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Two Sides to Same Drought: Measurement and Impact of Ethiopia's El Nino Drought

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Abstract

Climate change is likely to lead to more frequent and more severe droughts, with increased pressure for mitigation and management of the same. However, the measurement of drought and its socio-economic impact are poorly understood, questioning our ability to deal efficiently with future challenges. This analysis shows that the 2015 El Nino drought in Ethiopia was a severe meteorological and self-reported drought, with substantially less rainfall than average and a high share of households reporting drought. The drought was, however, not an agricultural drought, as vegetation indices did not diverge from average levels and agricultural production levels also remained normal. This is supported by a multitude of data sources and is in part due to the meteorological drought hitting areas that were less important for overall agricultural production. Drought indicators used to predict agricultural outcomes (rain and vegetation in growing season, and predicted agricultural losses) do not show any impact of drought on household consumption. In contrast, outcome-based indicators (self-reported drought exposure and harvest vegetation anomalies) do show a negative impact on household welfare. The negative drought impact observed for vegetation anomalies in the harvest seasons is, however, driven by high consumption among households that had normal to better vegetation anomalies. Households that were most exposed to drought did relative better than those that had a normal season. These results can be linked to the limited agricultural drought as well as large scale mitigation efforts with well-targeted distribution of food aid that covered more than twelve percent of households. The results show that how drought is measured matters for results and indicate that mitigation efforts in response to the 2015 drought seem to have been effective.

Keywords: Drought measurement, impact assessment, drought emergency response
JEL Classification: I32, O13, Q1, R28

1. Introduction

Climate change means increases in weather anomalies with socio economic impact and potential suffering, and an increased need for effective mitigation and management to alleviate the impacts of shocks . Drought is one climatic outcome that with climate change is likely to become more frequent and more severe (Dai, 2012). Though the link between drought and socio-economic outcomes, including dire human outcomes, seems very intuitive, the link is not well understood, in part because drought in itself is defined in many ways. In a review of ways drought can be measured and defined, Bachmair et al. (2016) conclude that "A comprehensive synopsis of existing drought indicators is impractical given the vast (and growing) number of available indicators". Given the multitude of drought indicators, the impact of droughts still is poorly understood, and there is little consensus on which drought indicators are most meaningful for impact on society (Bachmair et al. 2016). This paper contributes to a better understanding of the link between drought measurement and socio-economic impact of drought by analyzing the impact of drought, defined in multiple ways, on household well-being measured by consumption.

As a case study the analysis is based on Ethiopia, a country with a long history of severe droughts with, at times, catastrophic consequences. Ethiopia is an interesting case study as it faces frequent spells of drought and has a long history of trying to cope with the socio-economic impacts of drought through a number of different policy instruments. The analysis centers around the 2015 drought that was reported as the worst in five decades with more than 10 million people estimated to be in need of emergency food aid, on top of the chronically food insecure of about eight million people (UNICEF 2015).

Past assessments of droughts` impact on consumption in Ethiopia have typically relied on self-reported drought exposure. This analysis includes more recent drought indicators, such as satellite-based vegetation (NDVI) and rain (CHIRPS), that are now standard use in meteorological 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. Past assessments of drought impact on consumption in Ethiopia have used hydrological drought measures 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). Predicted agricultural losses does imbed rain satellite data, as these are used to predict specific crop losses.

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[2].

Consumption data is seven day recall data and a comparable consumption per adult equivalent aggregate is included with the survey data (Ethiopia - Socioeconomic Survey 2017). The consumption data was collected in February through April in 2014 and again in same months in 2016. The timing of the survey is such that a minimum of three months have passed since completion of the last harvest. Hence, it should capture both the direct effects of the drought (on household agricultural production) and some indirect equilibrium effects working through prices and other channels. Descriptive statistics shows that average consumption levels 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 has not resulted in changes in savings yet. The analysis will show if the drought can explain this pattern.

2.2 Drought indicators

Droughts can be hard to quanitify as onset and ending can be unclear. This analysis uses four standard types of drought indicators: 1) rain anomalies based on satellite images (CHIRPS), 2) predicted crop losses from the "Livelihoods, Early Assessment, and Protection" (LEAP) project, 3) vegetation anomalies based on satellites (Normalized Differenced Vegetation Index - NDVI), and 4) households' self-reported exposure to drought.

The above indicators are all commonly used drought indicators, but they differ in key aspects and type of indicator (Wilhite and Glantz, 1985). 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 drought indicator. Vegetation anomalies in the growing season is usually also seen as an agricultural drought indicator. Self reported drought on the other hand is not clearly defined as a type of drought. 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 drought exposure might differ by household. However, self-reported drought exposure is included because much of

[2] 2.8 percent of rural households present in 2014 were not found in 2016. The attritional households have similar means to non-attritional households for four out of five drought indicators. Only rain anomalies have a significantly (5%) different means across attritional and non-attritional households.

the past work on drought impact has used this indicator, usually due to the lack of better alternatives. Further, 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.

Rain anomalies during growing season, predicted crop losses, as well as vegetation anomalies are also *predictors* of agricultural outcomes, as opposed to self-reported drought exposure and vegetation anomalies for the harvest season, which can be seen as agricultural outcome measures. The former is critical for mitigation efforts, while the latter likely more important for socio economic impact.

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 main 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 districts (woredas) throughout Ethiopia based on water balance (Hill and Porter 2016). The data is estimated as percentage crop loss in the main season (the main growing season in Ethiopia) at woreda level. Woreda is the third administrative level, below the zone, 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 self-reported drought exposure also reflects socio-economic drought, and not just meteorological or agricultural drought. The 39 percent of communities that report 50 percent or less of households were hit by the drought is a clear indication of endogeneity in self-reported drought exposure. Such endogeneity would give a severe upward-bias in impact analysis using regression analysis. The drawbacks of self-reported drought exposure are major concerns that should warrant caution when used for analytical purposes, including impact assessments.

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 main harvest season (August to October). The former is the value when VCI is used as a monitoring tool, while the latter is the actual vegetation outcome, reflecting agricultural production. VCI is also being used as a monitoring tool in Ethiopia (Eshetie et al. 2016; Tagel Gebrehiwot 2016). The index is merged with the household survey data based on households' GPS locations, using inverse distance to center points as weights.

3. Method

The key interest is the impact of drought on households' well-being, where well-being is measured by consumption. Agricultural production is a direct transition mechanism between drought and households' well-being in Ethiopia, 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 (ESS, 2016). 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 could increase farm income of net producers despite the lower harvest; a few farmers are insured against weather-induced crop-losses, and losses can also give access to external assistance. Further, there are likely to be both market and non-market indirect effects with different time lags impacting households (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

$$\Delta lnY_{it} = \delta D_i + \theta \Delta H_{it} + U_{it}$$

Where $\Delta \ln Y$ 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, while U is the error term. Following the discussion in section 2.2, Equation 1 is estimated with D being: 1) z-scores for rainfall during the main growing season, 2) estimated crop losses as a percentage of expected output , 3) vegetation anomalies measured through VCI in the main growing season, 4) self-reported drought exposure at household level, and 5) vegetation anomalies measured through VCI in the main harvest season. A first-difference regression controls for all unobserved time-invariant factors, while ΔH 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. 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. Any household changes not included in ΔH will be included in U.

4. Analysis

4.1 The 2015 drought according to different drought indicators

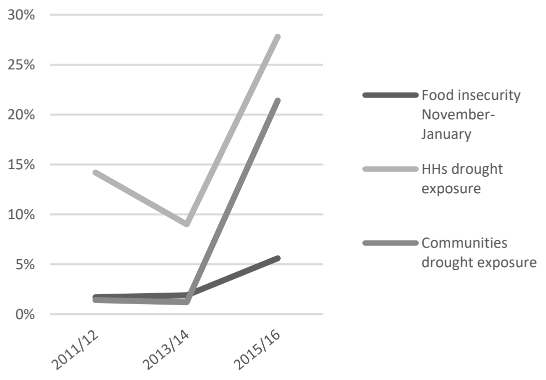
Though widely reported to be a historical drought, different drought indicators come to different conclusions. Household self-reported data from ESS indicate that the 2015 season was worse than previous years. This is true for the 28 percent of households that reported a drought, compared to only 9 and 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 (Fig. 1a). Similarly, the share of households that reported to be food insecure in the months immediately following the end of the main harvest season (November through January) increased to more than 5 percent in 2015/16, compared to around 2 percent in 2011/12 and 2013/14 (Fig. 1a).

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) (Fig. 1b).

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 (Fig. 2a). 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 (Fig.2b). 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 estimated crop losses 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).

Fig. 1a Self reported drought exposure 2011-2015

Fig. 1b Rain anomalies 2000-2016



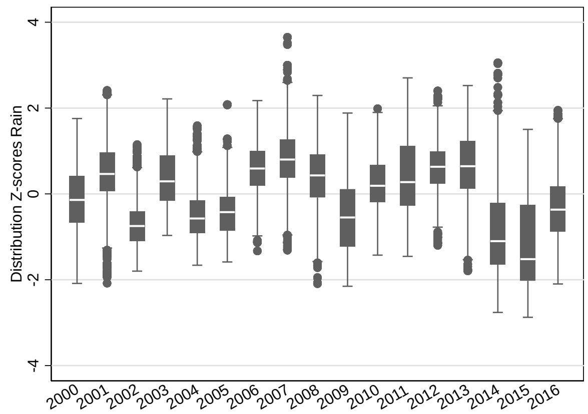
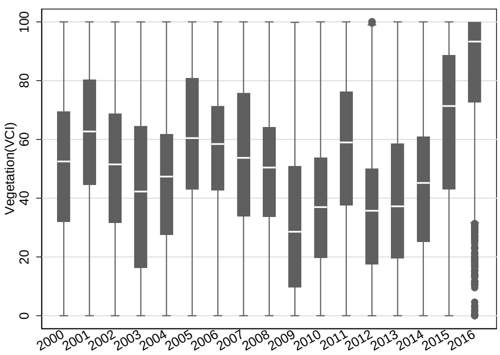


Fig. 1a Self-reported drought exposure and food insecurity is survey data (ESS 2012, 2014 and 2016). Fig 1b Rain anomalies are z-scores based on CHIRPS presented as box-plots for each year. The white stripe in the middle of the solid grey box is the median value, the upper hinge of the solid grey box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

Fig. 2a Vegetation Anomalies 2000-2016

Fig. 2b Grain production and predicted crop losses



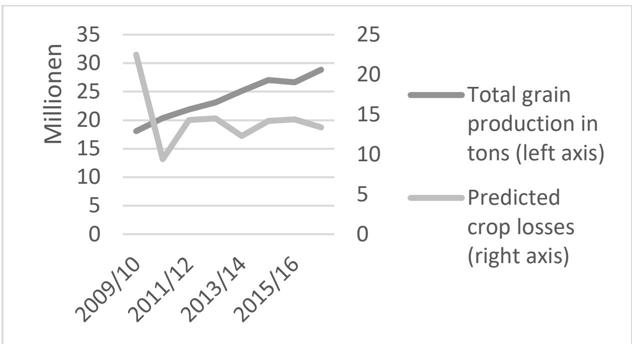


Fig.2a: Vegetation anomalies are VCI values presented in box-plots for each year for the growing season. The white stripe in the middle of the solid grey box is the median value, the upper hinge of the solid grey box is the 75th percentile of distribution, while the lower one is the 25th percentile.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

Hence, the indicators point to a severe meteorological and self-reported drought in 2015, but not a severe agricultural drought. Looking at the correlation between these indicators for each household in ESS, it is positive that all have a significant correlation with the expected signs (Table 1). However, the correlation between self-reported drought exposure and rain anomalies is very weak. Previous work based on farmers in northern in Ethiopia has also found that actual rainfall and perceived rainfall do not correlate well (Meze-Hausken 2004).

Table 1 Correlation between drought indicators in 2015

	Self-reported	Rain anomalies	Vegetation anomalies growing season	Vegetation anomalies harvest season	Predicted crop loses
Self-reported	1.00				
Rain anomalies	-0.07***	1.00			
Vegetation anomalies growing season	-0.41***	0.29***	1.00		
Vegetation anomalies harvest season	-0.43***	0.25***	0.69***	1.00	
Predicted crop loses	0.34***	-0.30***	-0.54***	-0.53***	1.00

Note that Vegetation and rain anomalies are continuous variables with observations for each household in ESS, while self-reported drought exposure is a dummy for same households. Predicted crop losses is a value for each woreda.

A focus on the spatial distribution provides further details on the vegetation anomalies and the limited impact on agricultural production. Spatially, poorer-than-normal rains in the main growing season are observed for all of central and northern Ethiopia (Fig. 3a). Worse-than-normal vegetation, on the other hand, was mostly concentrated in a smaller area in the northeast of the country (Fig.3b and Fig. 3c). Importantly, the vegetation drought was mostly observed in areas that have limited agricultural production (Fig. 3d).

Fig. 3a Rain anomalies growing season 2015

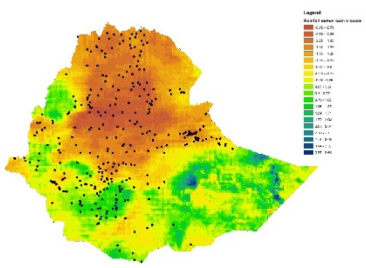


Fig. 3b Vegetation anomalies growing season 2015

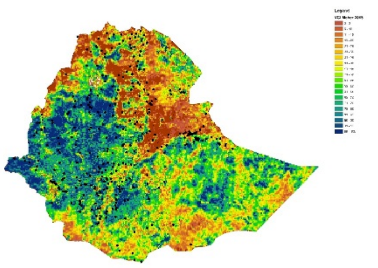


Fig. 3c Vegetation anomalies harvest season 2015

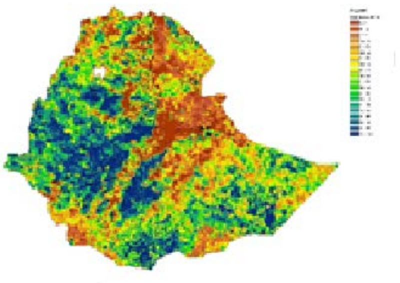


Fig. 3d Average grain production

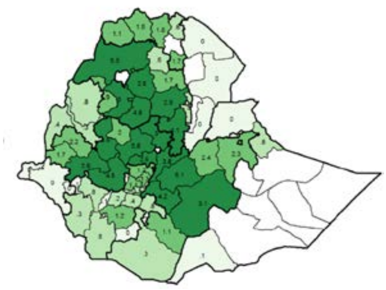


Fig. 3a: Z- scores for rain anomalies in the main growing season. Fig. 3b: VCI for the main growing season. Fig. 3c: VCI for the main harvest season Fig. 3d: Share of total agricultural grain production by zone, averages for 2011-2015 (CSA, 2011, 2012, 2013, 2014, 2015). Black dots are locations of household survey points in the ESS survey.

Interestingly, the divergence between rain and vegetation anomalies (Fig. 1-3) is not just driven by a time lag, as illustrated by the relatively persistent spatial patters in vegetation anomalies in the growing and harvest seasons (Fig. 3b and Fig. 3c). 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). Here, large discrepancies between rain and vegetation anomalies are found in Ethiopia, but especially so in Zimbabwe, Zambia, Malawi and Mozambique. This divergence might explain why other research has 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 Impact of drought on consumption

Table 2 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 asset index, log of holdings of livestock measured in Tropical Livestock Unites (TLU), if someone in the household entered or exited the Productive Safety Net Program (PSNP), if the household received food aid, or if the household obtained lines of credit during the 2015 season, give almost identical results, further indicating that results are robust. Using similar data, Hirvonen et al. also find that there is no overall impact of the 2015 drought measured by rain anomalies on child malnutrition (Hirvonen, 2018.)

None of the drought predictors (rain and vegetation anomalies in the growing season and predicted crop losses) show an impact on consumption (Table 2). In contrast, drought outcome measures (self-reported and VCI for harvest) show 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 large impact. Drought impact on consumption based on vegetation anomalies, on the other hand, indicates a much smaller impact of 7 percent lower consumption at the mean for a one standard deviation worse VCI score (VCI SD is 34, 34*0.002=7 percent). This is in line with expectations, given an expected upward-bias in the self-reported drought exposure.

Table 2 First-difference regression for impact of drought on consumption by drought indicator

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 (0.03)	-0.02 (0.03)	-0.00 (0.00)	-0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	-0.169*** (0.062)	-0.164** (0.064)	0.002** (0.001)	0.002** (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

*Notes: Table shows the δ coefficient from Equation 1. Standard errors in parentheses * p<0.10, ** <0.05, *** p<0.01*

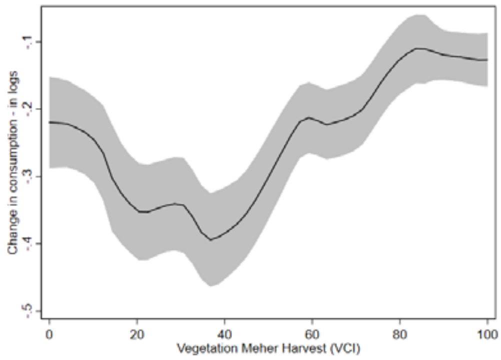


Fig 4. Local polynomial smoothing between change in consumption expenditures between 2014 and 2016 and VCI harvest anomalies in 2015. Grey areas are 95 percent confidence intervals. Graph use household weights.

A closer look at the bivariate relationship between change in consumption and harvest vegetation anomalies (Fig. 4) shows that the positive coefficient in Table 2 seems to be driven by VCI values in the range 40 to 100 (Fig. 4). This shows that households that had better-than-normal vegetation were relatively better off (the y-scale is negative, as all households on average had lower consumption). Meanwhile, for those that had the worst harvest vegetation anomalies (VCI values 0 to 40) the correlation runs the other way (Fig. 4). That is, those households exposed to the worst vegetation drought were relatively better off than those that were exposed to a moderate drought. Including squared and cubic terms for drought in Regression 1, also indicate a non-linear impact (Table 3). Further, splitting the sample into to those with a VCI below or above 40 result in a significant impact of drought on consumption for both groups, but with opposite signs. Thus, this confirms the bivariate results in Fig. 4 in regressions with control variables. Hence, for those most exposed to drought there is a negative coefficient, indicating that more drought is associated with better welfare level, while those above 40 have a positive coefficient indicating that less drought (or greener) is better for welfare (Table 3)[3].

Table 3 First-difference regression for impact of drought on consumption different specifications

[3] Quantile regressions work for different parts of the dependent variable (here change in log consumption) and would therefore not be the relevant method for this situation.

Drought indicator	First difference Full sample	First difference VCI<=40	First difference VCI>40	Impact VCI functional forms	Impact VCI functional forms	Impact VCI functional forms
Vegetation in harvest season	0.002***	-0.004***	0.004***	-0.004***	-0.014***	-0.010
	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	0.000)
Vegetation in harvest season squared				0.000***	0.000***	0.000
				(0.000)	(0.000)	(0.000)
Vegetation in harvest season cubic					-0.000***	0.000
					(0.000)	(0.000)
Vegetation in harvest season quartic						0.000
						(0.000)
Household covariates	x	x	x	x	x	x
Observations	2745	887	1858	2745	2745	2745
R square	0.02	0.03	0.02	0.02	0.03	0.03

*. Notes: Table shows the beta coefficient from Equation 1. Standard errors in parentheses * p<0.10, ** <0.05, *** p<0.01. Regression use household survey weights, but not design effects at cluster level as some clusters have too few observations for the regressions in column two and three.*

4.3 Policy mitigation of drought

That households with very poor harvest vegetation were relatively better off could be due to the massive distribution of food aid and the scale-up of the PSNP. As reflection of past drought experiences, Ethiopia monitors drought closely and alarm bells were ringing in 2015, resulting in both government and non-government actors 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 dramatically (increased by 120 percent), while the PSNP program also expanded (Table 4). The PSNP program is designed to address chronic food insecurity and only operates in selected woredas and is not designed to be a drought emergency program. However, the program was expanded in reaction to the drought. Free food was a notable contribution to household welfare as it was valued at three percent of total food consumption for the year at the median, and seven percent at the mean, for those receiving it.

Table 4 Share of rural households receiving external assistance by program type

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%

Source ESS 2014 and 2016.

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, presumably the poorest, the variables would be endogenous to consumption and results, therefore, biased (Puri et al. 2017).

Instead, we assess whether the support programs reached those most exposed to the drought. Equation 2 is used to test whether households' entry into the assistance programs during the expansion was significantly driven by drought anomalies. Here, $\Delta\ Assitance$ is households' entry into any of the programs listed in Table 4, given that they were not enrolled in the program in 2014, while $\delta\mathrm{D}$ is the harvest vegetation anomalies and $\theta\Delta\mathrm{H}$ is defined as in Equation 1. Equation 2 is estimated with a logistic regression and marginal effects are presented in Table 5. The regression does not consider exit of the program as the focus here is on targeting those exposed to drought.

Equation 2

$$\Delta\ Assitance_{it} = \delta D_i + \theta\Delta H_{it} + \varepsilon_{it}$$

Results for Equation 2 shows that the distribution of free food and the PSNP program(s) did target locations with unusually poor vegetation (Table 5). At the mean, the coefficients are equivalent of a six percent higher chance of entering the free food program for one standard deviation worse VCI score. Similarly, for a one standard deviation worse VCI score there was a two percent higher chance of entering the PSNP or PSNP labor program.

The bivariate relationship, using non-parametric smoothing, indicates that the significant result on drought targeting is highly concentrated in the lower end of the distribution (Fig. 5). Hence, the coefficients based on averages, in Table 5, might therefore underestimate the true likelihood of a household with very poor vegetation having received assistance. Both the free food program and the PSNP program seem well-targeted toward households with low vegetation (Fig. 5), as the likelihood of receiving these programs increased systematically with lower vegetation than normal, especially for those with the worst VCI score.

Table 5 Regression for entry into program on harvest vegetation anomalies

Drought indicator	Δ PNSP	ΔFree food	Δ Cash or food for work	Δ Inputs for work	Δ Other assistance	Δ PNSP employment
VCI harvest	-0.0006*** (0.0003)	-0.0017*** (0.0006)	-0.0001 (0.0001)	0.0000 (0.0001)	-0.0001 (0.0001)	-0.0006* (0.0004)
Household covariates	x	x	X	x	x	x
Obs	2839	2779	2911	2994	2972	2676

*Notes: Table shows the δ coefficient from Equation 2. Standard errors in parentheses * p<0.10, ** <0.05, *** p<0.01. Regression use survey weights and design.*

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

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

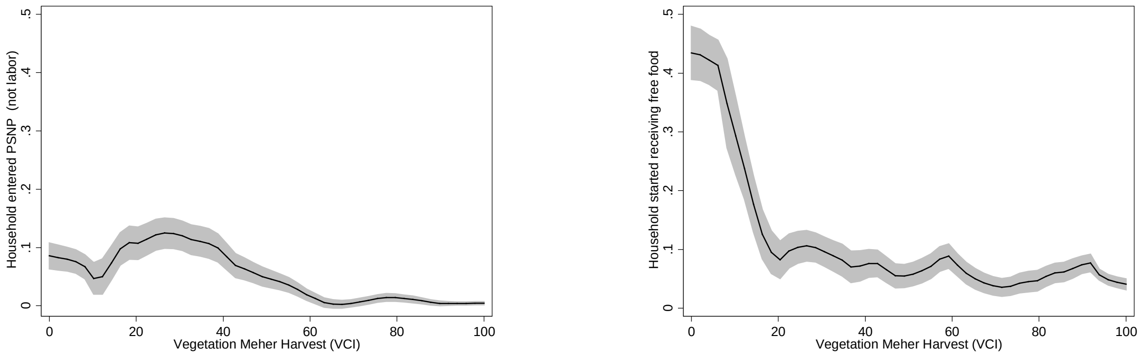


Figure 5. A: Local polynomial smoothing between receiving PSNP assistance and VCI anomalies. B: Local polynomial smoothing between receiving free food assistance and VCI anomalies. Grey areas are 95 percent confidence intervals. To focus on the expansion, both A and B exclude households that received assistance in 2014.

Households with a VCI score under 10 had a 40 percent chance of receiving food aid (Fig. 5b), which, at the median, was valued at three percent of annual consumption. Hence, it is plausible that support programs explain the observed lack of drought impact among households with the worst vegetation (Fig. 4). However, note that the data and analysis are insufficient to claim 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.

5. Discussion

The analysis brings together several data sources and shows that mass suffering due to the El Nino drought in Ethiopia was likely avoided due to several factors. First, the drought as observed through vegetation anomalies was limited in spatial coverage and mostly hit areas with limited importance for agricultural production. Second, the massive policy response, supporting those that were worst hit by drought (measured by vegetation anomalies), likely limited its socio-economic impact. It is encouraging that the drought-monitoring and targeting efforts used to distribute free food seems to have worked well. One could question if the program was too generous as those that were most-exposed to drought fared better than those less-exposed. However, further conjectures should also consider that consumption, on average, was lower for all households, irrespective of vegetation state, in 2016 than in 2014, and that grain prices and wages were stable in the same period. Thus, the prevailing evidence from this analysis does not seem to add up to a complete understanding of the lower consumption observed in 2016.

The analysis also raises 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). There is new literature pointing to increased resilience in grain prices in response to weather variability (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. Though both aspects point to increased resilience, neither improved markets nor mitigation of socio-economic impact would explain the divergence in rain and vegetation anomalies observed in both Ethiopia and most of East Africa in 2015 (Winkler et al, 2017). In Ethiopia, others have also noted a missing link between rainfall variability and food security (Lewis 2017) and a missing link between rain variability and crop yield in the Amhara region (Bewket 2009), which, combined with this study, could question the sufficiency of rain variability based on satelites as a drougth indicator for socio economic impact. There are multiple potential reasons for such observed patterns. Change in land use, ground water levels, or maybe measurement issues, are but a few potential reasons. The smaller agriculture season (belg) coincides with the growing season of the main season (meher), which could impact the vegetation anomalies, but not the rain anomalies, and thereby generate some divergence. However, existing literature on drought monitoring does not seem to see this as an issue (Eshetie et al. 2016; Tagel Gebrehiwot 2016). Unfortunately, a full assessment of this topic is much beyond the scope of this work, though is seems key to understanding how drought is best measured in respect to socio-economic impact, as well as in other aspects.

In addition to this, the work illustrates how impact assessment using 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 detect a significant impact on consumption. However, the lack of impact can be because a standard first difference impact assessment as applied here, which in many settings is considered the gold-standard, is an insufficient analytical tool, as it does not include the mitigating impact of drought response. Instrumental variables techniques could potentially address this.

All in all, the paper shows that the lack of a best practice for drought measurement and lack of a similar framework for understanding the socio-economic impact af drought, could be routed in several challenges both with measurement of drought as well as with assessment metholodology.

References

Bachewe F, F. Yimer, B. Minten, and P. Dorosh. . , (2016) Agricultural prices during drought in Ethiopia: An assessment using national producer data (January 2014 to January 2016) ESSP Working Paper 88 Washingto DC: International Food Policy Research Institute

Bachmair S et al. (2016) Drought indicators revisited: the need for a wider consideration of environment and society Wiley Interdisciplinary Reviews: Water 3:516-536 doi:10.1002/wat2.1154

Bayissa Y, Tadesse T, Demisse G, Shiferaw A (2017) Evaluation of Satellite-Based Rainfall Estimates and Application to Monitor Meteorological Drought for the Upper Blue Nile Basin, Ethiopia Remote Sensing 9:669

Bewket W (2009) Rainfall variability and crop production in Ethiopia Case study in the Amhara region In: Proceedings of the 16th International Conference of Ethiopian Studies, ed by Svein Ege, Harald Aspen, Birhanu Teferra and Shiferaw Bekele, Trondheim

Calvo C, Dercon S (2013) Vulnerability to individual and aggregate poverty Social Choice and Welfare 41:721-740 doi:10.1007/s00355-012-0706-y

CSA (2011) Agricultural Sample Survey 2010/2011 (2003 E.C.) - Volume I - Report on area and production of major crops (Private peasant holdings, meher season). The Central Statistical Agency (CSA) of Ethiopia,

CSA (2012) Agricultural Sample Survey 2011/2012 (2004 E.C.) - Volume I - Report on area and production of major crops (Private peasant holdings, meher season). The Central Statistical Agency (CSA) of Ethiopia,

CSA (2013) Agricultural Sample Survey 2012/2013 (2005 E.C.) - Volume I - Report on area and production of major crops (Private peasant holdings, meher season). The Central Statistical Agency (CSA) of Ethiopia,

CSA (2014) Agricultural Sample Survey 2013/2014 (2006 E.C.) - Volume I - Report on area and production of major crops (Private peasant holdings, meher season). The Central Statistical Agency (CSA) of Ethiopia,

CSA (2015) Agricultural Sample Survey 2014/2015 (2007 E.C.) - Volume I - Report on area and production of major crops (Private peasant holdings, meher season). The Central Statistical Agency (CSA) of Ethiopia. ,

CSA (2016) Crop production Forecast Sample Survey, 2016/17 (2009 E.C). REPORT ON AREA AND CROP PRODUCTION FORECAST FOR MAJOR CROPS. The Central Statistical Agency (CSA) of Ethiopia,

CSA (2016.) Agricultural Sample Survey 2015/2016 (2008 E.C.) - Volume I - Report on area and production of major crops (Private peasant holdings, meher season). The Central Statistical Agency (CSA) of Ethiopia,

Dai A (2012) Increasing drought under global warming in observations and models. Nature Climate Change 3:52.

Demeke AB, Keil A, Zeller M (2011) Using panel data to estimate the effect of rainfall shocks on smallholders food security and vulnerability in rural Ethiopia Climatic Change 108:185-206 doi:10.1007/s10584-010-9994-3

Dercon S (2004) Growth and shocks: evidence from rural Ethiopia Journal of Development Economics 74:309-329

Dercon S, Hoddinott J, Woldehanna T (2005) Shocks and consumption in 15 Ethiopian villages, 1999-2004 Journal of African economies 14:559

Dercon S, Krishnan P (2000) Vulnerability, seasonality and poverty in Ethiopia The Journal of Development Studies 36:25-53 doi:10.1080/00220380008422653

Eshetie SM, Demisse GB, Suryabhagavan KV (2016) Evaluation of vegetation indices for agricultural drought monitoring in East Amhara, Ethiopia International Journal of Scientific Research

Ethiopia - Socioeconomic Survey (2017) World Bank. http://econ.worldbank.org/WBSITE/EXTERNAL/EXTDEC/EXTRESEARCH/EXTLSMS/0,,contentMDK:23512006~pagePK:64168445~piPK:64168309~theSitePK:3358997,00.html. 2017

Fuje H (2018) Welfare Dynamics and Drought in Ethiopia Memo

Funk C et al. (2015) The climate hazards infrared precipitation with stations—a new environmental record for monitoring extremes 2:150066 doi:10.1038/sdata.2015.66

Hirvonen KS, Thomas Pave; and Bundervoet, Tom. (2018.) Impact of Ethiopia's 2015 drought on child undernutrition. ESSP Working Paper 114. Washington, D.C. and Addis Ababa, Ethiopia: International Food Policy Research Institute (IFPRI) and Ethiopian Development Research Institute (EDRI).

Hill R, Fuje H (2017) What is the Impact of Drought on Prices? Evidence from Ethiopia Memo

Hill RV, Porter C (2016) Vulnerability to Drought and Food Price Shocks Evidence from Ethiopia World Bank Policy Research Working Paper 7920

Kogan FN (1995) Application of vegetation index and brightness temperature for drought detection Advances in Space Research 15:91-100 doi:https://doi.org/10.1016/0273-1177(95)00079-T

Lei Pan (2009) Risk Pooling through Transfers in Rural Ethiopia Economic Development and Cultural Change 57:809-835 doi:10.1086/598766

Lewis K (2017) Understanding climate as a driver of food insecurity in Ethiopia Climatic Change 144:317-328 doi:10.1007/s10584-017-2036-7

Little PD, Stone MP, Mogues T, Castro AP, Negatu W (2006) 'Moving in place': Drought and poverty dynamics in South Wollo, Ethiopia The Journal of Development Studies 42:200-225 doi:10.1080/00220380500405287

Meze-Hausken E (2004) Contrasting climate variability and meteorological drought with perceived drought and climate change in northern Ethiopia Climate research 27:19-31

Porter C (2012) Shocks, consumption and income diversification in rural Ethiopia Journal of Development Studies 48:1209-1222

Puri J, Aladysheva A, Iversen V, Ghorpade Y, Brück T (2017) Can rigorous impact evaluations improve humanitarian assistance? Journal of Development Effectiveness 9:519-542 doi:10.1080/19439342.2017.1388267

Tagel Gebrehiwot AVdV, Ben Maathuis (2016) Governing agricultural drought: Monitoring using the vegetation condition index Ethiopian Journal of Environmental Studies & Management 9:354 – 371 doi:http://dx.doi.org/10.4314/ejesm.v9i3.9

UNICEF (2015) Ethiopia Humanitarian Situation Report SitRep #7 – Reporting Period, November-December 2015

Wilhite, D.A.; and M.H. Glantz. 1985. Understanding the Drought Phenomenon: The Role of Definitions. *Water International* 10(3):111–120.

Worqlul AW et al. (2017) Assessing potential land suitable for surface irrigation using groundwater in Ethiopia Applied Geography 85:1-13 doi:https://doi.org/10.1016/j.apgeog.2017.05.010

Ya D, Michael JH, Melissa W (2011) Measuring economic impacts of drought: a review and discussion Disaster Prevention and Management: An International Journal 20:434-446 doi:10.1108/09653561111161752

Zewdie W, Csaplovics E, Inostroza L (2017) Monitoring ecosystem dynamics in northwestern Ethiopia using NDVI and climate variables to assess long term trends in dryland vegetation variability Applied Geography 79:167-178 doi:http://dx.doi.org/10.1016/j.apgeog.2016.12.019