainfall in the growing season, even worse in 2015 than in previous historical drought years (2009 and 2002/2003) (Figure 1.A).

Agriculturally, anomalies in vegetation, on the other hand, show 2015 in general being an average or even better-than-average year for most of the country (Figure 2.A). Agricultural production data indicate that 2015 was below the trend, but only one percent below production levels of the year before and above the level produced two years prior (Figure 2.B). Estimated crop loss data show that crop losses were about the mean for the 2005-2016 period. Estimated crop losses and measured crop harvests are data-independent as crop loss data is based on meteorological data and crop-specific models, while crop harvests are based on field harvest samples. Hence, on average, the crop production prediction models in 2015 seem to adequately take into account the specificities of weather patterns and crop production, and estimate agricultural production consistently with the measured harvests. Other data related to agriculture also support that 2015 did not have a widespread agricultural drought as both food prices and wages were remarkably stable from 2014 to 2016 (Bachewe 2016).

Spatially, poorer-than-normal rains in the meher season are observed for all of central and northern Ethiopia (Figure 3.A). Worse-than-normal vegetation, on the other hand, was mostly concentrated in a smaller area in the northeast of the country (Figure 3.B and 3.C). Importantly, the vegetation drought was mostly observed in areas that have limited agricultural production (Figure 3.D), which explains why agricultural data points to 2015 as close to a normal year.

Interestingly, the divergence between rain and vegetation anomalies is not just driven by a time lag. The concentration of poorer vegetation, even in the growing period, was also concentrated in the northeast. Analysis of rain and vegetation anomalies from 2000 to 2016 in all of East Africa also highlights large discrepancies between rain and vegetation anomalies in 2015 (Winkler et al, 2017), with large discrepancies found in Ethiopia, but especially so in Zimbabwe, Zambia, Malawi and Mozambique. This divergence might explain why others have also recently identified a missing link between rainfall variability and food security in Ethiopia (Lewis 2017) as well as a missing link between rain variability and crop yield in the Amhara region of Ethiopia (Bewket 2009).

4.2 Policy mitigation of drought

As reflection of past drought experiences, Ethiopia monitors drought closely, and alarms were ringing in 2015, resulting in both government and non-government expanding drought mitigation programs. In the ESS data, this is seen in the share of households receiving external assistance increasing from 11 to 19 percent of all rural households from 2014 to 2016. In particular, the free food program expanded (increased by 120 percent), but the public PNSP programs also expanded (Table 1). For those receiving the free food, it was valued at three percent of total food consumption for the year at the median, and seven percent at the mean.

Ideally, a combined regression analysis would assess both the impact from drought and mitigating impact from programs in response to the drought on households' well-being. However, as the PNSP program and the free food distribution target households in need, the variables would be endogenous to consumption and results, therefore, biased ((Puri et al. 2017).

To assess if the support programs reached those exposed to drought, Equation 2 tests whether households' entry into the assistance programs during the expansion was, in fact, driven by drought anomalies. Here, $\Delta\, Assitance$ is households' entry and exit of any of the programs listed in (Table1), while $\delta \mathrm{D} + \theta \Delta \mathrm{H}$ are defined as in Equation 1.

Equation 2 $$\Delta\, Assitance = \delta D + \theta \Delta H$$

Table 2 shows that the distribution of free food and the general PSNP program did target locations with unusually poor vegetation. At the mean, the coefficients show that there is a five percent higher chance of entering the free food program for one standard deviation worse VCI score. Using non-parametric smoothing, however, indicates that the significant drought targeting is highly concentrated in the lower end of the distribution and the coefficients based on averages, in Table 2, might underestimate the true likelihood of a household with very poor vegetation having received assistance (Figure 4). Both the free food program and the PNSP program seem well-targeted towards households with low vegetation (Figure 4), as the likelihood of receiving these assistances increases systematically with lower vegetation than normal, especially for those with the worst VCI score.

4.3 Impact of drought on consumption

Table 3 shows the δ coefficients from Equation 1 with and without the household control variables (H). As expected for panel data, there is a limited impact from controlling for time-varying household characteristics, indicating that results are robust. Regressions with an extended set of controls, including log of an assets index, log of holdings of livestock measured in Tropical Livestock Unites (TLU), if someone in the household entered or exited the PNSP labor program, if the household received food aid, or if the household obtained lines of credit during the 2015 season, give almost identical results, indicating that results are robust.

Table 3 shows that none of the drought predictors show an impact from drought on consumption, which is in contrast to outcome-measured drought (self-reported and VCI for harvest) showing a significant negative impact of drought on consumption. Household self-reported exposure indicates that consumption levels are 17 percent lower due to the drought, a very large impact. Drought impact on consumption based on vegetation anomalies, on the other hand, indicates a much smaller impact of 7 percent lower consumption for one standard deviation worse VCI score (VCI SD is 34.2, 34.2*0.002=7 percent). This is fully in line with expectations, given an expected upward-bias in the self-reported drought exposure. Self-reported drought exposure is correlated with harvest vegetation anomalies, and increasingly so, for worse VCI scores (Figure 5). However, the unknown upward-bias makes self-reported drought exposure a bad drought indicator, which, in the author's opinion, should not be used for impact assessments. For farmers in northern Ethiopia, it has also been found that actual rainfall and perceived rainfall do not correlate well (Meze-Hausken 2004).

A closer look at the relationship between change in consumption and harvest vegetation anomalies shows that the negative impact on consumption from vegetation anomalies is in the range 40 to 100. That is, households that had better-than-normal vegetation were relatively better off (the y-scale is negative as all households on average had lower consumption), while those that had the worst harvest vegetation anomalies also fared relatively better than those with normal vegetation (Figure 5). That households with very poor harvest vegetation were relatively better off could be due to the massive distribution of food aid and other programs. Households with a VCI score under 10 had 40 percent chance of receiving food aid, which at the median was valued at three percent of annual consumption (Figure 4). That support programs explain the observed patterns is a plausibility, but the analysis does not establish causality between the relatively successful targeting of support program towards poor harvest vegetation anomalies and the lack of a negative impact on consumption for this group.

Noteworthy, in this case, none of the predictor drought indicators (rain, predicted crop losses, or vegetation during the growing season) seem to have the accuracy or power to capture the average impact on consumption that seems to be present when using outcome drought indicators.

5. Discussion

The analysis brings several data sources together and shows that mass suffering due to drought was likely avoided in part due to a drought that was limited and mostly hit areas with limited importance for agricultural production, and likely also due to massive policy response supporting those that were worst hit by drought. In addition to this, the work illustrates how impact assessment by subjective drought reporting is upwards-biased. The use of predictor-based drought indicators compared to outcome-based indicators also shows that the predictor-based ones, in this case, are not powerful enough to show the full impact.

The analysis also raises some questions. The divergence between rain and vegetation anomalies can indicate that agricultural production is resilient to weather, though this is generally not expected given Ethiopia's low degree of irrigation (Worqlul et al. 2017). Increased resilience resonates with recent evidence showing decreasing impact of weather variation on grain prices over time (Hill and Fuje 2017). The increased resilience of grain prices to drought is attributed to both improvement in market access and better policy mitigation of drought impact. However, neither improved markets nor impact mitigation would explain variations in rain and vegetation anomalies. The smaller agriculture season (belg) coincides with the growing season of the meher season, which could impact the vegetation anomalies but not the rain anomalies. However, existing literature on drought monitoring does not seem to see that as an issue (Eshetie et al. 2016; Tagel Gebrehiwot 2016). Hence, a more detailed and localized analysis is needed to understand the drivers of the divergence of rain and vegetation anomalies.

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A. Rain anomalies 2000-2016

B. Self reported drought exposure 2011-2015

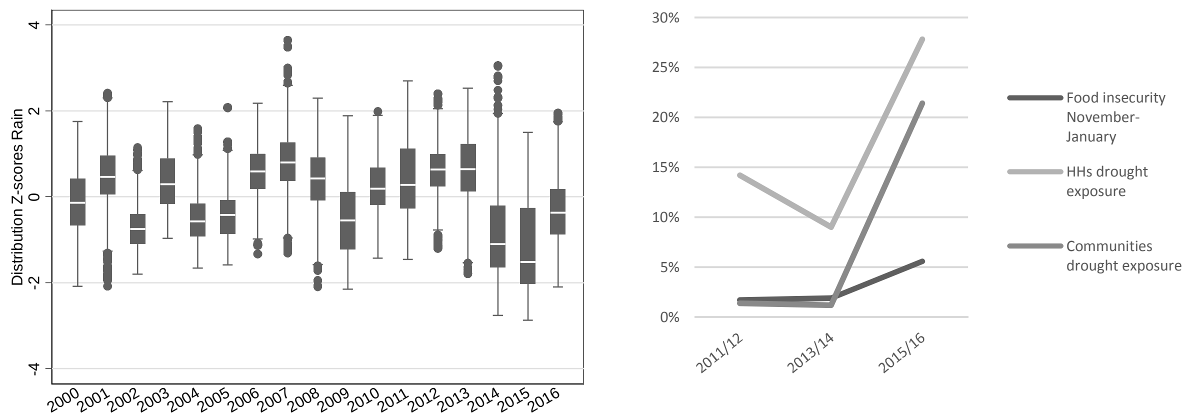


Figure 1. A: Rain anomalies are z-scores based on CHIRPS presented as box-plots for each year. The white stripe in the middle of the solid grey box is the median value, the upper hinge of the solid grey box is the 75th percentile of distribution, while the lower one is the 25th percentile. B: Self-reported drought exposure and food insecurity is survey data (ESS 2012, 2014 and 2016).

A. Vegetation Anomalies 2000-2016

B. Grain production and predicted crop losses

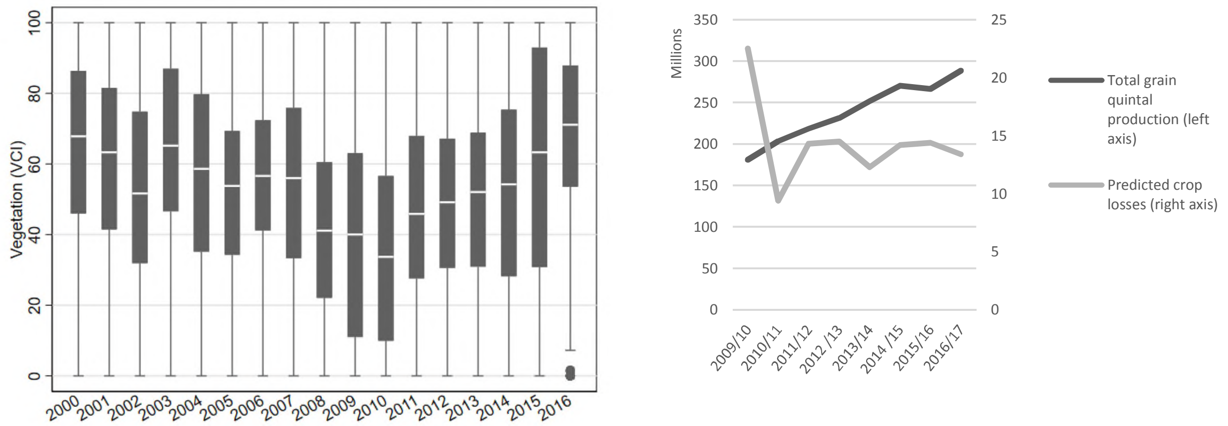
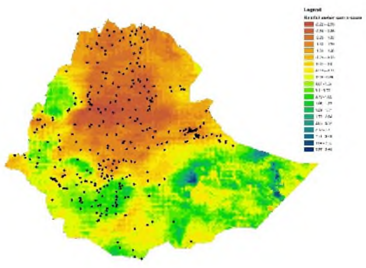
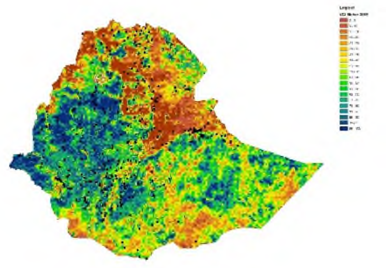


Figure 2. A: Vegetation anomalies are VCI values presented in box-plots for each year for the growing season. The white stripe in the middle of the solid grey box is the median value, the upper hinge of the solid grey box is the 75th percentile of distribution, while the lower one is the 25th percentile. B: Total grain production is from CSA(CSA, 2014, 2015, 2016, 2016.). Estimated crop losses are from Hill and Porter (Hill and Porter, 2016).

A. Rain anomalies growing season 2015

B. Vegetation anomalies growing season 2015





C. Vegetation anomalies harvest season 2015

D. Average grain production

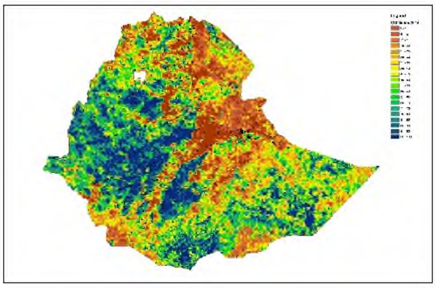
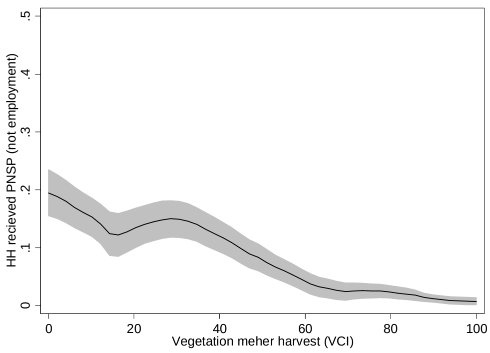


Figure 3. A: Z- scores for rain anomalies in the meher growing season. B: VCI for the meher growing season. C: VCI for the meher harvest season D: Share of total agricultural grain production by zone, averages for 2011-2015 (CSA, 2011, 2012, 2013, 2014, 2015). Black dots are locations of household survey points in the ESS survey.

A. Non-linear correlation between receiving PNSP and vegetation anomalies

B. Non-linear correlation between receiving free food and vegetation anomalies



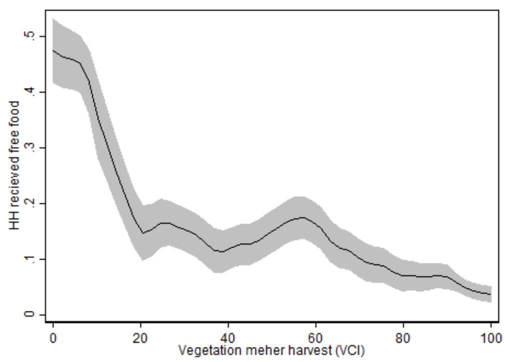


Figure 4. A: Local polynomial smoothing between receiving PNSP assistance and VCI anomalies. B: Local polynomial smoothing between receiving free food assistance and VCI anomalies. Grey areas are 95 percent confidence intervals. To focus on the expansion, both A and B exclude households that received assistance in 2014.

A. Non-linear correlation between self-reported drought and vegetation anomalies

B. Non-linear correlation between change in consumption and vegetation anomalies

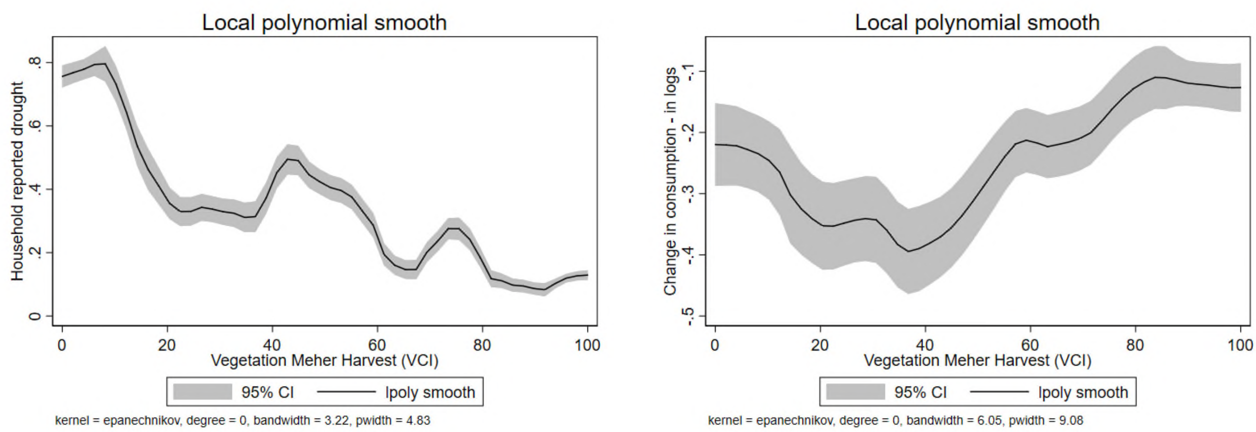


Figure 5. A: Local polynomial smoothing between self-reported drought exposure and vegetation drought anomalies (VCI). B: Local polynomial smoothing between change in consumption between 2014 and 2016 and vegetation drought anomalies (VCI). Grey areas are 95 percent confidence intervals.

Year	PNSP	Free food	Cash or food for work	Inputs for work	Other assistance	PNSP employment
2014	3,6%	5,5%	2,6%	0,0%	0,7%	7,2%
2016	4,5%	12,1%	2,5%	0,3%	0,9%	8,9%

Table 1 Share of rural households receiving external assistance by program type. Source ESS 2014 and 2016.

Drought indicator	Δ PNSP	ΔFree food	Δ Cash or food for work	Δ Inputs for work	Δ Other assistance	Δ PNSP employment
VCI harvest	-0.0007**	-0.0015***	0.0000	-0.0000	0.0000	-0.0002
	(0.0003)	(0.0007)	(0.0002)	(0.0001)	(0.0002)	(0.0004)
Obs	3,001	3,001	3,001	3,001	3,001	3,001

*Table 2 First difference regression for program participation on harvest vegetation anomalies. Notes: Table shows the δ coefficient from Equation 2 for each of the support programs. Standard errors in parentheses * p<0.10, ** <0.05, *** p<0.01*

Type of indicator	Predictor						Outcome			
Drought indicator	Rain in growing season		Predicted crop losses		Vegetation during growing season		Self-reported households		Vegetation in harvest season	
Impact on log consumption	-0.01	-0.02	-0.00	-0.00	0.00	0.00	-0.169***	-0.164**	0.002**	0.002**
	(0.03)	(0.03)	(0.00)	(0.00)	(0.00)	(0.00)	(0.062)	(0.064)	(0.001)	(0.001)
Household covariates		x		x		x		x		x

Observations	2822	2745	2833	2756	2822	2745	2833	2756	2833	2756
R square	0.00	0.01	0.00	0.01	0.00	0.01	0.01	0.02	0.01	0.02

*Table 3 First-difference regression for impact of drought on consumption by drought indicator. Notes: Table shows the δ coefficient from Equation 1. Standard errors in parentheses * p<0.10, ** <0.05, *** p<0.01*