Ethiopia: Recent trends in consumption and multi-dimensional poverty[1]

1. Introduction

Ethiopia has seen strong growth over the past 15 years, resulting in a 2.5-fold increase in per capita GDP between 2000 and 2015 (from Birr 2,990 in 2000 to Birr 7,530 in 2015[2] – about US$ 619 in current prices). Aggregate growth has increased the welfare levels of Ethiopian households, witnessed by a decline in the poverty rate from 44 percent in 2000 to 30 percent in 2011 (based on the national poverty line). Poverty reduction was mainly driven by robust growth in agriculture-the mainstay of the Ethiopian population-and improved access to basic services. Welfare levels converged during the period of strong growth, with regions that were initially poorer experiencing faster welfare improvements[3]. Inequality remained low with a Gini of 0.3.

Since the last poverty measurement in 2010/11, Ethiopian households have been hit by a series of shocks[4]. The 2011/12 Horn of Africa drought severely affected the Eastern and Southern parts of Ethiopia and resulted in an estimated 4.5 million people in need of food aid[5]. Failure of two consecutive rainy seasons in 2015, labeled the worst drought in 50 years, led to a sharp increase in humanitarian requirements with more than 10 million Ethiopians in need of food aid[6]. The 2015/16 El Nino drought was followed by the *Indian Ocean Dipole*-induced drought in 2017, mainly in the spring-rain-dependent woredas of Oromiya, SNNPR, and Somali Regions. As a result, humanitarian requirements have remained high at an estimated 8.5 million people in need of relief assistance[7].

Economic growth was affected by the recent drought but nevertheless stayed strong. According to World Bank data**,** growth in 2016 was a respectable 7.6 percent, down from 10.4 percent in 2015 and the lowest growth rate since 2003[8]. The drought in 2015 appeared to have only marginally affected production levels in agriculture, with *Meher* season production in 2015/16 being slightly lower than in 2014/15. A good *Belg* season in 2016 however meant that overall agricultural production still increased between 2014/15 and 2015/16, albeit only marginally (but decreased on a per capita-basis)[9].

This study examines the trends in household welfare levels during the recent 2012-2016 period. It provides a thorough analysis of changes in welfare for households in rural areas, small towns and big cities, focusing both on monetary (consumption) and non-monetary dimensions. The study also attempts to estimate the impacts, if any, of the two droughts (2011/12 and 2015/16)

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[1] This summary note is based on background papers by Habtamu Fuje ("Recent welfare dynamics and drought in Ethiopia") and Harriet Kasidi Mugera ("Multidimensional poverty dynamics in Ethiopia"). Thomas Sohnesen and Filippo Cuccaro (Consultants) provided useful research assistance.

[2] In 2010/11 prices.

[3] World Bank. (2015). Ethiopia Poverty Assessment. Washington DC: The World Bank

[4] At the time of writing, the 2015/16 Household Consumption Expenditure Survey results had not yet been released.

[5] Based on the July 2011 Joint Government-Humanitarian Partners' Document.

[6] Based on the 2016 Joint Government-Humanitarian Partners' Document.

[7] Based on the mid-year review of the 2017 Joint Government-Humanitarian Partners' Document.

[8] World Development Indicators, 2017.

[9] FDRE. 2017. Agricultural Sample Survey 2015/16, Ethiopia: Central Statistics Agency.

on household welfare. Given that the microdata of the most recent Household Consumption Expenditure Survey (2015/16 HCES) is not yet available, the study uses panel data from the Ethiopian Socioeconomic Survey (ESS), conducted in 2012, 2014 and 2016. The panel data allows us to track and analyze dynamics of consumption, mobility of households into and out of the bottom 40 percent of the consumption distribution, and identify households that were chronically and transiently in the bottom 40 percent since 2012. In addition, these three waves of ESS provide a unique opportunity to study the impacts of two recent droughts on household wellbeing.

This report is organized into three sections. The first section describes recent dynamics in consumption expenditures by analyzing changes in real consumption between 2012 and 2016 in rural areas, small towns, big cities, and across regions. The section also presents consumption growth incidence analysis, and describe mobility of households into and out of the bottom 40 percent of the income distribution. Section two focuses on non-monetary dimensions of welfare by describing the trends in multi-dimensional poverty. Section three investigates the impacts of drought on real consumption in rural areas.

2. Recent trends in consumption[10]

To measure monetary welfare, we use total household consumption expenditure per adult equivalent in 2016 (ESS3) prices. The consumption aggregate includes expenditures on and own-consumption of food (with a recall period of 7 days) and also includes spending on a selection of important nonfood items, including education. Health spending is not included in the aggregate to avoid that large expenses incurred following adverse health shocks would signal an increase in household welfare. The nominal consumption aggregate we use is the one provided and described in the public use files of the Living Standards Measurements Study[11]. To convert the nominal consumption aggregate provided by the LSMS into a spatially adjusted real consumption aggregate, three alternative spatial and temporal adjustments were made. In the first adjustment ('Fisher'), the official food and nonfood consumer price index (CPI) is used to express food and nonfood consumption expenditures in April 2016 prices, respectively, and the Fisher spatial index is used for spatial adjustment of food expenditures using survey-based unit values[12]. In the second adjustment ('HICES'), the food and nonfood CPI is used for temporal adjustment, and spatial adjustment is done based on regional price index used by Ministry of Finance and Economic Development (MoFED) in the Household Income, Consumption and Expenditure Survey (HICES). In the third adjustment ('Unit price'), food expenditures are spatially and temporally adjusted using the Paasche price index and Fisher spatial index, based on survey unit values. For nonfood expenditures, the nonfood CPI is used[13].

Regardless of the approach used, consumption trends tell a qualitatively similar story—real median consumption levels have declined slightly during the 2012-2016 period[14]. Figure 1 presents median real consumption per adult equivalent after temporal and spatial adjustments based on the three approaches. While median household consumption decreased in rural areas and

[10] Just before completing this study, in October 2017, the GoE published the new poverty figures based on the 2015/16 Household Consumption Expenditure Survey (HCES). Trends in HCES differ to some extent from the ones presented here (based on the ESS). The methodology of the ESS and HCES is different, which may explain the different results. As soon as the HCES data will be publicly available, the team will examine whether the two data sources can be reconciled.

[11] http://econ.worldbank.org/WBSITE/EXTERNAL/EXTDEC/EXTRESEARCH/EXTLSMS/0,,contentMDK:23635542~pagePK:64168445~piPK:64168309~theSitePK:3358997,00.html

[12] There is no spatial deflation of nonfood expenditures.

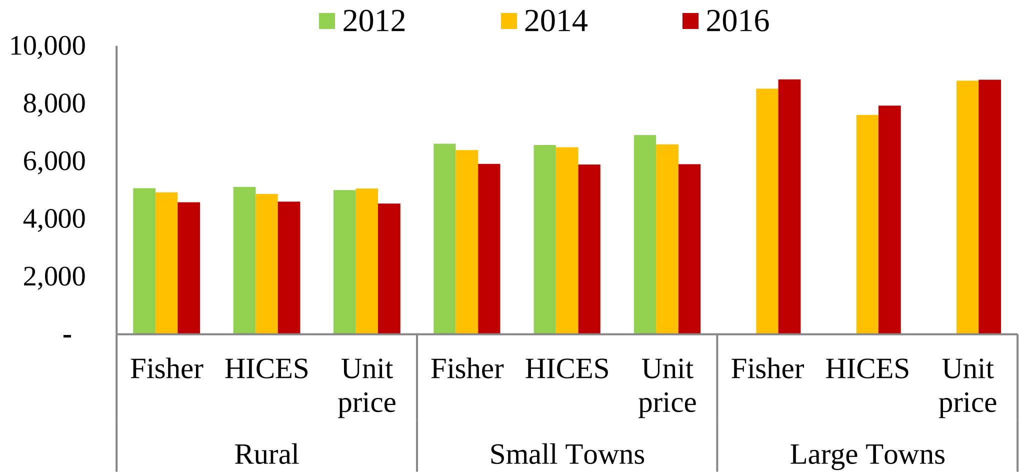
[13] Survey unit values refer to food only. Nonfood expenditures are always delated using the official nonfood CPI provided by CSA.

[14] The decline in *mean* consumption was however significantly larger.

small towns, in particular between 2014 and 2016, consumption in cities increased. The trend in cities is however sensitive to the deflation method used, with unit values showing a stagnation in consumption. The "median household" in rural areas consumed ETB 4,578 per adult per year in 2016, down from 5,059 in 2012, while in towns consumption declined from ETB 6,604 to ETB 5,903. At ETB 8,833, median consumption levels are substantially higher in cities[15].

Figure 1: Median consumption levels have decreases in rural areas and small towns

(Median consumption expenditures per adult equivalent, 2012-2014-2016)



Note: Median consumption per adult equivalent in 2016 prices. Source: ESS1; ESS2; ESS3.

Due to its advantage over the other two approaches, the rest of the report will use the 'Fisher' method, i.e. Fisher spatial and CPI temporal adjustments. The two main advantages of Fisher spatial index are that: (1) it allows us to capture a more refined and detailed spatial differences in living cost—HICES allows spatial adjustment only at region level; (2) it also allows the spatial living cost differences to vary over time[16].

The trends presented in Figure 1 are robust to the possibility of selective attrition and missing values. Of the 3,466 rural households interviewed in 2012, 3,323 were re-interviewed in 2014 and 3,272 in 2016. Overall, 94 percent of rural households interviewed in 2012 were still in the sample by 2016. As expected, attrition is higher in urban areas: 85 percent of small town households interviewed in 2012 were still in the sample by 2016, while 84 percent of city households interviewed in 2014 were still in the sample by 2016 (see Annex 1 for a discussion of attrition in the ESS). When we control for attrition and only consider those households that were interviewed in all survey rounds, the picture is largely similar (Table 1): A stagnation in consumption in rural areas and small towns between 2012 and 2014, followed by a decline between 2014 and 2016 (Table 1). The decline since 2014 is only statistically significant in rural areas, not in towns. On the other hand, cities have experienced a statistically significant increase in median consumption

[15] The GoE's HCES survey shows positive consumption trends in both cities and rural areas, with urban areas however performing better (NPC, 2017).

[16] Another more pragmatic reason to use the Fisher method throughout this paper is the discrepancy between the official CPI and prices as measured from the ESS. Between ESS1 and ESS2, inflation as measured by CPI was substantially higher than as measured by survey prices. Between ESS2 and ESS3, inflation as measured by CPI was much lower than the increase in survey prices. By using the Fisher method we align with the official inflation figure. Using unit values would result in larger consumption declines between 2012 and 2016.

between 2014 and 2016, in line with positive developments in the labor market in cities[17]. The consumption trends are also robust for the imputation of missing consumption values (Annex 2).

Table 1: Consumption trends without attrition

Survey	Rural	Small town	Cities
2012	5,075	6,308	NA
2014	4,936	6,361	8,444
2016	4,580	5,903	8,833
N	3,222	417	1,248

Note: Table shows median consumption per year per adult equivalent in 2016 prices, using the Fisher spatial deflation and CPI temporal deflation. Only households that were interviewed in all three survey rounds are included. Source: ESS1; ESS2; ESS3.

Given that the ESS are not year-long surveys, one may be concerned about the effects of seasonality. To minimize these effects, household consumption data were collected between February and April for both ESS2 and ESS3, and between January and March for ESS1. Though the timing of data collection was the same in ESS2 and ESS3[18], the exact month in which a household was re-interviewed could differ. Annex 3 shows that the trend in consumption is robust for the exact month of (re)-interview, though with a peculiar pattern for households who were re-interviewed in a different month than the month they were interviewed in during a previous round. One may also be concerned that Ethiopia's *Lent*, a 55-day fasting period whose timing differs across years, biases the consumption trend. Annex 3 shows that this is unlikely to be the case.

Finally, several other trends appear consistent with a decrease in household disposable income. The share of food in total consumption increased between 2014 and 2016, consistent with households attempting to maintain food consumption in the face of declining income. Food shares increased significantly in Tigray, SNNPR and Amhara between 2014 and 2016, but not in Oromiya. Item-level consumption seems to suggest an income and substitution effect, as consumption of higher-value food items (*enjera*, animal products, sugar) decreased while consumption of Irish potatoes, a low-value item, sharply increased (Annex 4).

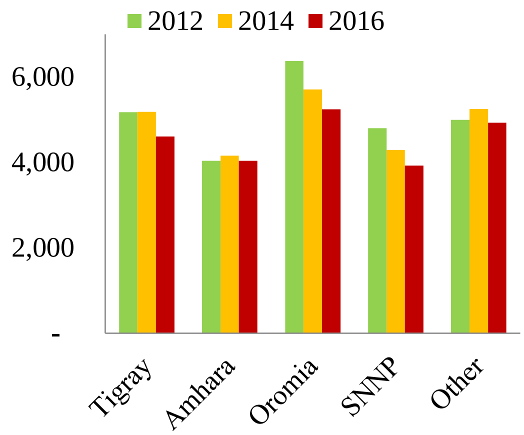
Consumption trends differ across region and time period. Between 2012 and 2014, real consumption was mostly stable, though decreased significantly in SNNPR and Oromiya (Figure 2). Since 2014, median consumption levels also decreased significantly in Tigray. Overall, median consumption levels of households in the ESS sample declined by 11 percent in Tigray and by 18 percent in both Oromiya and SNNPR (between 2012 and 2016). Consumption in Amhara and "Other" regions—Afar, Somali, Benshagul Gumuz, Gambela, Harari and Dire Dawa—remained flat.

Figure 2: Consumption declined since 2014

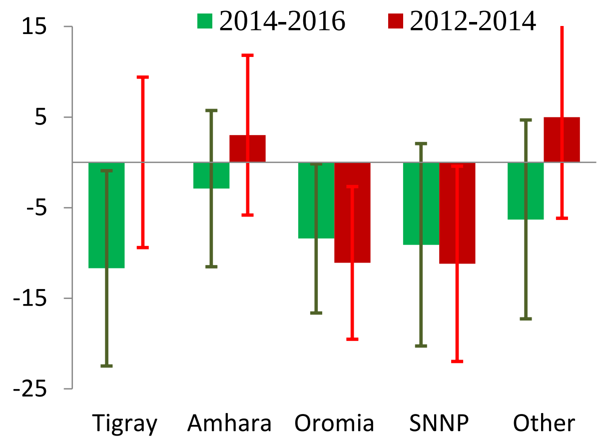
(Median consumption by region) *(% Change in consumption, 2012-2014; 2014-2016)*

[17] We have also used the Fitzgerald, Gottschalk and Moffit (1999) method to deal with selective attrition. This method consists of inversely weighting observations by their probably of selection (i.e. their predicted probability of being in the sample all survey rounds). Results are similar.

[18] As most of the significant changes in consumption happened between 2014 and 2016, we focus on this period for the sensitivity checks.



Source: ESS1; ESS2; ESS3.



Source: ESS1; ESS2; ESS3.

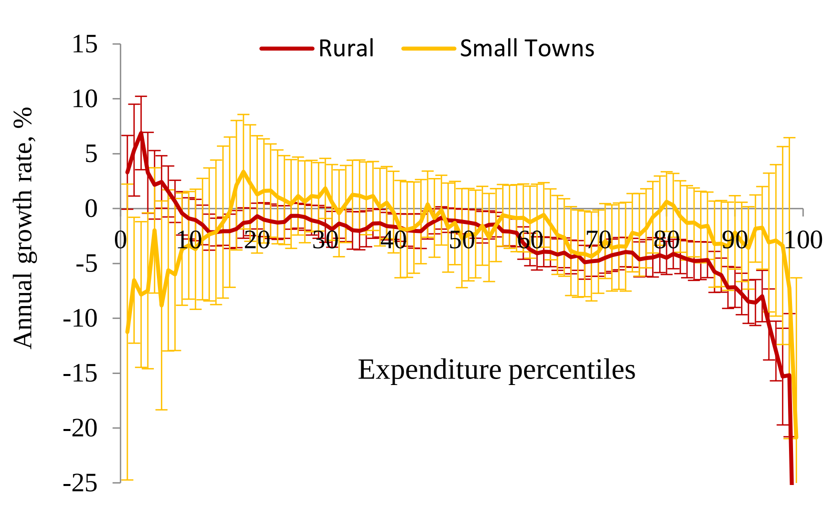
Between 2012 and 2014, the poorest percentiles in rural areas experienced positive mean consumption growth while consumption in the upper half of the distribution contracted. Consumption growth in towns was not significantly different from zero at any part of the distribution, mainly related to the small sample size in towns (Figure 3). Between 2014 and 2016, consumption in rural areas and small towns contracted across the distribution, though more so for the poor (the upward-sloping red and yellow curves in panel B of Figure 3). In cities, consumption growth was positive for the top 60 percent of the distribution but negative for the bottom 40 percent, with a particularly large decrease for the bottom ten percent (green curve in panel B of Figure 3). Overall, mean consumption growth for the bottom 15 percent amounted to % at the national level, mirroring the finding of the poverty assessment that consumption of the poorest 12 percent in Ethiopia contracted between 2000 and 2011.

The incidence of growth across the distribution differs between regions and time periods. Between 2012 and 2014, consumption growth was positive across the distribution in Amhara and Tigray, but was negative in Oromiya, especially at the bottom percentiles (blue curve in panel C of Figure 3). Between 2014 and 2016, consumption growth was negative (except for the "other" regions) and the bottom 40 percent experienced the strongest declines. The poor in Tigray, Oromiya and Amhara experienced a particularly strong decline in consumption since 2014 (panel D of Figure 3). Though the patterns presented in Figure 3 appear consistent with a story of "the poor becoming poorer", the panel element of ESS suggests that this is not entirely the case. There is a large amount of consumption mobility across survey waves, and the poorest households in ESS1 are not necessarily the poorest in ESS2 or ESS3. Preliminary analysis shows that *only* 12 percent of rural households were in the bottom 40 percent all three survey rounds, and that 45 percent of households that were in the bottom 40 percent in 2012 no longer were so by 2016[19]. What remains however true is that average consumption levels among those households who are in the bottom 40 percent (whichever these households actually are) decreased between 2012, 2014 and 2016.

[19] Ongoing work is focusing on household consumption mobility and dynamics.

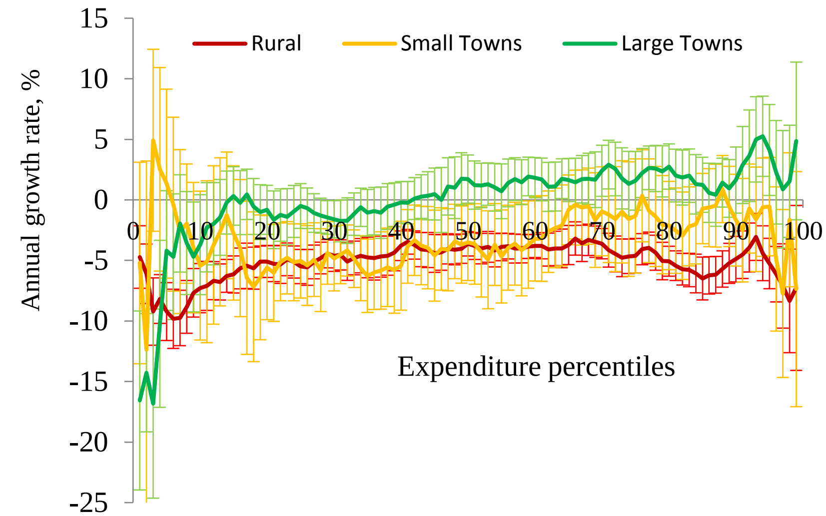
Figure 3: Growth incidence curves, 2012-2014-2016

A. 2012-2014



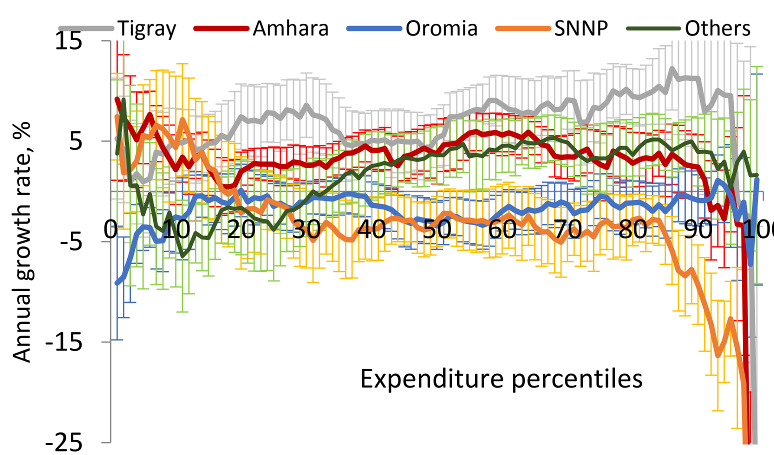
Source: ESS1; ESS2;

B. 2014-2016

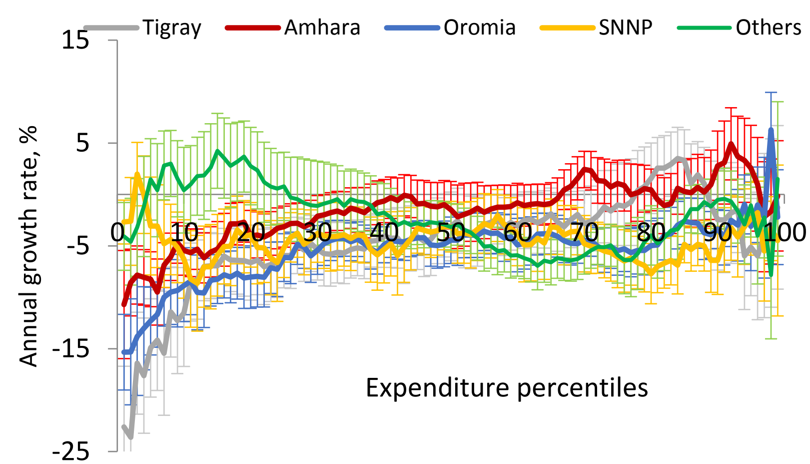


Source: ESS1; ESS2; ESS3.

C. 2012-2014, by Region



D. 2014-2016, by Region



3. Recent trends in multi-dimensional poverty

The decline in household consumption expenditures documented in the previous section may not come as a surprise given the severe droughts of 2011/12 and 2015/16. Most Ethiopian households depend on rainfed agriculture to generate income, and the drought has negatively affected agricultural production (though less than feared). Despite this, we would nevertheless expect a continued improvement in non-monetary dimensions of living standards: While income or consumption in largely agrarian countries is vulnerable to the vicissitudes of the weather, non-monetary dimensions such as health and education are more responsive to investments in public services. In addition, trends in income or consumption are not always correlated with trends in non-monetary dimensions of living standards[20]. In this section, we look at the trends in multidimensional poverty across the three ESS survey rounds.

Multidimensional indicators of poverty have gained popularity in recent years and typically try to condense deprivations in several dimensions of well-being into a single indicator. We use the same multidimensional poverty (MDP) measure as Seff and Jolliffe (2015). This measure broadly follows the OPHI approach, incorporating three dimensions of wellbeing— education, health, and living standards—with each dimension weighted to represent one-third of the deprivation index. Individual indicators are weighted equally within a given dimension. The MDP measure consists of nine indicators, summarized in Box 1. There are two notable departures from the standard OPHI method: First, our nutrition indicator only focuses on children and does not include adult undernutrition (this was not measured in the ESS). We also use stunting (height-for-age) as a nutrition indicator while OPHI uses weight-for-age (underweight). Second, we do not include an indicator of recent cases of child mortality within the household because this information was only collected in wave 2 of the ESS and thus cannot be assessed in the panel dimension. Table 2 summarizes the differences between the standard OPHI measure and ours. Households that are deprived in at least one third of the weighted indicators shown in Table 2 are considered multi-dimensionally poor, and the poverty headcount is defined as the share of the total population living in multi-dimensionally poor households (Alkire & Foster, 2011). For the sake of uniformity, we use the standard cut-off point (one third) in the analysis. Setting a higher cut-off point will result in lower *levels* of multi-dimensional poverty, but do not affect the *trends* over time.

Multi-dimensional poverty in Ethiopia has historically been high, and substantially higher than consumption poverty. In 2011 for instance, MDP and consumption poverty were estimated at 87 percent and 30 percent, respectively[21]. MDP has also been stickier: While consumption poverty decreased from 44 percent to 30 percent between 2000 and 2011, MPD decreased more modestly, coming down from 94 percent in 2000. The high MDP levels have mainly been driven by poor child nutrition outcomes and a low stock of education in the country, which is largely a legacy from previous times[22]. Nevertheless, solid progress was made between 2000 and 2011, with overlapping deprivations decreasing and the number of individuals in Ethiopia who suffer from multiple deprivations falling[23].

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[20] Bourguignon et al., 2010; Alkire et al., 2014. Using panel data, Seff and Jolliffe (2016) find that trends in monetary and non-monetary dimensions of well-being in Ethiopia between 2012 and 2014 were statistically independent.

[21] OPHI, 2016; World Bank, 2015.

[22] In the MDP methodology, a household is deprived in "years of schooling" if no adult member in the household has completed at least five years of schooling. Due to extremely low levels of schooling among older generations of Ethiopians, most households are deprived in this indicator.

[23] Ambel et al., 2015.

Box 1 Construction of the multi-dimensional poverty headcount

To construct the multi-dimensional poverty headcount used in this study we consider nine binary indicators. Each indicator is weighted so as to give equal weight to each of the three dimensions of living standards (education, health, and living conditions). An individual living in a household that is deprived in at least one third of the weighted indicator is consider multi-dimensionally poor. The MDP numbers presented in this section will differ from the OPHI ones (that are usually based on the DHS survey) due to a number of differences in indicators. The trends are however consistent within the ESS surveys as the same approach is used for all survey rounds.

Table 2: Dimensions and indicators of MDP

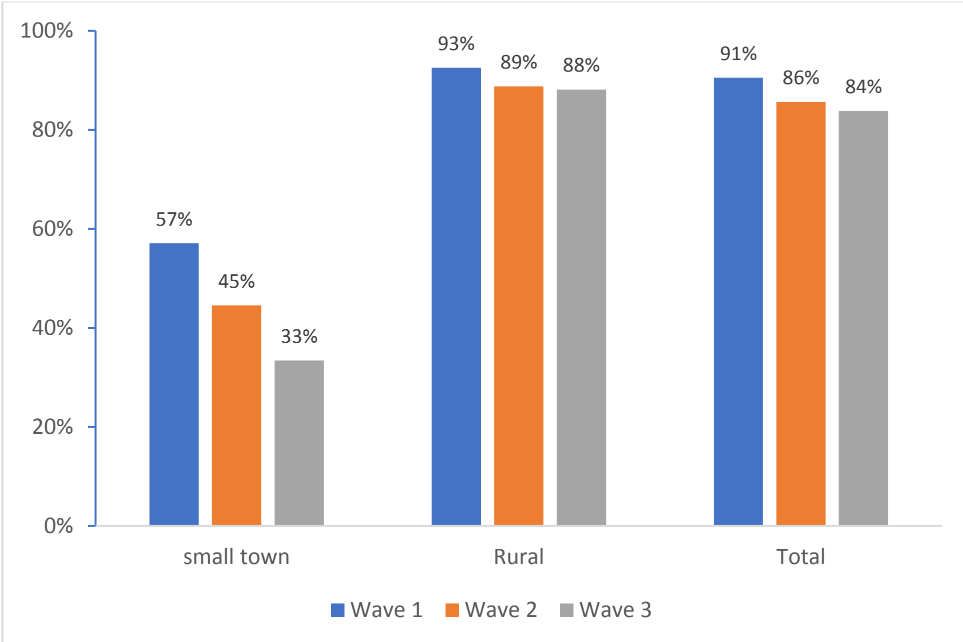
Dimension	Indicator	Deprivation cut-offs	Weight
Education	School Attendance	If at least one child in the household between 7-15 years of age is not attending school	1/6
	Years of schooling	No household member has attained 6 years of schooling	1/6
Health	Nutrition	At least one 6-59-month-old child in the household is stunted	1/9
	Water	Household does not have access to an improved water source	1/9
	Improved sanitation facilities	Household that have no access improved sanitation facilities	1/9
Living Conditions	Access to electricity	Household has no access to electricity	1/12
	Cooking Fuel	If the household did not use solid cooking fuel (uses wood/straw/ shrubs/grass /charcoal / none)	1/12
	Type of Floor	Households with an earth/sand and dung floor.	1/12
	Asset Ownership	Household does not have a radio, TV, or phone OR no transportation asset AND no refrigerator	1/12

Source: Seff and Jolliffe, 2015.

In line with expectations, multi-dimensional poverty in the ESS sample has declined between 2012 and 2016. In rural areas, MDP declined from 93 percent in 2012 to 89 percent in 2014 and 88 percent in 2016 (Figure 4). Small towns experienced a much stronger decline in MDP from 57 percent in 2012 to 45 percent in 2014 and 33 percent in 2016, a 24 percentage points drop over a period of only four years. Taking rural and small towns together, MDP decreased from 91 percent in 2012 to 84 percent in 2016. At the national level, also including big cities that were added to the ESS in round 2, MDP decreased from 74 percent in 2014 to 70 percent in 2016 (driven by small towns).

Figure 4: MDP in rural areas and small towns decreased between 2012 and 2014

(MDP rate, 2012-14-16)



Note: Big cities are not included in this graph. Source: ESS1; ESS2; ESS3.

There was a marked difference in the pace of MDP reduction between the two periods. Between 2012 and 2014, MDP decreased significantly in both rural areas and small towns. Between 2014 and 2016 however, MDP stagnated in rural areas (the decline of one percentage point is not statistically significant), while there was still a significant drop in towns[24]. This pattern qualitatively fits with the patterns in consumption expenditures documented previously: Stable consumption expenditures in rural areas and small towns between 2012 and 2014, followed by a drop between 2014 and 2016. While a multi-dimensional measure of living standards would logically be less sensitive to the drought than a monetary measure, it seems that progress on reducing MDP slowed as well between 2014 and 2016, at least in rural areas[25].

The decrease in MDP in rural areas and small towns between 2012 and 2014 was mainly driven by education, access to water, and household asset holdings. The share of households deprived in clean water declined from 44 percent to 38 percent, the share of households in which no member has at least six years of education decreased by seven percentage points and the share of household deprived in assets declined by eight percentage points (Table 3). Weaker but still significant (in a statistical sense) progress was made on access to electricity. Between 2014 and 2016, deprivation in both education indicators further declined while nutrition deprivation also declined, though progress on other dimensions stalled. Much of the progress between 2014 and 2016 was concentrated in small towns.

Table 3: Share of households deprived in the underlying indicators, 2016

	2012	2014	Std error of the diff	2016	Std error of the diff
At least 1 child age 7-15 not in school	0.252	0.252	0.005	0.233	**0.005**

[24] It may be surprising that towns experienced at the same time a decrease in consumption and an improvement in MDP. Seff and Jolliffe (2015) however finds that trends in consumption poverty and MDP are not correlated in Ethiopia.
[25] Bruck and Kebede (2013) indeed find that droughts play a role in consumption poverty only.

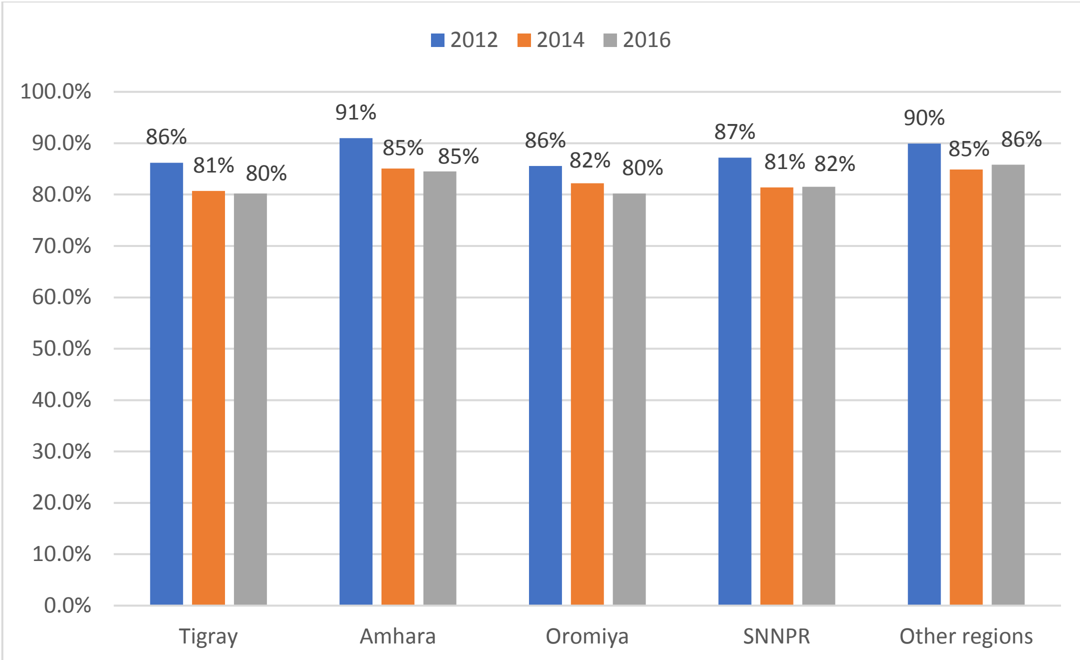
	(0.007	(0.007)		(0.007)	
No one in household has at >= 6 years of education	0.665	0.591	**0.0113**	0.555	**0.0116**
	(0.078)	(0.081)		(0.008)	
A child age 6-59 months is stunted	0.2301	0.217	0.0099	0.191	**0.0048**
	(0.007)	(0.007)		(0.007)	
No access to improved drinking water	0.437	0.376	**0.0116**	0.376	0.0114
	(0.008)	(0.008		(0.008)	
No access to improved sanitation	0.435	0.422	0.0116	0.422	0.0116
	(0.008)	(0.008)		(0.008)	
Household does not have access to electricity	0.827	0.795	**0.0091**	0.795	0.0095
	(0.006)	(0.007)		(0.007)	
Household does not use solid cooking fuel	0.979	0.977	0.0034	0.977	0.0035
	(0.002)	(0.003)		(0.003)	
Household does not have a finished floor	0.95	0.941	0.0053	0.9406	0.0055
	(0.004)	(0.004)		(0.004)	
Household missing community or mobility/livelihood asset	0.628	0.549	**0.0115**	0.5492	0.0117
	(0.008)	(0.008)		(0.008)	

Note: Standard errors in brackets. Differences in bold are statistically significant at the 5% level or less. Source: ESS1; ESS2; ESS3.

While all regions experienced substantial declines in MDP between 2012 and 2014, none of the regions had a significant decline between 2014 and 2016. MDP dropped by approximately five to six percentage points between 2012 and 2014 but stagnated thereafter (Figure 5). Except for household asset holdings, which significantly improved across the board, the decrease in MDP between 2012 and 2014 was driven by different factors in different regions. In Tigray, the MDP reduction was driven by improvements in education and access to electricity, and, while access to improved water and sanitation worsened. In Amhara, access to water and sanitation improved. In Oromiya, nutrition and access to water improved, while SNNP did well on years of schooling, nutrition and water (see Annex 5). Between 2014 and 2016, there were few significant changes in the underlying indicators, though school attendance significantly worsened in the "other" regions (Gambella, Benishangul-Gumuz, Afar, and Somali).

Figure 5: MDP declined in all regions between 2014 and 2016, stagnated thereafter

(MDP rate by region 2012-14-16)



Note: Big cities are not included in this graph. Source: ESS1; ESS2; ESS3.

Focusing on the most recent survey round, MDP remains high in rural areas. Based on our definition of multi-dimensional poverty (Box 1), 88 percent of rural households were multi-dimensionally poor in 2016. The high levels of MDP in rural areas can be mainly explained by the small number of household containing a member who has at least completed six years of education-largely a historical legacy (Table 4 and Figure 6). The high level of deprivation in electricity (91 percent) is also a main contributor to the overall MDP rate. Though not a major driver of high MDP rates, it is worth noticing that 25 percent of rural households were deprived in school attendance in 2016, meaning that at least one child aged 7-15 in the household was not attending school.

Table 4: Share of households deprived in the underlying indicators, 2016

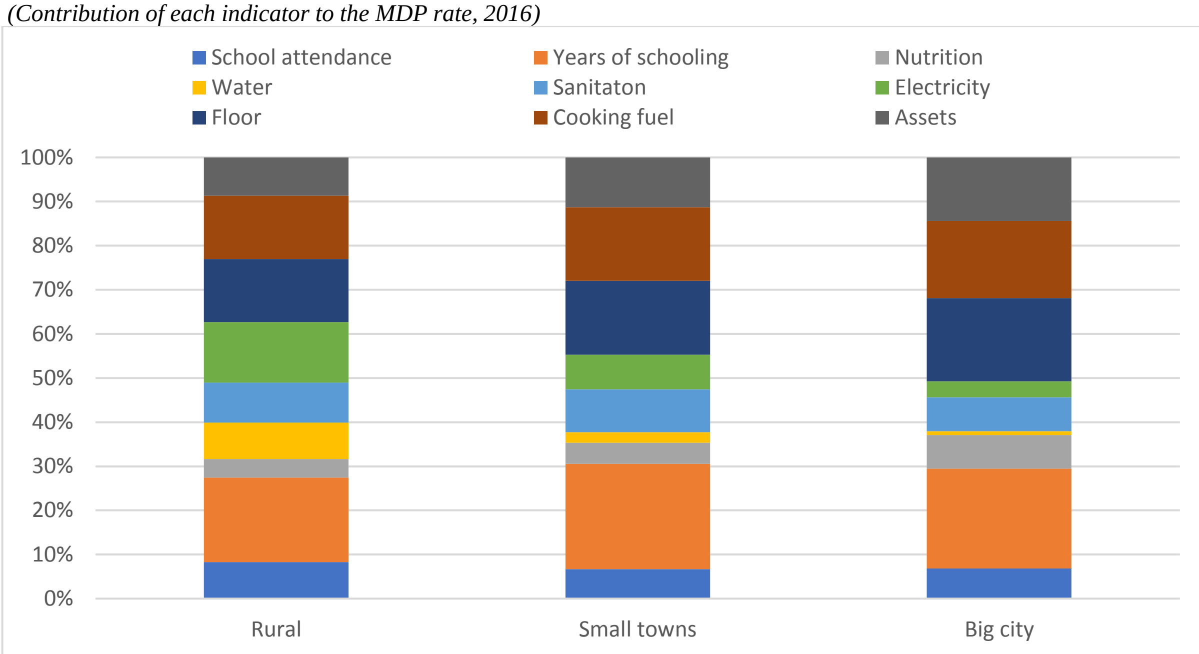
Share of HHs deprived in:	Rural	Small towns	Big city	Total
School attendance	25.2%	7.3%	4.8%	19.8%
Years of schooling	58.8%	23.5%	12.1%	46.8%
Nutrition	28.9%	16.4%	12.3%	17.8%
Water	39.2%	4.4%	0.8%	29.0%
Sanitaton	42.3%	17.9%	7.5%	33.6%
Electricity	90.8%	18.3%	4.5%	68.3%
Floor	98.8%	92.2%	75.0%	93.4%
Cooking fuel	97.1%	80.2%	52.0%	86.6%
Assets	53.3%	48.6%	63.7%	55.3%

Source: ESS3. World Bank staff calculations

MDP is a lot lower in urban areas. In 2016, 33 percent of households in small towns and 20 percent of households in cities were multi-dimensionally poor. In both cities and small towns, MDP is mainly driven by the high rates of deprivation in years of schooling and the absence of improved floors and improved sources of cooking fuel. Urban households are a lot less likely than rural ones to be deprived in school attendance and years of schooling, though deprivation in assets and housing material (floor) remains high[26].

Figure 6: Education, floor material, and cooking fuel are the main contributors to overall MDP

(Contribution of each indicator to the MDP rate, 2016)



Source: ESS3. World Bank staff calculations

4. Explaining the decrease in consumption expenditures: The impact of the drought

4.1 Recent drought episodes and welfare

During the study period (2012-2016), Ethiopia has experienced two major drought episodes that required massive food security responses: 2011/12 and 2015/16. Both droughts have been considered as among the worst droughts in decades. In some areas of the country, the 2011-2012 Horn of Africa drought was considered as the worst in the past six decades. In three Horn of Africa countries—Ethiopia, Somalia, and Kenya—a total of 12 million people were in need of assistance. The worst affected regions include northern Kenya, southern Ethiopia, and south-central Somalia (Oxfam, 2011, 2012). Similarly, the 2015/16 drought has been reported to be Ethiopia's worst drought in the past five decades. About 10.2 million people in Ethiopia needed assistance. The drought was a result of rain failure during both *Meher* (the main harvest) and *Belg* (spring harvest) seasons in 2015. It affected Afar and the northern Somali region, central and eastern Oromia, eastern Amhara and southern and central Tigray region (WFP, 2016, 2017). Government spending on different types of emergency relief spiked in 2015/16 (emergency relief spending amounted to ETB 13.1 billion in 2015/16, up from ETB 5.2 billion the previous year)[27].

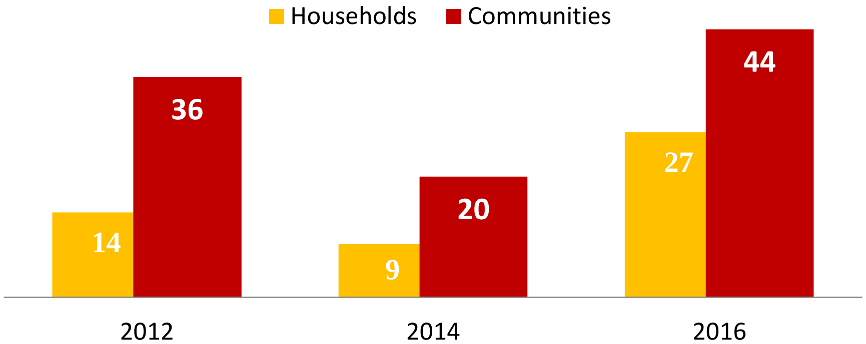
[26] It is counter-intuitive to see that deprivation in assets is higher in cities than in rural areas. This is however explained by the construction of the asset deprivation indicators, which considers assets such as land and livestock. Since urban households tend not to own these, deprivation in assets is higher in urban areas.

[27] NPC, 2017.

The ESS questionnaires contain self-reported information on drought exposure. The household questionnaire asks farm households whether they have experienced drought in the 12 months prior to the survey date, while the community questionnaire asks community leaders whether the community have been affected by drought in the 24 months prior to the survey. The results show that 27 percent of farm households reported to have been affected by drought in the 12 months leading up to the 2016 survey. 14 percent of farm households reported drought in the 12 months preceding the 2012 survey, while only nine percent of households reported droughts in the months before the 2014 survey (Figure 6). The results from the community surveys are qualitatively similar: More communities faced drought in months leading up to the 2016 (44 percent) and 2012 surveys (36 percent), while 2014 was a better year. In the analysis that follows, we will use the household self-reported indicator of drought exposure as it has shorter recall period (12 months vs 24 months for the community one). We will however test whether the results hold when using the community measure.

Figure 7: 2011/12 and 2015/16 appear to have been drought years

(Share of households and communities that report being affected by drought)



Source: ESS1; ESS2; ESS3.

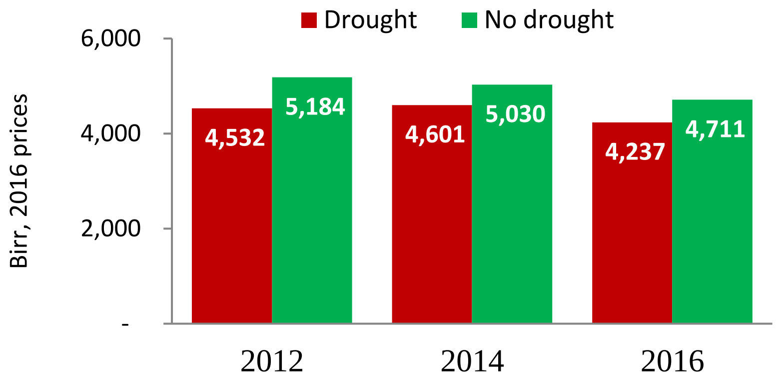
Before proceeding into discussing of reported drought, it is important to note some of the major limitations of self-reported drought data. First, it is based on households'/communities' recollection of rainfall patterns in recent years. Even if households are likely to have a vivid memory of droughts that affected their livelihoods in a major way, their memories tend to be time bound. Second, the most vulnerable households with fewer coping strategies and/or experiencing other idiosyncratic shocks might be affected by even minor rainfall declines and are more likely to report them as droughts than better-off and more resilient households. Self-reported indicators are likely to be partly endogenous, which will bias the estimated drought effects upwards. Ongoing work is looking at satellite-based measures of drought using rainfall and vegetation.

Looking at the descriptive statistics, households that reported being affected by drought had lower consumption levels than unaffected households. The difference is statistically significant for 2014 and 2016, the worst drought years (Figure 8). These figures do not imply causation, as poorer households are probably more likely to report being affected by a drought. Looking at consumption *growth* rather than levels, both drought-affected and unaffected households had similar growth rates between 2012 and 2014. Between 2014 and 2016 however, consumption growth was significantly lower (negative) for households that reported being affected by the 2015/16 drought, which experienced an annual consumption contraction of 10 percent (Figure 9).

Importantly, the different consumption trend for drought-affected vs unaffected households between 2014 and 2016 does not appear to be due to a different pre-existing trend: Between 2012 and 2014, the consumption trend was similar for household affected by the 2015/16 drought and households not affected by this drought (Figure 10). The different consumption trends for these groups after 2014 is thus not due to a pre-existing different trend, which supports one of the main assumptions of a difference-in-differences estimation.

Figure 8: Drought-exposed household have lower consumption levels…

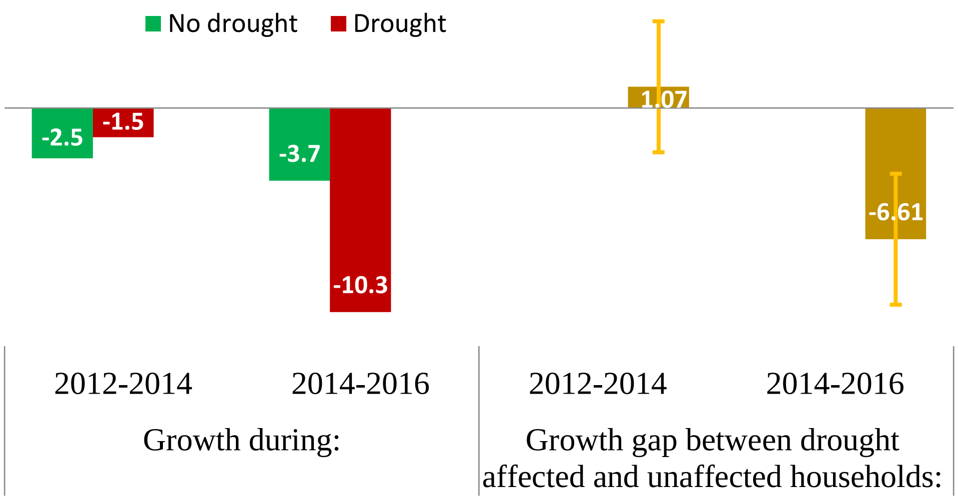
(Median consumption for drought-affected and unaffected households)



Source: ESS1; ESS2; ESS3.

Figure 9: and also had lower consumption growth between 2014 and 2016

(Annualized growth in median consumption for drought-affected and unaffected households)



Source: ESS1; ESS2; ESS3.

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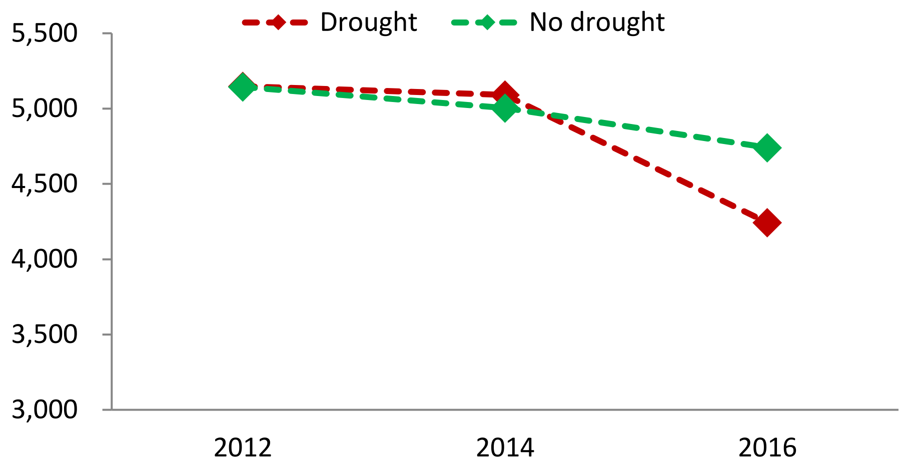
Figure 10: Consumption trends for affected and unaffected households diverge after 2014

(Median consumption for households that were affected and unaffected by drought in 2016)



Note" Drought-affected households are households that were affected by drought in 2016 but not in 2014. Unaffected households are households that reported never been affected by drought. Source: ESS1; ESS2; ESS3.

4.2 Estimating the impact of the drought

1. Empirical Specifications

Findings presented in section 1 show that real consumption in the ESS sample has declined during 2012-2016 period. Descriptive results indicate that drought affected households have experienced larger decreases in their consumption. Below, we investigate whether the two recent droughts have contributed to the decrease in consumption. For farm housheolds in Ethiopia, which are dependent on rainfed agriculture, consumption is driven by rainfall, and drought-induced declines in production could adversely affect consumption[28]. After controlling for household characteristics (X), the impact of drought (D_{it}) on household $i's$ consumption in a given year (t) could be framed as follows:

$$Y_{it} = \gamma_i + \omega D_{it} + X'\beta + \varepsilon_{it} \quad (1)$$

…where Y_{it} is real adult equivalent consumption (in logarithm) of household i in year t; D_{it} is a dummy equal to one if household i has reported experiencing severe drought in the past 12 months and zero otherwise; γ_i is household fixed effects; t refers to survey year 2012, 2014 and 2016; X

[28] Agricultural production figures show that production declined by in the 2015/16 Meher season as compared to the previous year (CSA, 2016).

is a vector of time variant household characteristics; and ε_{it} is a random error term. This specification will estimate the overal impact of drought on household welfare, as measured by drought induced percentage decline (captured by ω) in real consumption.

Regional Heterogeneity: Regions in the East and South of the country were more affacted by the drought. The impacts of drought is thus likely to show considerable variations across regions. To analyze the differential impacts of droughts across regions we interact drought dummy with region fixed effects ($Region_i$) as follows:

$$Y_{it} = \gamma_i + \sum_r[(\omega_r D_{it} * Region_{ri}] + X'\beta + \epsilon_{it} \quad (2)$$

…where r (in $Region_{ri}$ and ω_r) refers to the region in which household i resides in and it includes Tigray, Amhara, Oromia, SNNP and “Others”; ω_r is the drought induced percentage decline in consumption in region r. $Region_{ri}$ is a dummy equal to one if household i resides in region r and zero otherwise. Note that including $Region_{ri}$, which is time invariant, as an additional covariate will not be necessary because household FEs are already included.

Differential Impact on the Poor: To analyze the differential impacts of drought on households that were poor at the baseline survey in 2012, we interact their baseline poverty status with drought dummy. For this analysis, the baseline survey is used to determine poverty/bottom 40% status of households, and the recent two waves (2014 and 2016) are used for drought impact analysis. In other words, the differential impacts on poor households (i.e. those in the bottom 40 percent of the income distribution at baseline), relative to non-poor (i.e. those in the top 60 percent) is analyzed by interacting drought with two dummies for poor and non-poor households as follows:

$$Y_{it} = \gamma_i + \omega_p D_{it} * Poor_{ib} + \omega_{np} D_{it} * NonPoor_{ib} + X'\beta + \mu_{it} \quad (3)$$

…where t=2014, 2016. $Poor_{ib}$ is a equal to one if household i is poor, i.e. in the bottom 40 percent, during the baseline survey in 2012 and zero otherwise. $NonPoor_{ib}$, which is orthogonal to $Poor_{ib}$, is a dummy equal to one if household i is non-poor (i.e. top 60%) in 2012 and zero otherwise. The coefficients ω_p and ω_{np} capture the impacts of drought (% change in consumption) on poor and non-poor households, respectively.[29]

Drought and Safety net: Poor households that have access to public transfers under PSNP are more likely to better manage drought shocks than other poor households. Access to safety net transfers could attenuate the impacts of drought. To estimate the potential alleviating effects of PSNP, an estimation with a double interaction (drought and PSNP) is conducted

[29] Note that as $Poor_{ib}$ and $NonPoor_{ib}$ are constant over time, including them in Equation 3, along with the household fixed effects, is not possible.

$$Y_{it} = \gamma_i + \sum_{s=0}^{1}[\omega_s D_{it} * PSNP_{sit}] + \theta PSNP_{1it} + X'\beta + e_{it} \quad (4)$$

…where $PSNP_{sit}$ stands for two orthogonal dummies ($PSNP_{0it}$ and $PSNP_{1it}$) pertaining to access to safetynet through PSNP. $PSNP_{1it}$ is a dummy equal to one if household i is PSNP beneficiary, and zero otherwise. $PSNP_{0it}$ is a dummy equal to one if the household is not PSNP beneficiary, and zero otherwise. ω_1 and ω_0 capture the impact of drought on PSNP and non-PSNP households, respectively.

Impact of Recent (2015/16) Drought: As discussed above, according to international organizations and humanitarian sources, Ethiopia experienced one of its worst drought in decades in 2015/16 with the failing of two consecutive rainy seasons (*Belg* and *Meher*) in 2015. By the end of 2015, more than 10 million people were estimated to be in need of food aid (UNICEF, 2016; WFP, 2016, 2017). Despite its severity, the drought does not seem to have affected production much: the crop production report from the 2015/16 *Meher* season shows a mere one percent decline in production relative to 2014/15.[30] The ESS offers a unique opportunity to study the drought and its impacts, given that the drought was bracketed by two successive rounds of the survey (2014 and 2016).

In order to analyze the impact of this recent drought on welfare, two empirical approaches are implemented: (1) difference-in-difference (DiD) using 2014 and 2016 data, and (2) fixed effects estimates, as in equation 1 above, with addition interaction term between survey year FEs and drought. In the DiD approach, households that were not affected by drought in 2014 are divided into two groups based on their drought exposure in 2016: a treatment group consisting of those that were affected by drought and a control group that has not been affected. More specifically, the following classic DiD estimation is performed:

$$Y_{it} = \alpha + I(t = 2016) + Drought_i + \omega Drought_i * I(t = 2016) + X'\beta + \varepsilon_{it} \quad (6)$$

…where $Drought_i$ is a dummy equal to one if household i has experienced drought in 2016, but not in 2014, and zero if the household is not affected by drought in both years. $I(t = 2016)$ is an indicator function which equal to one if the survey year is 2016 (post-drought) and zero if it is 2014 (pre-drought).

In the fixed effects approach, data from the entire survey period (2012-2016) is used to estimate the impacts of drought in different years as follows:

$$Y_{it} = \gamma_i + \sum_k[(\omega_k D_{it} + 1) * I(Year = k)] + X'\beta + \epsilon_{it} \quad (7)$$

[30] CSA (2016). Agricultural Sample Survey: Report on Area and Production of Major Crops. Federal Democratic Republic of Ethiopia: Central Statistics Agency.

…where k refers to survey year (2012, 2014 or 2016); $I(Year = k)$ is an indicator function equal to one if the survey year is k and zero otherwise; and ω_k is the percentage change in consumption due to drought in year k.

2. Results

Results from the econometric analysis show large drought effects. On the national level, exposure to drought (self-reported by households) reduced real consumption expenditures by 14 percent, controlling for fixed effects and time-varying household characteristics (Annex Table 13). On a regional level, households in Oromiya region experienced the largest drought-related declines in consumption (25 percent), followed by SNNP (19 percent) and Amhara (11 percent). Despite being affected by the 2015/16 drought, drought in Tigray region was not associated with a decrease in consumption. Surprisingly, households who reported to be affected by drought in the "other" regions (Gambela, Benishangul Gumuz, Afar, Somali and rural areas of Dire Dawa) had *higher* consumption levels compared to unaffected households.

Analysis of the differential impacts of drought on poor and non-poor households shows that drought had a more severe impact on the poor. Households that were poor in 2012 (that is, were in the bottom 40 percent in terms of consumption in 2012) and were affected by drought between 2014 and 2016 experienced an 18 percent decline in consumption during 2014-2016 period (Annex Table 14). Drought between 2014 and 2016 affected the consumption of households that were initially non-poor too: Non-poor households that were affected by drought between 2014 and 2016 experienced a 14 percent decline in consumption (Table 6, column 4). This is after controlling for all covariates. Column 1 shows the estimated impact when asset ownership and reported food insecurity is not controlled for.

Analyzing the potential effects of PSNP in mitigating adverse welfare impacts of drought if difficult given the small sample size of beneficiaries. About 10 percent of households included in the ESS were PSNP beneficiaries either in the form of direct transfer or public works. This small sample size weakens the statistical power to detect any PSNP effects in attenuating the adverse impact of drought. The overall direction of effect could likely be accurate, but the magnitude need to be taken with a grain of salt. Results suggest that households that have access to public transfers under the PSNP appear to have better managed shocks. During the 2014-2016 period, their consumption has not declined due to drought (Annex Table 15). Even though the sign of the coefficient is negative, after controlling all relevant variables, households that have access to PSNP have not experienced a statistically significant decline in consumption (Table 7, column 5). Despite not being statistically significant, the estimated coefficient is big, indicating that there is substantial heterogeneity across PSNP beneficiaries in the mitigating effect of PSNP.

The most recent El-Nino drought also appears to have negatively impacted consumption. Table 8 shows a difference-in-differences estimate by comparing the average consumption of drought affected and unaffected households, before the recent drought (in 2014) and after the drought (in 2016). The results suggest that the drought reduced consumption of exposed households by 8.4 percent (Annex Table 15). As expected, when more control variables are added, the estimated impact decreases (Table 8, from column 1 to 3). The coefficient of the drought dummy is positive—indicating that the drought affected households have had higher consumption prior to their exposure to drought. The coefficient of 'post-2014' dummy is negative, and this shows that consumption of all households has declined over time, i.e. after the recent drought of

2015/16 (Table 8)[31]. Annex Table 16 presents result from FEs estimation where drought is interacted with three dummies corresponding to the three survey years. The recent drought has reduced consumption by at least 7.6 percent (Table 5-6). The FEs estimate, which captures the differential effects of drought in different years, picks up comparable impact: due to the recent drought a 7.6 percent decline in consumption is observed (Table 9). The FEs estimates capture the drought induced declines in consumption of affected households in different years. During the two years (2012 and 2016), when major droughts have affected many households, strong adverse effects on consumption have been recorded. The 2012, more accurately the 2011/12, drought decreased consumption of affected households by 9.7 percent. Similarly, as noted above, the recent drought (2015/16) led to a 7.6 percent decline in consumption (Annex Table 16).

The discussion so far focused on the impact of drought on total household welfare. Documenting the impact of drought on food consumption alone could provide an insight about the food security implications of severe droughts. Results show that households affected by drought experienced a decline in food consumption by 12 percent—compared to a 11.4 percent decrease of total consumption (Annex Table 17). The recent (2015/16) drought led to a 9.2 percent decline in food consumption (Annex Table 19). Drought-induced decline in food consumption shows the same heterogeneity across regions as overall consumption. Poor households appear harder hit, with a decline in food consumption by 22 percent, compared to a 13 percent decrease for non-poor households (Annex Table 18). Drought-affected households in the PSNP did not experience a decline in food consumption, while non-PSNP households did.

[31] The DiD estimation is only valid if both groups (exposed and non-exposed to the drought) had similar consumption trends before the drought happened. Figure 10 already showed that both groups of households had similar consumption trends prior to the recent drought, validating a key assumption of DiD estimation.

4. Conclusion

Based on the ESS data, households in rural Ethiopia have experienced a significant decrease in consumption between 2012 and 2016. The decrease in consumption happened between 2014 and 2016, when all Regions (except for Amhara and the "other" Regions) experienced a strong contraction in consumption. Consumption in cities on the other hand has increased between 2014 and 2016, in line with improving urban employment outcomes. Consumption in small towns did not change significantly.

Multidimensional poverty has improved despite declining consumption levels. In rural areas, MDP decreased between 2012 and 2014 but stagnated thereafter, which seems qualitatively consistent with the consumption trends. The biggest progress was made in small towns, where the MDP rate plummeted from 57 percent in 2012 to 33 percent in 2016, mainly thanks to sharply declining deprivation levels in years of schooling (as younger cohorts come of age at a time where access to education is much improved). In rural areas, education deprivation remains substantial despite improvements: In 2016, one in four rural households was deprived in school attendance, meaning that had at least one school-age child who was not attending school.

Recent droughts appear to have contributed to the adverse welfare trends in rural areas. According to estimates based on self-reported drought measures, exposure to droughts between 2012 and 2016 has reduced consumption of affected households by 11-13 percent, with effects being larger for poor households. The recent El Nino droughts (2015/16) also negatively affected consumption of drought-exposed households. Ongoing work is using remote sensing drought-measures to remove the bias inherent in using self-reported measures. The regressions also suggest a protective effect from the PSNP, with drought-affected households in PSNP experiencing a smaller consumption decrease compared to drought-affected non-PSNP households.

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Annex 1: Attrition in the ESS surveys

As usual in longitudinal surveys, the ESS has a certain rate of attrition. Of the 3,466 rural households interviewed in 2012, 3,323 were re-interviewed in 2014 and 3,272 in 2016. Overall, 94 percent of rural households interviewed in 2012 were still in the sample by 2016 (Table 1). As expected, attrition is higher in urban areas: 85 percent of small town households interviewed in 2012 were still in the sample by 2016, while 84 percent of city households interviewed in 2014 were still in the sample by 2016 (Annex Table 1). Given that this report focuses on trends, the nature of attrition is important: If better-off (worse-off) households were systematically more likely to drop out of the sample, any trend we present may be biased downward (upward).

Annex Table 1: Sample size and attrition, ESS surveys

	2012	2014	2016	Attrition 12-14	Attrition 14-16	Attrition 12-16
Rural	3,466	3,323	3,272	4.1%	1.5%	5.6%
Small towns	503	453	427	9.9%	5.7%	15.1%
Cities	NA	1,486	1,255	NA	15.5%	NA

Source: ESS1; ESS2; ESS3.

Annex Table 2 compares the baseline (ESS1) characteristics of households that were interviewed in all three rounds and households that attrited. Attrition is clearly selective, though the nature of selection in different between rural and urban areas. In rural areas, households that dropped out were on average smaller, younger, and economically worse-off at baseline. These households had lower consumption levels, lower asset holdings (as measured by the score on a composite non-agricultural asset index), less land, and were twice as likely to be female headed. Heads of attritor households in rural areas were less likely to have gone to school, but were *more* likely to have completed secondary education or more. This suggests a dual pattern of attrition in the rural sample, with small, poor, female-headed households (mainly widows and divorced women) dropping out of the sample, as well as households headed by younger people with better education levels (who presumably moved to urban areas). Overall, though, worse-off households were more likely to drop out of the rural sample, meaning that rural consumption trends will be biased upwards if attrition is not accounted for.

Annex Table 2: Characteristics of attrition

	Rural		Small towns		Cities	
	In sample	Attrited	In sample	Attrited	In sample	Attrited
HH size	5.2	3.2	4.3	2.3	3.6	2.5
Dependency ratio	0.83	0.52	0.57	0.25	0.46	0.31
Age HH	43.9	36.4	40.4	32	39.6	31.6

Female HH (%)	17.7	36.5	30.8	33.7	41.9	37.6
Married HH (%)	77.6	50.2	65.8	47.5	52.7	47
Widowed HH (%)	11.4	26	10.8	6.1	13.8	6
HH went to school (%)	37.2	32.7	65	71.7	77.7	89.3
HH completed secondary (%)	1	11.1	22.6	34.5	31.6	33.1
Asset index score	-0.01	-0.066	0.75	0.65	-0.002	-0.203
Land per adult (ha)	1.29	0.52	0.16	0.003	na	na
Real consumption per ae	7,045	6,602	8,300	9,440	9,940	10,711
N	3,236	176	414	61	1,245	238

All numbers in table are averages weighted by the sample weights. Consumption is expressed in 2016 ETB per year per adult. Source: ESS1; ESS2; ESS3.

In small towns and cities, the opposite pattern prevails: Households that dropped out of the sample were on average better off (better educated and higher consumption levels) than households that were interviewed in the three rounds (two rounds for cities). Attritors in urban areas are younger and better educated (and likely more mobile). Small town and city trends will be biased downwards if attrition is not accounted for.

Annex 2: Imputation of missing consumption values

All three waves of the ESS have a number of missing values for the main variable of interest, consumption expenditures. About 3.5 percent of households had missing consumption data in ESS1 and ESS2, rising to 4.8 percent in 2016. With the exception of ESS1, missing conversion factors account for the bulk of missing consumption values[32]. The share of households not reporting any consumption at all has declined across survey waves, possibly thanks to improved enumerator training and experience (Annex Table 3).

Annex Table 3: Breakdown of missing consumption values

	ESS1	ESS2	ESS3
Missing values	137	191	237
Did not report any consumption	*70*	*66*	*50*
Missing conversion factors	*67*	*125*	*187*
N	3,969	5,262	4,954

Source: ESS1; ESS2; ESS3.

The likelihood of the missing values biasing the consumption trend is fairly small. First, the number of missing values is too low to really have a big influence on the overall trend. Second, descriptive analysis (not shown) suggests that missing consumption values due to conversion factors appear random (in the sense of not being correlated with observable household characteristics). Households not reporting any consumption at all are substantially different (small, young and mainly urban), but the number of households not reporting any consumption is small. We do however impute the missing consumption values to see to what extent they affect the trend.

To impute the missing consumption values, we constructed a simple consumption model based on a rich set of covariates included in the data. For each wave, we estimated two different models, the first one to impute consumption for rural households and the second for urban households. For each model, we implemented a cross validation exercise to identify the best p-value for the stepwise regression. In the cross validation step a certain set of explanatory variables is chosen. This choice is subject to change according to the result of the regression. The set of explanatory variables vary between the rural and urban models. In general, the variables used in the stepwise regressions are demographic information as household size and composition, education levels, gender of the household head, presence of employed members; housing information such as material of walls, roof and floor, number of rooms and cooking facilities; source of income, ownership of assets such as mobile phone, radio, refrigerator, gold and access to electricity among others; livestock holdings have been used for the rural models. The models also include dummies for location (different Ethiopian regions) and occurrence of shocks.

Once the variables and p-values are identified by the cross-validation exercise, STATA's multiple imputation command is used to obtain 40 different consumption imputations for each household with a missing consumption value. The average of these imputations is then selected to impute the household's consumption value.

[32] When a conversion factor to convert local to metric units was missing, the consumption value for the household was set as missing.

As expected, the imputation exercise does not significantly affect the consumption trend. If any, the decrease in consumption between 2014 and 2016 in small towns becomes weaker once missing values are imputed (Annex Table 4). Regional trends with missing data imputed are largely similar to the ones presented in Figure 2 (where missing values were not imputed).

Annex Table 4: Imputation does not change the consumption trends

		Without Imputation	
Survey	Rural	Small town	Large towns / cities
2012	5,073	6,747	
2014	4,955	6,389	8,526
2016	4,601	5,948	8,821
		With Imputation	
	Rural	Small town	Large towns / cities
2012	5,053	6,708	
2014	4,936	6,373	8,547
2016	4,575	6,107	8,886

Note: The lower panel shows the consumption trends with the missing data imputed; all values are in 2016 ETB. Source: ESS1; ESS2; ESS3.

Annex Table 5: Imputation does not change the regional consumption trends

	2012	2014	2016
Tigray	5,202	5,187	4,668
Amhara	4,054	4,181	3,972
Oromiya	6,358	5,693	5,213
SNNP	4,830	4,342	3,876
Other	4,917	5,254	4,928

Note: All consumption values are in 2016 ETB. Source: ESS1; ESS2; ESS3.

Annex 3: Seasonal influences on consumption

The ESS surveys are not year-round surveys and can therefore not control for seasonality of consumption. To minimize the possibility of seasonality affecting the comparability of trends, the consumption modules for the three rounds of the ESS surveys were administered during the same period of the year (between January and April). If there would exist significant fluctuations in consumption across these months, one could still be worried about the robustness of consumption trends if households are interviewed in different months in the different survey rounds.

Overall, of the 4,508 households that were interviewed both in 2014 and 2016, 3,947 (88 percent) were interviewed in the same month in both 2014 and 2016 (Annex Table 6). It is thus unlikely that the consumption trend between 2014 and 2016 is biased by differences in the timing of the interviews. A comparison of consumption trends by month of interview seems to confirm this: Real annual median consumption expenditures of households interviewed in the same month in both years decreased from ETB 5,256 in 2014 to ETB 4,932 in 2016, a statistically significant decline (Annex Table 7). The decrease in consumption was higher for households interviewed in different months in different years (Annex Table 7), which suggests that seasonal patterns may play a role. Given the small share of the sample that was interviewed in different months in different years, this does not bias the overall consumption trend.

Annex Table 6: Interview month, 2014 and 2016

	2016				
	Interview month	January	February	March	N
2014	February	3	3,820	244	4,067
2014	March	0	299	127	426
2014	April	0	10	0	10
2014	May	0	0	5	5
2014		3	4,129	376	**4,508**

Source: ESS2; ESS3.

Annex Table 7: Median consumption expenditures by month of interview, 2014 and 2016

	2014	2016	N
Same month	5,256	4,932	3,947
Different month	6,933	5,784	561

Table shows median consumption expenditures for households interviewed in the same month in 2014 and 2016 and households interviewed in different months. The change in median consumption between 2014 and 2016 for households interviewed in the same (different) month is statistically significant at the one (five) percent level. Consumption is expressed in 2016 ETB per year per adult. Source: ESS2; ESS3.

Another concern is the potential influence of *Lent.* The Lent is the main fasting period in Orthodox Christianity, lasting 55 days. As the exact timing of *Lent* differs from year to year, one may argue that failing to account for Lent may bias consumption trends, as no animal products can be consumed during Lent. Lent may also increase the risk of underreporting as some people might feel obligated to report less consumption, if the public norm is to fast. In 2014, 33 percent of the sample was interviewed during Lent, while in 2016 11.5 percent of the sample was interviewed during Lent (). All else equal, we would expect consumption in 2014 being more downwardly affected by Lent (and thus the consumption decrease between 2014 and 2016 to be higher, controlling for Lent).

The impact from Lent is assessed through a difference-in-difference regression as in (1), where y_{it} is log real consumption, T is time (a year 2016 dummy), D is a dummy for being interviewed during Lent, and is X_{it} household specific control variables.

$$y_{it} = \alpha + \beta_1 T + \beta_2 D_{it} + \beta_3 D_{it} * T + \delta X_{it} + \epsilon_{it} \qquad (1)$$

Annex Table 8 shows the results from this regression. Column (2) is the base regression showing that households interviewed during Lent on average report 16 percent *higher* consumption than those interviewed outside Lent. Column (3) adds three additional control variables. With only three control variables the large impact on consumption from Lent is no longer significant. As Lent is a religious fast, column (4) include interactions between the household head belonging to orthodox, catholic or other religions. The latter category is small (2.5% of total sample) and the excluded category is Muslims. The column indicate that the religious denomination is not a key determinant (coefficients are generally in significant) of the reduction in consumption, when interviewed during Lent, except for the few belonging to other denominations. Adding control variables in column (5) confirms that the observed impact of Lent is not robust to controls. To summarize, the *Lent* is not biasing the observed consumption trends.

Annex Table 8: Impact of *Lent* on consumption trend

VARIABLES	(2)	(3)	(4)	(5)
Year (2016)	-0.15***	-0.11***	-0.15***	-0.11***
	(0.03)	(0.03)	(0.03)	(0.03)
Lent	0.16***	0.04	0.15***	0.04
	(0.04)	(0.03)	(0.04)	(0.03)
Year-Lent interaction	0.16**	0.05	-0.06	-0.04
	(0.07)	(0.05)	(0.11)	(0.08)
Year-Lent-Orthodox interaction			0.33***	0.14
			(0.12)	(0.09)
Year-Lent-Catholic interaction			0.19	-0.03
			(0.21)	(0.14)
Year-Lent-Other religion interaction			0.57*	0.44*
			(0.32)	(0.23)
Orthodox			0.07	-0.03
			(0.04)	(0.05)
Catholic			-0.08	-0.08
			(0.07)	(0.06)
Other religion			-0.37***	-0.36***
			(0.09)	(0.08)
HH size		-0.06***		-0.06***
		(0.00)		(0.00)

log_TLU_total		0.16***		0.15***
		(0.03)		(0.02)
urban		0.58***		0.57***
		(0.05)		(0.05)
Constant	8.47***	8.54***	8.46***	8.58***
	(0.03)	(0.04)	(0.04)	(0.06)
Observations	9,014	9,014	9,014	9,014
R-squared	0.03	0.20	0.05	0.21

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Note: The lower panel shows the consumption trends with the missing data imputed; all values are in 2016 ETB. Source: ESS1; ESS2; ESS3.

Annex 4: Robustness of the decline in consumption

Consumption levels in Ethiopia, especially in rural areas and small towns, appear to have decreased since ESS1 (2012). To explore the robustness of this result, this section looks at the trends in food shares and consumption of higher- and lower-value food items. If households really became poorer over time, the share of food in total expenditures would be expected to stagnate or increase, as households try to maintain food consumption in the face of adversity[33]. Within food consumption, we would also expect consumption of and expenditures on higher-value food items to decrease as households respond to the income shock by substituting towards cheaper sources of calories. In this section we examine to what extent the patterns in the ESS data are consistent with these theoretical predictions.

Annex Table 9: Food shares marginally increased between 2014 and 2016

	2012	2014	2016	Diff (14-16)
National	NA	73.4	74.8	-1.4***
Rural & small towns	80.9	78	78.3	-0.3
Rural	82.6	79.3	79.3	0
Tigray	79.1	76.1	78.8	-2.7***
Amhara	79.7	76.4	77.4	-1*
Oromiya	81.4	78.5	79.4	-0.9
SNNP	81.6	78.9	77.9	1.1**
Other	81.9	79.1	78.4	0.8

Note: The table shows the share of food expenditures in total expenditures. *** p<0.01, ** p<0.05, * p<0.1. Source: ESS1; ESS2; ESS3.

At the national level, the share of total expenditures devoted to food significantly increased between 2014 and 2016, which is consistent with a reduction in overall consumption levels (Annex Table 9). Food shares in rural areas (and in small towns) decreased between 2012 and 2014 and stagnated between 2014 and 2016, which, qualitatively, fit with the observed consumption dynamics: A stable rural consumption level between 2012 and 2014 followed by a significant decrease between 2014 and 2016. The stable food shares in rural areas and small towns between 2014 and 2016 hide different trends across regions. In Tigray, Amhara and Oromiya, food shares first decreased between 2012 and 2014 before increasing again between 2014 and 2016, consistent with a reduction in overall household income or expenditures in these regions. In SNNP and "other" regions, food shares decreased consistently across surveys rounds, though the decrease was stronger in 2012-14 than in 2014-16.

Item-level consumption shows a largely similar pattern. The share of rural households consuming higher-value foods such as enjera (processed teff), meat and animal products, coffee, and sugar declined, in particular since 2014 (for meat and dairy the decline since 2014 was not significant). On the other hand, consumption of Irish potatoes, a low-value item, increased substantially while consumption of lower-value cereals such as wheat, maize and sorghum increased insignificantly (Annex Table 10). Though potatoes and teff are far from being perfect substitutes, the sharp increase in potato consumption came at a time of large price increases for teff (an increase of close to 30 percent in the median price), while potato prices remained stable (Annex Table 11).

[33] However, it may also be the case that households actually cut back on food to maintain essential nonfood consumption or to avoid selling off assets. This kind of asset-smoothing

Annex Table 10: The share of households consuming different items, 2012-2014-2016

	2012	2014	2016	Diff (14-16)
Enjera (processed teff)	42	50.3	45.5	4.8***
Maize	59	58.9	59.4	-0.5
Wheat	39.2	40.3	41.3	-1.0
Sorghum	41.6	38.8	39.8	-1.0
Potatoes	22.5	28.3	42.7	-14.4***
Meat	24	16.1	15.4	0.7
Poultry	3.9	2.9	1.8	1.1**
Eggs	12.1	13.7	9.2	4.5***
Milk, cheese, yoghurt, other dairy	39.8	38.5	37.6	0.9
Coffee	77.4	81.4	76.9	4.5***
Khat	12	15.7	14.8	0.9
Sugar	40.5	47.3	41.5	5.8***

Note: The table shows the share of households consuming different items. *** p<0.01, ** p<0.05, * p<0.1. Source: ESS1; ESS2; ESS3.

Annex Table 11: Median price for selected food items in rural areas, 2014-2016

Items	Median price 2014	Median price 2016	% increase
Teff	14.0	18.0	28.6
Wheat	10.0	12.0	20.0
Maize	6.0	6.0	0.0
Sorghum	7.0	7.0	0.0
Horsebeans	10.0	18.0	80.0
Potato	8.0	8.0	0.0
Coffee	75.0	75.0	0.0
Eggs	2.0	3.0	50.0

Note: The table shows the median price per unit for selected food items. The prices were measured at the level of the ESS enumeration area (the closest market). Source: ESS2; ESS3.

Annex 5: Changes in underlying deprivations by Region

Annex Table 12: Share of households deprived in the underlying indicators, ESS1-ESS2-ESS3

ESS1 – Rural areas and small towns

Dimension	Indicator	Tigray	Amhara	Oromia	SNNP	Other regions
Education	School Attendance	23%	25%	30%	30%	24%
	Years of schooling	60%	71%	60%	66%	71%
Health	Nutrition	24%	22%	24%	31%	23%
	Water	33%	48%	50%	49%	42%
	Improved sanitation facilities	64%	55%	34%	17%	56%
Living Conditions	Access to electricity	86%	88%	90%	90%	89%
	Cooking Fuel	98%	97%	99%	95%	99%
	Type of Floor	95%	98%	98%	92%	96%
	Asset Ownership	64%	75%	51%	60%	48%

ESS2 – Rural areas and small towns

Dimension	Indicator	Tigray	Amhara	Oromia	SNNP	Other regions
Education	School Attendance	18%	26%	30%	32%	23%
	Years of schooling	52%	67%	56%	56%	65%
Health	Nutrition	23%	23%	19%	25%	20%
	Water	36%	42%	32%	36%	40%
	Improved sanitation facilities	73%	52%	37%	19%	49%
Living Conditions	Access to electricity	81%	86%	87%	86%	80%
	Cooking Fuel	97%	98%	99%	99%	98%
	Type of Floor	90%	98%	97%	91%	96%
	Asset Ownership	46%	65%	46%	56%	42%

ESS3 – Rural areas and small towns

Dimension	Indicator	Tigray	Amhara	Oromia	SNNP	Other regions
	School Attendance	17%	18%	28%	25%	28%

Education	Years of schooling	50%	63%	53%	52%	61%
Health	Nutrition	17%	17%	20%	22%	20%
	Water	35%	42%	32%	37%	40%
	Improved sanitation facilities	74%	51%	38%	19%	49%
Living Conditions	Access to electricity	80%	85%	86%	85%	79%
	Cooking Fuel	97%	98%	99%	99%	97%
	Type of Floor	89%	98%	97%	91%	96%
	Asset Ownership	46%	64%	46%	57%	42%

Source: ESS1; ESS2; ESS3.

Annex 6: Regression tables

Annex Table 13: Impact of drought on household consumption

	(1)	(2)	(3)	(4)
	Overall	By region	Overall	By region
Overall/National impact:	-13.9***		-11.4***	
	(1.9)		(2.0)	
Impact in each region:				
Tigray		0.3		2.8
		(6.7)		(6.7)
Amhara		-10.5***		-10.2***
		(3.5)		(3.6)
Oromia		-24.5***		-20.7***
		(3.5)		(3.6)
SNNP		-18.8***		-16.0***
		(3.8)		(3.8)
Other		14.3**		16.8**
		(6.7)		(6.7)
R-square				
Overall	0.07	0.08	0.10	0.12
Within	0.05	0.06	0.08	0.08
Between	0.10	0.11	0.14	0.16
Number of observations	9,305	9,305	9,268	9,268
Number of households	3,522	3,522	3,521	3,521
Covariates included:				
Household FEs	Yes	Yes	Yes	Yes
Household characteristics	Yes	Yes	Yes	Yes
Asset ownership	No	No	Yes	Yes
Self-reported food insecurity	No	No	Yes	Yes

Note: Dependent variable is log of real consumption per adult equivalent in 2016 prices.
*** p<0.01, ** p<0.05, * p<0.1. Source: ESS1; ESS2; ESS3.

Annex Table 14: The differential impact of the drought on poor households and PSNP households

	(1)	(2)	(3)	(4)	(5)	(6)
Impact on drought affected:						
Top 60% households	-16.9***			-14.1***		
	(2.9)			(3.1)		
Bottom 40% households	-23.2***			-18.1***		
	(3.7)			(3.9)		
Impact on drought affected:						
Non-PSNP households		-22.3***			-19.2***	
		(2.6)			(2.8)	
PSNP households		-9.2*			-3.0	
		(5.0)			(5.1)	
R-square						
Overall	0.04	0.04	0.05	0.09	0.09	0.11
Within	0.07	0.07	0.07	0.11	0.11	0.11
Between	0.05	0.04	0.05	0.11	0.11	0.11
Number of observations	6,291	6,291	6,291	6,269	6,269	6,269
Number of households	3,371	3,371	3,371	3,369	3,369	3,369
Covariates included:						
Household FEs	Yes	Yes	Yes	Yes	Yes	Yes
Household characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Asset ownership	No	No	No	Yes	Yes	Yes
Self-reported food insecurity	No	No	No	Yes	Yes	Yes

Note: Dependent variable is log of real consumption per adult equivalent in 2016 prices. The regressions only include the 2014 and 2016 ESS rounds. The household's consumption in 2012 is used to classify them in the bottom 40% or top 60% *** p<0.01, ** p<0.05, * p<0.1. Source: ESS2; ESS3.

Annex Table 15: Impact of 2015/16 drought on household consumption, DiD

	(1)	(2)	(3)
Post-2014*Drought	-16.8***	-10.4***	-8.4***
(i.e. impact)	(3.4)	(3.2)	(3.1)
Post-2014	-4.3**	-9.8***	-10.4***
	(1.7)	(1.6)	(1.6)
Drought	5.1**	6.8***	9.8***
	(2.4)	(2.3)	(2.2)
R-squared	0.13	0.27	0.33
Number of observations	5,719	5,698	5,698
Covariates included:			
Household characteristics	Yes	Yes	Yes
Asset ownership	No	Yes	Yes
Self-reported food insecurity	No	Yes	Yes
Distance from public services	No	Yes	Yes
Region FEs	No	No	Yes

Note: Dependent variable is log of real consumption per adult equivalent in 2016 prices.
*** p<0.01, ** p<0.05, * p<0.1. Source: ESS1; ESS2; ESS3.

Annex Table 16: Impact of 2015/16 drought on household consumption, fixed effects estimation

	(1)	(2)
Impacts of drought (% change in consumption) in the year:		
2016	-12.2***	-7.6***
	(2.5)	(2.6)
2014	-0.7	1.1
	(3.8)	(3.9)
2012	-10.5***	-9.7***
	(3.1)	(3.2)
R-square		
Overall	0.08	0.12
Within	0.08	0.11
Between	0.09	0.16
Number of observations	9,305	9,268
Number of households	3,522	3,521
Covariates included		
Household FEs	Yes	Yes
Household characteristics	Yes	Yes
Asset ownership	No	Yes
Self-Self-reported food insecurity	No	Yes

Note: Dependent variable is log of real consumption per adult equivalent in 2016 prices.
*** p<0.01, ** p<0.05, * p<0.1. Source: ESS1; ESS2; ESS3.

Annex 7: Impact of drought on food consumption

Annex Table 17: Impact of drought on household food consumption

	(1)	(2)	(3)	(4)
	Overall	By region	Overall	By region
Overall/National impact:	-15.2***		-12.0***	
	(2.1)		(2.3)	
Impact in each region:				
Tigray		1.1		4.6
		(7.5)		(7.5)
Amhara		-13.4***		-12.6***
		(4.0)		(4.0)
Oromia		-26.1***		-21.2***
		(3.9)		(4.1)
SNNP		-19.7***		-16.6***
		(4.2)		(4.3)
Other		16.3**		19.6***
		(7.5)		(7.6)
R-square (within group)	0.05	0.05	0.07	0.08
Number of observations	9,305	9,305	9,268	9,268
Number of households	3,522	3,522	3,521	3,521
Covariates included:				
Household FEs	Yes	Yes	Yes	Yes
Household characteristics	Yes	Yes	Yes	Yes
Asset ownership	No	No	Yes	Yes
Self-reported food insecurity	No	No	Yes	Yes

Note: Dependent variable is log of real food consumption per adult equivalent in 2016 prices. *** p<0.01, ** p<0.05, * p<0.1. Source: ESS1; ESS2; ESS3.

Annex Table 18: The differential impact of the drought on food consumption of poor households and PSNP households

	(1)	(2)	(3)	(4)	(5)	(6)
Impact on drought affected:						
Top 60%	-17.6***			-12.8***		
	(3.4)			(3.6)		
Bottom 40% households	-27.9***			-21.6***		
	(4.3)			(4.4)		
Impact on drought affected:						
Non-PSNP households		-25.4***			-20.8***	
		(3.0)			(3.2)	
PSNP households		-8.5			0.1	
		(5.8)			(5.9)	
R-square (within group)	0.06	0.06	0.07	0.10	0.10	0.10
Number of observations	6,397	6,397	6,397	6,375	6,375	6,375
Number of households	3,477	3,477	3,477	3,475	3,475	3,475
Covariates included:						
Household FEs	Yes	Yes	Yes	Yes	Yes	Yes
Household characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Asset ownership	No	No	No	Yes	Yes	Yes
Self-reported food insecurity	No	No	No	Yes	Yes	Yes

Note: Dependent variable is log of real food consumption per adult equivalent in 2016 prices.
*** p<0.01, ** p<0.05, * p<0.1. Source: ESS1; ESS2; ESS3.

Annex Table 19: Impact of drought on household food consumption, DiD

	(1)	(2)	(3)
Post-2014*Drought	-19.5***	-13.3***	-11.0***
(i.e. impact)	(3.6)	(3.5)	(3.4)
Post-2014	-4.1**	-8.7***	-9.4***
	(1.8)	(1.8)	(1.8)
Drought	9.0***	9.0***	12.3***
	(2.6)	(2.5)	(2.5)
R-squared	0.11	0.22	0.27
Number of observations	5,719	5,698	5,698
Covariates included:			
Household characteristics	Yes	Yes	Yes
Asset ownership	No	Yes	Yes
Self-reported food insecurity	No	Yes	Yes
Distance from public services	No	Yes	Yes
Region FEs	No	No	Yes

Note: Dependent variable is log of real food consumption per adult equivalent in 2016 prices. *** p<0.01, ** p<0.05, * p<0.1. Source: ESS1; ESS2; ESS3.

Annex Table 20: Impact of drought on household food consumption, Fixed Effects

	(1)	(2)
Impacts of drought (% change in consumption) in the year:		
2016	-10.1***	-9.2**
	(3.5)	(3.6)
2014	-1.0	1.2
	(4.3)	(4.4)
2012	-14.1***	-9.1***
	(2.8)	(2.9)
R-square (within group)	0.08	0.10
Number of observations	9,305	9,268
Number of households	3,522	3,521
Covariates included:		
Household FEs	Yes	Yes
Household characteristics	Yes	Yes
Asset ownership	No	Yes
Self-Self-reported food insecurity	No	Yes

Note: Dependent variable is log of real food consumption per adult equivalent in 2016 prices. *** p<0.01, ** p<0.05, * p<0.1. Source: ESS1; ESS2; ESS3.