The Impact of the 2015 El Niño-Induced Drought on Household Consumption: Evidence from Rural Ethiopia

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Abstract

This paper evaluates the impact of the 2015 El Niño-induced drought on household consumption in Ethiopia. A Difference-in-Difference method was used to compare consumption changes over time in a group unaffected by the drought to the changes in a group affected by the drought. Using the ESS household-level consumption aggregate data, we find that the 2015 drought reduces affected household's annual consumption by 8% and the reduction was largely driven by changes in the lower tails of the consumption distribution. Overall, we find a significant consumption decline due to the 2015 drought and much of the decline has been experienced among the consumption poor indicating shock resilience inequality among rural households.

1. **Introduction**

Rural communities in developing countries face several types of shocks that threaten their wellbeing. These include, climatic shocks like droughts & floods, and economic shocks like market & price fluctuations. Their adverse impacts is often associated with decreased expenditures, reduced food consumption, distress sales of productive assets, and out-migration-all of which may undermine people's short and long-term welfare status (Dercon et al., 2005a; Little et al., 2006; Gray and Mueller, 2012).

However, the magnitude and likelihood of such negative impacts has been shown to vary within affected populations mainly due to differences in their vulnerability, which is a function of a given household's exposure to the shock and its ability to cope without compromising its long term economic and social status (Bohle et al., 1994; Watts and Bohle, 1993). Because of vulnerability differences households affected by similar magnitudes of shocks experience change differently in their wellbeing outcomes (Blaikie et al., 2014). Understanding the real impacts of the realized shocks and their future likelihood has become an ever-more important focus for policy makers since the 2001 World Development Report (World Bank., 2014) recognising the persistent effect of shocks on long term wellbeing.

Among the major shocks, drought is the most frequent and catastrophic in many developing countries, Particularly rural areas where agriculture is the major livelihood, droughts often cause substantial income loss and recurrent seasonal food shortages with further agravation of existing vulnerability to famine (Devereux et al., 2008). The frequency and impacts of drought shock in Ethiopia has been increasing from time to time since the 1980's. The top five catastrophic drought episodes that led for many humanitarian catastrophe and placed millions of people for urgent assistance include the 1972-74, 1983-84, 2002-03, 2010-11 and the 2015 droughts.

Understanding the real impacts of such catastrophic droughts in general and in Ethiopia in particular on household wellbeing have been the focus of many empirical studies. For example, studies such as (Alderman et al., 2006) estimated drought impact on human capital; (Dercon et al., 2005b; Hill, R. V. & Porter, C., 2017) on household consumption; (Dercon, 2004) on growth; (Demeke et al., 2011) on multi-dimensional food security; (Thiede, B. C., 2014) on wealth inequality. A focus on such large-scale national drought shocksmay arguably receive a high degree of intrinsic policy interest for the management of risks and emergencies. Rural Ethiopia is the focus of these previous studies, including this study, due to the strong linkage between rural livelihoods and weather conditions. Estimated impacts of these studies however reflected the unique contexts of a particular

drought episode as well as the country's emergency management capability of the time. This study focuses on changes in consumption due to rural household's exposure to the 2015 El Niño-induced drought that caused a massive spike in humanitarian needs during most of the months in 2016. This drought is the worst in 60 years since the driest periods of 1950s (Michael B. R. et al., 2016).

All the above studies showed the significant impact of a particular drought exposure on various wellbeing outcomes with further suggestion that wellbeing outcomes vary systematically across different types of households due to differences in their capacity to deal with shocks. However, these studies have both theoretical and methodological limitations to which this study is primarily designed to address. In terms of theoretical limitation, none of the above studies used a valid theory of change, constructed to explain the causal chain of drought impacts, that is necessary to determine the choice of methodological design as well as interpretation of the estimated impact. Despite unclear theoretical foundation, most of the above studies tried to include various household and community specific characteristics in their estimation procedure depending on the available data. However, without a theoretical foundation explaining the causal chain of impact, it is very difficult to identify and control confounding effects other than the effect of intervention or exposure of interest. As a result, covariates that cause systematic differences in outcomes between drought affected and non-affected comparison groups are not fully identified and their potential confounding effects addressed inadequately. For example, relevant factors such as adaptive capacity and access to safety nets, that may cause systematic differences in outcomes with shock exposure, are not controlled in estimation procedures of previous studies. Hence, unbalanced distribution of such factors that determine ability of exposure units to deal with shocks between affected and non-affected groups may cause differences in outcomes, even in the absence of a particular shock exposure.

In addition to the limitation related to the use of a valid theory of change, with the exception of (Thiede, B. C., 2014), the methodology used for treatment assignment is based on subjective reported shock occurrence instead of unbiased objective criteria, leading to biased estimation of impacts attributable to shock exposure. Furthermore, the data set they used include the 1989-2004 ERHS (Ethiopia Rural Household Survey) and the 2005-2011 EDHS (Ethiopia Demographic & Health Survey) which are either repeated cross-sectional or incomplete panel datasets with wider time gaps between baseline and follow-up data collection periods. As a result, estimated shock effects are presented without differentiating short-term and long-term effects of shocks on specified outcome of interests. Similarly, using a dataset collected in a wider time frame, previous studies

employed inadequate methodological considerations to account for the changes in outcomes caused by changes in group composition as well as changes in confounding covariates over time.

In addressing these limitations of previous studies, this study exploits the opportunities of a quasi-experimental design by taking advantage of the timeline of the recent drought crisis and the unique Ethiopian Socioeconomic Survey (ESS) of 2011/12 to 2015/16 (Central Statistical Authority et al., 2017). This study makes use of a valid theory of change represented by risk chain model as suggested by (Heitzmann et al., 2002) in order to understand causal chain of shock impacts that is necessary to identify controls for potentially confounding changes. With availability of data on key covariates and objective indicator for treatment assignment, the ESS rich data set allows us to perform a combined method of Propensity Score Matching (PSM) and Difference-in-Difference (DID) impact estimation procedure to investigate consumption effect of the 2015 drought that occur between the last two survey periods.

The crisis timeline and the timeframe for ESS data collection (see Figure 1 in section 2) allows us to capture the effect of the drought on household consumption in the short term. With the upcoming ESS data for 2018 to be available in the near future, the same research design could be used to capture relatively longer-term effect of the 2015 drought. More importantly the ESS data set meets the minimum requirements of two observations before the event and one observation after the event which is necessary to test the fundamental assumption of DID model. The paper is organized as follows. The next section presents description of the 2015 drought exposure in Ethiopia. Section 3 presents the theory of change and research hypotheses. Section 4 outlines the data used to generate the outcome and covariate variables and the empirical method to estimate the impact of drought on household consumption. Section 5 discusses study results on the impact of drought on household consumption. Finally Section 6 concludes with some policy and further research recommendations.

2. The 2015 Drought Exposure in Ethiopia

The 2015 drought in Ethiopia was one of the worst droughts that the country experienced in decades (FDRE, 2016). Its mangnitude was at least comparable to historical episodes of droughts that caused dramatic food crisis in the mid-1970s and 1980s. El Niño is known to contribute to drought conditions in Ethiopia (Haile, 1988). The 1972 and 1884 droughts were the most severe and affected almost all administrative regions (Wolde-Georgis, 1997). Some studies such as (Degefu, 1987)); Wolde-Mariam (1986) and Caviedes (2000) documented

evidences that the occurrence of these most devastating droughts in Ethiopia are linked to the occurrence of El Niño events in the Pacific Ocean.

Similarly, in 2015, one of the highest Sea Surface Temperature (SST) was recorded in the Pacific Ocean during which Ethiopia experienced one of the worst drought episode over decades. The 2015 drought caused the failure of the two main rainy seasons that supply over 80 per cent of Ethiopia's agricultural yield and employ 85 per cent of the workforce. Figure 1 shows the crisis timeline with associated humanitarian needs as reported in the official humanitarian document of the country released in 2016. The short-term impact of the drought on consumption could be observed following the failure of the typical *belg* (short rainy season) and *kiremt* rains (long rainy season) between February and September of the year 2015. The numbers in the figure represents the total number of people in millions who required food assistance during the period of the drought as estimated in the official Humanitarian Requirement Document (FDRE, 2016).
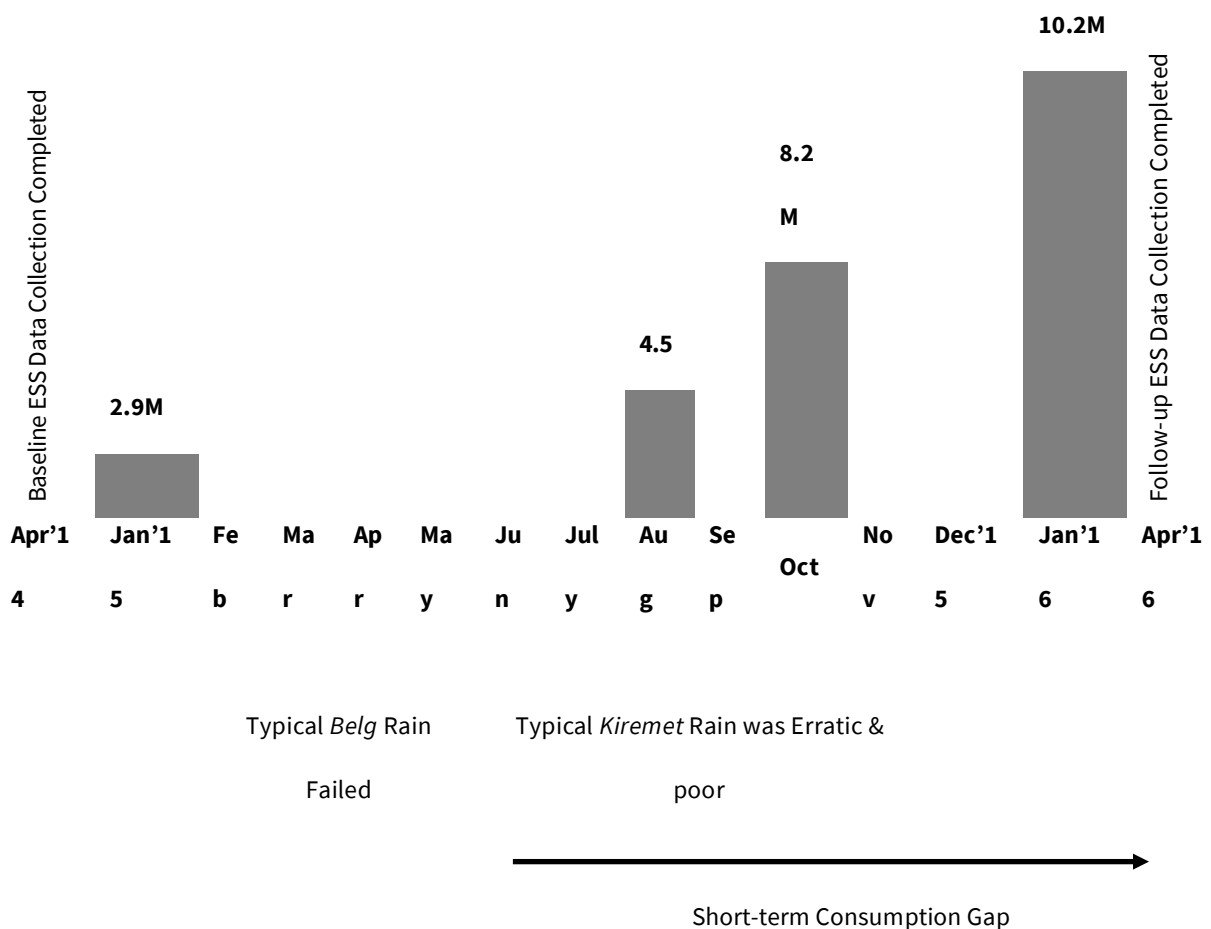
Figure 1: The 2015 El Niño -Induced Drought Crisis Timeline

In June 2015, the Government declared the failure of the spring belg rains causing the national belg harvest, which accounts 10% of the countries production, to fall well below average in June/July. This affected smallholder farmers and pastoralists in the north-eastern rangelands of Afar and the northern Somali regions as well as eastern cropping areas of northeastern Amhara, eastern Tigray, and central and eastern Oromia. A Government-led multi- agency assessment on the impact of agricultural yield and livestock concluded that 4.5 million people were in need of emergency food assistance in August which increased by 75% from the initial projection of 2.9 million. Subsequently, the summer rains were weak and erratic due to El Niño, which negatively affected kiremt rain dependent farmers and tipped pastoralists into severe food insecurity in late July. The summer rains started late and both June and July were very dry in eastern cropping areas, including northeastern Amhara, eastern Tigray, central and eastern Oromia, and the lowlands along the Rift Valley in Southern Nations, Nationalities, and Peoples' Region (SNNPR). As a result of late rainfall, fewer crops were planted. long-cycle crops planted in May and short-cycle crops planted in June wilted. The Government led a pre-harvest, rapid multi-agency assessment in early October concluded that the number of people requiring emergency food assistance had increased to 8.2 million. Due to Elino-induced poor summer rainfall in 2015, the main seasonal assessment report indicated a 50% reduction of crop production in most of *kiremt* rain dependent areas of the country and number of population requiring emergency relief food assistance increased to 10.2 million in January 2016. A massive spike in humanitarian needs continued through much of 2016 (FDRE, 2016).

In response to the food emergency caused by the 2015 drought, the government of Ethiopia and humanitarian communities jointly estimated a total of 4.1 billion dollar (FDRE, 2016) that was required to meet humanitarian needs. Given this shock context, we took advantage of the timeline of the crisis and ESS data collection (See figure 1) to evaluate the impact of the 2015 El Niño-induced drought on consumption of rural households based on a DID estimation procedure.

3. Theory of Change and Research Hypothesis

For most impact studies of development programs, results chain (Gertler et al., 2016) is often used representing the theory of change that guides the development of research questions and choice of outcome indicators. In our case however, the theory of change is based on an asset-income-outcome causal chain suggested by (Dercon, 2001) often called the risk chain model (Alwang et al., 2001; Hoddinott and Quisumbing, 2010). According to (Heitzmann et al., 2002), risk chain model has three main components. The first component is the extent to which a household faces a shock which has a bearing on household's wellbeing. These shocks may be household-specific, commonly referred to as idiosyncratic, such as illness or death in the household, business failure, unemployment, among others. Another category of shocks is community-specific, also known as covariate shocks which include droughts, epidemics, floods, among others. The second component of risk chain illustrates the fact that the extent to which a shock will affect a household's welfare depends on its response to such events. Recently the term resilience is used to capture the latter component. According to FAO, this capacity is a function of access to basic services, access to social safety net, available assets, and adaptive capacity to deal with shocks. The third component of the risk chain depicts the welfare outcomes of the household. These could be measured in terms of the level of income, consumption, nutrition, heath or education (Dercon, 2001).

In general, the risk chain model postulates that the magnitude of negative wellbeing consequences is a function of not only the degree to which they are exposed to negative shocks that effect on their welfare, but also the extent to which they can cope with such shocks when they occur (Hoddinott and Quisumbing, 2010). In specific terms, the impact of a drought shock on welfare outcomes (in this case, consumption) is determined by the interaction between people's exposure to drought and their resilience capacity to deal with its effect on food and income sources. We are interested to estimate the change in consumption attributable to the 2015 drought exposure. This requires to obtain an appropriate counterfactual reflecting what would happen to consumption of drought affected groups if they had not exposed to the 2015 drought. Hence, as suggested by the risk chain model a valid counterfactual could be established by matching affected groups and non-affected comparison groups based on resilience characteristics.

With the above theoretical foundation describing the results chain, we propose two related hypotheses to be tested in this study. Given similar distribution of resilience factors against shocks, the first hypothesis is to test whether average consumption of affected groups was reduced significantly compared to average consumption among non-affected comparison groups. The second hypothesis is to test whether or not

consumption changes associated to the drought was largely driven from the lower consumption groups. For both hypotheses, the effect measure of interest is an average treatment effect on the treated (ATET) or causal effect in the exposed.

4. Data and Methods

The data that form the empirical analysis of this study is the rural category of the Ethiopian Socioeconomic Survey (ESS), three waves panel data conducted by Ethiopian Central Statistical Authority (CSA) and the World Bank (Central Statistical Authority and World Bank, 2013, 2015; Central Statistical Authority et al., 2017). The first, second and third waves were implemented in 2011–2012, 2013–2014, and 2015–2016 (hereafter referred to as the 2012, 2014, & 2016 ESS) respectively. The ESS data is part of the World Bank's Living Standards Measurement Study–Integrated Surveys on Agriculture (LSMS-ISA) project. The objectives of the ESS include the development of an innovative model for collecting agricultural data, inter-institutional collaboration, and comprehensive analysis of welfare indicators and socioeconomic characteristics.

In terms of survey design, the ESS is designed to collect panel data in rural, small town, and urban areas on a range of household and community level characteristics linked to agricultural activities. Considering the regional administration of the country and rural-urban classification, the ESS sample selection follows a two-stage probability sample selection. While the first stage of sampling entailed selecting primary sampling units, called enumeration areas, the second stage of sampling involved the selection of households from each enumeration area. Rural Ethiopia represents the majority of the country's total population (85%) (Central Statistical Authority, 2008) and due to the strong linkage between their livelihoods and weather conditions, we used the rural category of the ESS data only for this study.

Before undertaking any analysis, the ESS data was initially observed and cleaned. In doing so, the data of 3089 rural households fulfil the necessary data for this study in each wave full information of the outcome [household consumption expenditure] and covariate [resilience capacity] variables including satellite-based drought indicator). The second and the third surveys were used to represent the baseline and follow-up data that is used to compare mean changes in our outcome of interest before and after the drought (See Figure 1). The first ESS survey were used to estimate placebo effect as a test for the common trend assumption of the DID estimation procedure.

4.1. Outcome variable: Household consumption expenditure:

One common measure of poverty and wellbeing in developing countries is aggregated household consumption expenditures. Consumption, as opposed to household income, is the common measure of household welfare in Ethiopia. We used household consumption expenditure as our outcome variable based on the ESS consumption data. The components of ESS household consumption include food and non-food consumption-expenditures (Central Statistical Authority and World Bank, 2017). Food expenditures include expenses for 25 different food items with a recall period of the last seven days. While the non-food expenditures recall period was either the last one month or the last 12 months, depending on the item. Before totaling, all individual consumption expenditure values are expressed in annual terms.

Moreover, we undertake two major tasks in order to construct our outcome variables. First, we normalize the total household consumption expenditure on the basis of household composition (adult equivalent household size) to make it a comparable welfare indicator among households. Second, per adult equivalent household consumption expenditure has to be adjusted to account for both spatial and temporal price variations. We use spatial price indices available in the ESS dataset at regional level relative to national average prices to account for spatial price variations. Similarly, to adjust for inflation at the national level, making the values comparable across waves, we inflate the value of the first wave of household consumption to the second wave levels by a factor of 1.21 as reported in the 2015 annual report of the Central Statistical Agency (Central Statistical Authority, 2015). Moreover, we also deflate the value of the third wave consumption to second wave level by the same factor.

4.2. Covariate variables: resilience capacity against shock

The risk chain model postulates that the extent to which a shock will affect a household's welfare depends on not only the degree to which they are exposed to negative shocks, but also the extent to which they can cope with such shocks when they occur (Hoddinott and Quisumbing, 2010). Recently the term resilience is used to capture the latter component. Resilience capacity is a set of conditions, attributes, or skills that enable households to achieve resilience in the face of shocks including drought. We assume that, even without drought, there may be differences in consumption levels between drought affected and non-affected groups due to differences in their resilience capacities. Hence, in order to estimate the impact of drought on consumption, it is necessary to match both groups to balance on resilience characteristics.

The theoretical foundation of resilience capacity measurement used in this paper is based on the recommendations of the Food and Agriculture Organization (FAO) Resilience Index Measurement and Analysis (RIMA) model. In RIMA II, four types of resilience capacity are recognized. These include access to basic services (ABS), adaptive capacity (AC), Assets (ASS), and social safety nets (SSN). Given their complexity, these concepts cannot be measured using one single indicator. Measuring them requires combining a variety of indicators into an overall measure. The best method for such purpose is factor analysis. When factor analysis is employed, only the indicators that have a scoring coefficient of the expected sign (positive or negative) based on theoretical understanding of how the indicators work together to measure the overall concept are included. Factor analysis is implemented in STATA 14 using the principal-factor method for ABS, AC and ASS, while SSN pillar is constructed using minimum-maximum method of index construction.

In the ABS resilience pillar, we take four available variables that are associated with accessing basic services: households access to credit, health, extension services and household' residence distance to the district town. Except the variable town, all of the ABS variables have categorical scales. In the case of AC resilience pillar, four observed variables are used namely the diversification of households' income sources[1], the diversification of livestock reared by the household[2], the diversification of crops grown in the households' agricultural land[3] and the literacy status of the household head. The ASS component of resilience used three observed indicators, per capita size of agricultural land measured in hectare and the number of livestock the household owns measure in tropical

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[1]Income diversification index is created through factor analysis. A list of variables assumes value 1 or 0 is used, depending on whether or not a household has been involved in farming activity; employment activities; self-employment activities; received transfers and earned income from rent.

[2]Livestock diversifications is also created through factor analysis. A list of variables assumes value 1 or 0 is used, depending on whether or not a household has been involved in rearing cattle, shoats, equine and camels.

[3]Crop diversifications is created through factor analysis. A list of variables assumes value 1 or 0 is used, depending on whether or not a household has been involved in planting barely, beans, *chat (local tree)*, coffee, *enset*(local crop type*)*, maize, sorghum, *teff*(local crop type*)*, and wheat in their agricultural field in the past cropping season.

livestock unit (TLU)[4] to represent productive assets as well as the wealth index[5] in the case of the non-productive assets. Two indicators, namely formal and informal transfer of money to the household in the past twelve months represent the social safety net (SSN) pillar of resilience. The observed variables of the SSN pillars comprise all transfers received by the household in Ethiopian birr (ETB) in the past twelve months in per capita.

4.3.   A Measure of drought: Enhanced Vegetation Index (EVI) Anomaly

Several indices have been developed to measure and characterize droughts. The most common drought indices are developed based on synthesizing meteorological and hydrological variables such as precipitation, streamflow and soil moisture. Drought indices are calculated from assimilating drought indicators into a single numerical value. Among these indices Standardized Precipitation Index (SPI) (McKee, T.B. et al., 1993) which relies on precipitation and Palmer Drought Severity Index (Palmer, W.C., 1965) (PDSI) which uses precipitation and temperature are often considered to be robust measures of droughts. The limitation of such indices has been the difficulty to obtain quality data with adequate spatial coverage particularly in developing countries like Ethiopia where data recording and management systems are underdeveloped.

However, with the advancements in remote sensing technology such limitations have been overcome by using satellite data that are considered to be real time with high spatial and temporal resolutions over large areas. For this reason, the remote sensing technology outputs have been recently used at large to monitor droughts based on the development of vegetation indices. These include Normalized Difference Vegetation Index (NDVI). Relative to other indices NDVI is easiest and widely used to monitor droughts with innovative use of satellite data at high resolution and great spatial coverage (World Meteorological Organization (WMO) and Global Water Partnership (GWP), 2016). With some correction factors added to NDVI, better indices have been also developed

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[4]TLU standardizes different types of livestock into a single unit of measurement. The conversion factor adopted is: 1 camel; 0.7 cattle; 0.55 donkeys /mules/horses; 0.1 shoats.

[5]Wealth index- is created through factor analysis. A list of variables assumes value 1 or 0 is used, depending on whether or not a household has specific non-productive assets; such as a *gabi*(local cloth)*,* bed, clock, phone, radio, *mofer*(traditional ploughing tool)*machid* (traditional crop harvesting tool) plough axe.

which include Vegetation Condition Index (VCI) (Kogan, F.N., 1995) and Enhanced Vegetation Index (EVI) (Huete, A. et al., 2002). The former is normalized NDVI for each pixel on the basis of the maximum statistical range over the historical record of available imagery. The later provides complementary information about the spatial and temporal variations of vegetation, while minimizing many of the contamination problems present in the NDVI, such as those associated with canopy background and residual aerosol influences (Huete, A. et al., 2002).

The ESS data set includes EVI values for the growing periods of 2015 as well as the long-term average for the same period for each zone covered by the survey. The later EVI values represent the "normal" growing conditions for the vegetation in a given zone representing the long term EVI average of the period 1990-2015. Hence vegetation stress that a particular zone exhibits due to drought over a given year can be used to characterize the health of the vegetation relative to the norm. We calculated EVI anomaly for a given zone by substracting the zone's long-term average value of EVI for the growing periods from the 2015 growing period average EVI. The EVI anomaly reflects agricultural drought which is the most important type of drought in Ethiopia. Generally negative EVI anomalies would indicate vegetation stress reflecting a particular zone that experiences drought in 2015 during which experiencing a given vegetation stress is considered exposure (or treatment) in this study. The EVI anomaly calculated for the growing period in 2015 shows that more than half of enumeration areas included in the ESS survey exhibited negative deviations from normal vegetation development. In few severely affected areas, vegetation performance declines by 41% from the normal vegetation condition of the specified period. We assign locations' drought status by defining the EVI anomaly threshold at which a vegetation stress is considered a drought. We follow NASA classification system in which an anomaly class from negative 0.025 (-2.5%) to positive 0.025 (2.5%) EVI anomaly values represents a normal vegetation condition of a particular area which is typical for the period in consideration. Those anomaly classes (EVI anomaly < -0.025) and (EVI anomaly > 0.025) are generally considered as below-normal and above-normal vegetation conditions, respectively with the former relates to drought conditions. Hence, those areas, included in the ESS survey, that exhibit an EVI anomaly (< -0.025) were considered to be drought affected and subsequently sample households were assigned in the treatment group if they reside in those areas affected by drought and comparison groups otherwise.

4.4.   Analytic Strategy

In order to test the potential impact of the 2015 El Niño-induced drought on the consumption of rural households in Ethiopia, we followed a quasi-experimental approach based on the Difference in Difference (DID)

method. DID estimates the counterfactual for the change in outcome for the treatment group by calculating the change in outcome for the comparison group. As applied to our study, it compares the outcome (consumption) changes over time for the group unaffected (comparison group) by the intervention (drought exposure in 2015) with the group affected (treatment group) by the intervention, and attributes the difference in consumption to the effect of the intervention. Consumption aggregate data obtained from the ESS panel surveys of 2014 and 2016 were used representing consumption levels at the baseline, before the drought and during the follow-up period, after the drought, respectively.

This method allows us to take into account any differences between the treatment and comparison groups that are constant over time including differences due to unobserved time invariant factors (Gertler et al., 2016; Khandker et al., 2009). Furthermore, the exogenous placement of EVI anomalies reflecting drought exposure in 2015 across zones in the study area provides a natural experiment for examining the relationship between the 2015 drought and changes in consumption. Hence, selection bias will not be a problem because drought is a negative intervention or exposure and households are presumably neither targeted nor self-select into drought-affected areas. However, baseline levels and expected trends in consumption may vary systematically with drought exposure due to differences in choice of risk response mechanisms and shock response capacity among households. For this reason, we employed a companied method of PSM and DID to address such systematic differences. By using baseline data, we can match the treatment and comparison groups on baseline characteristics that may cause systematic differences so that any difference that arise in the outcomes of the treatment and comparison groups in the post intervention period is attributed to the intervention (the 2015 drought) itself. In this study, baseline characteristics used for matching include resilience capacity of households discussed above in four key pillars that affects both the capacity to deal with drought shock and the outcome of interest (consumption). Balancing on the distribution of these covariates between treatment and comparison groups would allow to construct a valid counterfactual.

We therefore employed propensity score methods in conjunction with the DID model, i.e. we run the DID model on only matched samples which are balanced on the distribution of confounding resilience pillars in both the treatment and comparison groups. Hence, the combined method would allow us to establish a valid counterfactual group and ensure that the estimated treatment effect is associated with the drought shock. The variables and the measurement of this confounding factors is discussed above (section 4.2) following FAOs methodology based on factor analysis. The propensity score is first estimated based on a logit function and we

chose kernel matching algorithm to balance the distribution of resilience capacity pillars between the two groups on the basis of the estimated propensity score. We chose this matching estimator as it balances the distribution of covariates with smaller mean differences between the two groups, and results in large matched sample size compared to other matching algorithms. This matching technique allows to avoid bad matches (Rosenbaum, P., 2002) by cutting off those observations whose propensity scores are smaller than the minimum and greater than the maximum of treated and comparison groups, respectively.

Using the matched samples obtained from the above matching procedure, we estimate our DID regression equation specified below to compute the effect of the 2015 drought on consumption. For this we employed a simplified estimation procedure developed by Villa, J.M., (2016) which allows to run both the PSM and DID estimation procedures simultaneously.

$$lny_{it} = \alpha T_i + \beta P_T + \gamma D_{it} + \varepsilon_i \qquad\qquad\qquad Eq.1$$

where the dependent variable lny_{it} is the natural logarithms of consumption by household i in year t measured in per capita expenditure in birr (adjusted to the 2014 real price); T_i is treatment status equal to 1 for households residing in the drought affected areas); P_T is period (a dummy variable equal to 1 for the follow-up period); D_{it} is an interaction term between treatment and time. The parameter γ measure the mean change in consumption associated with the drought event. The parameters α and β , measure individual and period fixed effects.

The matched samples with optimal balance in key covariates could reduce the bias in our estimation caused by systematic differences between treatment and comparison groups. Our DID estimation procedure on matched samples could remove both systematic differences between the two groups and the effects of time-invariant unmeasured confounding factors. However, DID works best on the assumption of common trend overtime for the outcome of the treatment and comparison groups in the absence of the intervention. This assumption holds if the effect of time varying covariates is the same for the treatment and comparison groups. In our case even after matching, we can't assume that the effect of covariates is the same for the treatment and comparison groups over time. This necessitate us to conduct a formal test of the validity of the common trend assumption in our data. Unfortunately, there is no direct test for the common trend assumption. However, we managed to check the outcome trends for the treatment and comparison groups by using more ESS data collected before the baseline period to perform a placebo test. We have done this test in our data and found that the common trend assumption holds (see section 5.3 table 4 for the placebo test result).

5. Results and discussion

This section presents estimates of the effect of the 2015 drought on household consumption. We report estimates of our DID model based on the matched comparison groups and equal-sized treatment groups. We start by describing average levels and trends of the outcome of interest and covariate distribution during 2014-2016. We also present baseline covariate balance among treatment and comparison groups both before and after matching based on resilience pillars. We then present and discuss estimates of the drought impact on consumption including additional impact estimates based on quantile difference-in-difference regression in order to compare the changes caused by the drought between the lower and upper tails of the consumption distribution.

5.1. Descriptive Statistics

Table 1 presents the mean levels and trends of consumption including distribution of covariates in both pre-drought and post-drought periods. Number of observations and mean values are presented in consecutive columns of the table for both periods. Mean consumption declines significantly during 2014-2016 period. Except access to basic services that do not vary overtime, significant changes in the mean levels of all covariates were observed during 2014-2016.

Table 1 Summary of Household Consumption and Resilience capacity by Year

Variables	G1(2014)	Mean1	G2(2016)	Mean2	MeanDiff
Consumption per adult eq. (2014 real price)	2883	4860	2774	4596	264.253***
Access to Basic Services	3196	0.525	3089	0.524	0.001
Adaptive Capacity	3196	0.547	3014	0.255	0.292***
Household Asset	3195	0.122	3088	0.596	-0.474***
Safety Net	3195	0.016	3089	0.008	0.007***

*** $p<0.01$; ** $p<0.05$; * $p<0.1$

Mean levels of resilience capacity decline on most of the resilience pillars during 2014-2016 indicating the deteriorating resilience capacity against shocks. In terms of adaptive capacity and safety net, both are

important for households to deal with and react against shocks, the observed decline might be due to wide coverage of the drought exposure in 2015 that may limit safety net coverages as well as access to alternative food or income sources as coping mechanisms. It might also indicate inadequate preparedness to deal with shocks well before the drought occurrence. However, non-declining trend in the mean level of household asset may reflect the asset smoothing behavior of a typical rural household in Ethiopia that tend to protect their assets during periods of stress instead of drawing down assets to meet consumption gaps caused by transitory shocks.

5.2. Covariate Balance between Treatment & Comparison Groups

Our estimates assume that the change in consumption in the comparison group is an unbiased estimate of the counterfactual. Propensity scores are used to balance treatment and comparison groups on a set of baseline characteristics of resilience against shock (on key covariates defined in section 4.2 above) in order to make the groups as similar as possible with respect to those observed bassline characteristics. Based on the propensity scores, we therefore perform kernel matching procedure to construct a valid counterfactual. The covariate balance before and after matching is presented in Table 2 & Table 3, respectively. The mean levels of the outcome of interest i.e. consumption and covariates are estimated at the baseline period (2014) for both treatment and comparison groups. The mean consumption at the baseline is significantly higher among comparison groups compared to the mean consumption among treatment groups in both cases, before matching as well as after matching.

Table 2 Mean Covariate Differences between Treatment & Comparison groups Before Matching

Variable(s)	Mean Control	Mean Treated	Diff.	|t|	Pr(|T|>|t|)
Consumption per adult eq. (2014 real price)	5019	4755	-263.4	2.75	0.0060***
Access to Basic Services	0.475	0.55	0.075	9.25	0.0000***
Adaptive Capacity	0.559	0.543	-0.015	1.85	0.0640*
Household Asset	0.127	0.12	-0.008	3.06	0.0022***
Safety Net	0.018	0.014	-0.005	2.33	0.0200**

*** p<0.01; ** p<0.05; * p<0.1

Before matching (Table 2), many of the differences in covariates between treatment and comparison groups were statistically significantly different at baseline. In three of the resilience pillars drought affected groups exhibited lower levels of assets and adaptive capacity as well as access to social safety net to deal with shocks. This implies that the two groups are systematically different and our estimate would have been biased even without the intervention (exposure to the 2015 drought).

Table 3 Mean Covariate Differences between Treatment & Comparison groups After Matching

Variable(s)	Mean Control	Mean Treated	Diff.	|t|	Pr(|T|>|t|)
Consumption per adult eq. (2014 real price)	5023	4755	-267.7	2.92	0.0035***
Access to Basic Services	0.549	0.554	0.005	0.61	0.54
Adaptive Capacity	0.55	0.544	-0.007	0.8	0.424
Household Asset	0.121	0.12	-0.001	0.45	0.653
Safety Net	0.014	0.014	0	0.08	0.939

*** p<0.01; ** p<0.05; * p<0.1

However, following matching (Table 3), no covariate seems likely to demonstrate a practical difference at baseline and our matching procedure assured the comparison group to be a reasonable counterfactual. All of the figures and estimates of our model reported below are based on the matched comparison groups.

5.3.   Impact estimates

Our impact estimates rely on the common trend assumption holding true and, hence, as a test for this key assumption, we presented both estimates of the drought effect and the placebo intervention effect in table 4. The latter was estimated using the two observations of the ESS data in the pre-drought period i.e. the 2012 and 2014 ESS data. The non-significant impact of the placebo intervention (table 4 column 3) reassured the valid drought impact estimate of our DID model (table 4 column 2). Our outcome of interest is represented by natural logarithms of household consumption expenditure (adjusted to the 2014 real price). Our estimate confirms that the 2015 drought reduced household consumption by about 8% compared to the average consumption level of the matched comparison groups. This is a robust evidence that mean consumption in 2016 would have been significantly higher in the absence of the drought that affected large parts of the country. The significant impact of the 2015 drought on consumption among affected groups is not surprising as it was one of the large-scale shocks

that the country experienced. However, compared to our impact estimate, the estimated magnitude of drought impact in many observational studies appeared to be overestimated. For example, our estimate is about two-fifth of what was predicted by (Dercon et al., 2005b) and for severe drought (Hill, R. V. & Porter, C., 2017) also estimated a 33% loss in total consumption which is four times larger than our estimate.

Table 4 Estimated Effect of the 2015 Drought & Placebo Effect on ln Consumption

Variables	Drought Effect	Placebo Effect
Diff-in-diff	-0.0787***	0.0431
	(0.0276)	(0.0265)
Observations	5,257	5,440
R-squared	0.007	0.017
Mean control t(0)	8.385	8.567
Mean treated t(0)	8.359	8.434
Diff t(0)	-0.0265	-0.133
Mean control t(1)	8.388	8.487
Mean treated t(1)	8.283	8.397
Diff t(1)	-0.105	-0.0899

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

There are at least three reasons that the ex-ante predictions were too pessimistic compared to our estimate. First these studies failed to consider shock resilience differences, among affected and non-affected groups, which may bias impact estimates even in the absence of any external intervention or exposure. Second, both studies above used ERHS panel datasets of 1998-2004 and 2015-2011 which are often criticized for limited sampling coverage and lacking data for some key household and community level indicators. Using reported shock occurrences in their estimation procedures may also overestimate the drought effect on consumption. Moreover, these datasets involve longer time ranges between the baseline and follow-up periods which makes it more difficult to control confounding effects that may bias estimation of the effect of a particular drought exposure. This may also present a challenge to define the time frame for measuring drought exposure and the

estimated impact may reflect the longer-term impact of droughts unlike our study which focuses on a specific drought episode and its short-term impact on household consumption. Early warning & emergency response system of the country has changed overtime and the varied estimated impacts reported in this study and in both studies mentioned above may also reflect such key contextual differences.

However, a reduction of consumption among drought affected population by 8% would have consequences more than just a temporary reduction in consumption. For instance, reference to a similar drought context (Dercon, 2004) demonstrates that covariates capturing the severity of the 1984-85 drought induced famine are causally related to slower growth in household consumption in the 1990s. Our estimate of drought effect on consumption, also include non-food consumption and expenditure for education which are often subject to household expenditure reduction during periods of shocks as a coping strategy for most of poor households. Such coping behavior often imply longer-term consequences. For example, studies such as (Hoddinott and Kinsey, 2001) and (Alderman et al., 2006) demonstrated that rainfall shocks are causally related to reduced human capital formation and that the magnitudes of these effects are meaningful. The later study estimates a seven percent loss in lifetime earnings among children affected by the 1982-84 drought shock in rural Zimbabwe.

5.4.   Descriptions of Change Across Consumption Groups

We also examine the extent to which the negative effects of the 2015 drought was driven by changes in the lower and upper quantile groups of household consumption. For this reason, we ran quantile DID at the 25th and 75th percentiles of household consumption using a simplified estimation procedure developed by (Villa, J.M., 2016) for a combined method of PSM and DID. Table 5 presents our estimates using quantile DID regression. The result confirmed that the 25th percentiles of consumption declines significantly (Table 5, Column 2) due to the 2015 drought indicating the estimated drought impact was largely driven from the lower tail of the consumption distribution.

Table 5 The 2015 Drought Effect Estimated at the 25th & 75th Consumption Percentiles

Variables	25th Percentile	75th Percentile
Diff-in-diff	-414.6***	-263.7
	(139.7)	(322.3)

Observations	5,257	5,257
Mean control t(0)	2914	6645
Mean treated t(0)	3046	6056
Diff t(0)	132.3	-589.3
Mean control t(1)	3056	6455
Mean treated t(1)	2774	5603
Diff t(1)	-282.3	-853

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

However, the decline in the upper tail of the distribution appears to be non-significant (Table 5, Column 3). The significant reduction in consumption among poor households may be largely due to the limited access to liquid assets that constrain their ability to meet the consumption gap caused by the drought shock. While the better-of households with wide range of coping options managed to maintain relatively high levels of food consumption during periods of shocks, the poor households tend to have gaps even in non-drought years. This implies a persistent effect of shocks on consumption of the poor.

The significant impact of the drought on consumption was largely expected given the previous literature on shocks and food security. Nonetheless, unlike ex ante predictions of previous studies, the findings of this study related to the estimated drought effect from a quasi-experimental impact estimation procedure may offer a more accurate estimated magnitude of drought impact liable to substantive policy implications. For example, the relatively large effect of the drought on consumption poor households may reveal the persistent effect of shocks that keep the poor to stay in a state of poverty traps. On the other hand, the non-significant impact of the drought on the better-off groups may reflect their ability to maintain food consumption during periods of stress. This is mainly because wealthy households tend to have wide range of coping options to maintain relatively high levels of food consumption. However, it is important to recognize that the observed distribution of a given shock's impact depends on the particular outcome of interest (Wisner, 2004). For example, in terms of livestock holdings, (Thiede, B. C., 2014) found that wealthy households were more exposed to the effects of rainfall deficits than the poor. In his study, the relatively large effect of rainfall deficits on better-of households' livestock stores may represent the tradeoff for increasing their ability to maintain relatively high levels of food consumption by liquidating their livestock wealth.

6. Concluding Remarks

The result of this study is based on a quasi-experimental design informed by a robust theory of change represented by a risk chain model by which the welfare impact of a particular shock could only be determined given the factors of resilience among exposure units against the shock. Hence, we employed a combined method of PSM & DID to estimate the impact of 2015 drought on consumption of affected groups by comparing their average consumption to that of non-affected groups given similar resilience characteristics between the two groups. This study exploits the advantage of the timeline of the 2015 drought crisis and the 2012-2016 unique Ethiopian Socioeconomic Survey to provide arguably among the most robust empirical evidence about the relationship between climatic shocks and consumption among rural households.

Although this study focuses on consumption as an outcome of concern, droughts often have a multitude of socio-economic and environmental consequences. Given the importance of the 2015 drought and ESS data availability on other key indicators such as crop production and ownership of productive assets, further research that apply a similar methodology could generate policy relevant insights related to the management of drought risk and resilience building initiatives. With more waves of ESS data to be available in the future, further studies with similar design may also quantify the persistent effect of shocks that determine the nature of poverty and vulnerability trajectories as a complementary line of inquiry to the more common focus on the social determinants of vulnerability or resilience to negative wellbeing outcomes (Celidoni, 2015; Chaudhuri and Datt, 2001; Demissie and Kasie, 2017)

The findings of this study and the further research indicated above are both theoretically and practically important. For example, theoretical explanation provided to shock related short-term consumption gap and persistent effect of long term wellbeing is still inadequate due to complicated shock response mechanisms adopted by affected communities. Some studies documented evidences that in hard times some households may choose to protect their consumption today by depleting their productive assets or withdrawing their children from school which may undermine future livelihoods (Devereux et al., 2008; Roncoli et al., 2001). In contrast some household may also choose to reduce consumption today to protect their future livelihoods (Waal and others, 1989). This has also negative effect on health and nutritional status which have persistent effects on labor capacity and health expenses subject to high vulnerability to future poverty (Roncoli et al., 2001; Webb and Harinarayan, 1999). Further research should build upon this study by using decomposition techniques and triple

DID methodology to quantify how choice of certain shock response mechanisms contribute to the overall changes in consumption and productive assets including resulting inequality among affected communities in terms of resilience to future shocks.

Evidences about livelihood and food insecurity effects of shocks attributable to the various shock response mechanisms employed by affected people may provide new policy insights for targeted strategic development focus and effective emergency response planning. This study and future research may support drought risk reduction investment decisions and enables to perform resilience tests of the overall response system against likely crisis to enhance emergency preparedness capabilities. This is particularly important in Ethiopia where emergency needs projections are often made based on analysis of past El-Niño events.

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