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RESEARCH ARTICLE

Adaptive capacity and subsequent droughts: evidence from Ethiopia

Utsoree Das, Salvatore Di Falco,* and Avichal Mahajan

Institute of Economics and Econometrics, GSEM, University of Geneva, Geneva, Switzerland
*Corresponding author: Salvatore Di Falco; Email: Salvatore.DiFalco@unige.ch

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Abstract
We estimate the impact of subsequent droughts on the revenues of farmers in Ethiopia factoring in their adaptive capacity. We find that after the first drought, there is no significant difference in the revenue of the farmers who experienced a drought, as compared to those who did not. However, there is a loss in revenue after the second drought, specifically for those farmers that are endowed with less assets. This finding underscores that a rise in the frequency of extreme events and shocks can potentially have significant local distributional implications, with wealth as a major distinguishing factor.

Keywords: adaptation; climate change; droughts; Ethiopia; welfare

JEL classification: O13; Q12; Q56

1. Introduction

The economic implications of adverse climate events in rain-fed production environments are mostly determined by farmers' adaptive capacity. Farmers may respond against less water availability or higher temperature by implementing a number of adaptation strategies (Mendelsohn *et al.*, 1994; Kurukulasuriya and Mendelsohn, 2008; Di Falco and Veronesi, 2013; Aragón *et al.*, 2021). A crucial related issue is, however, how farmers will be affected by the increase in the frequency of the extremes. The Intergovernmental Panel on Climate Change (IPCC) (e.g., IPCC, 2012) and Coumou and Rahmstorf (2012) emphasize that climate change will lead to a higher intensity and frequency of multi-year droughts in many parts of the world. Multi-year droughts are already prevalent in many parts of the globe (Dai *et al.*, 2004; Nicholls, 2004) and their implications are more complex in comparison to a single-year drought.[1]

[1]Peck and Adams (2010), for example, using a stochastic and dynamic programming model calculate that the marginal economic impact of a drought can increase up to 150% if droughts were also experienced in the previous period.

Table 1. Percentage of households who experienced a drought

	Percentage of households (%)
Panel a	
Drought in 2004	0
Drought in 2014	74
Drought in 2015	69
Panel b	
Drought in 2011	5
Drought in 2012	0
Drought in 2013	5

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In this paper we estimate the causal impact of subsequent droughts on the revenues of farmers in Ethiopia factoring in their adaptive capacity. We use household panel data collected in 2004 (used as baseline), 2014 and 2015, on household revenue (per hectare) from primary food crops (wheat, barley, maize, sorghum, millet, and teff), based on national-level prices from 2001 as our dependent variable. This is justified as our measure of revenue should be approximately orthogonal to the current prices, due to the diminishing time series correlation corresponding to an increase in the gap between the years. Given that the difference in revenues is ten years apart, this allows for adaptation to take place in a variety of ways, including switching between different crops (Kurukulasuriya and Mendelsohn, 2008), changing between different kinds of livestock (Seo and Mendelsohn, 2008) and adopting water and soil conservation techniques (Di Falco and Veronesi, 2013). We match revenue information with detailed local rainfall data. Rainfall data is normalized using the historical rainfall (from 1981 to 2003) received by the households. We measure droughts if the normalized rainfall is "−1" standard deviation away from the mean historical rainfall. Our sample experienced important droughts in 2014 and 2015, whereas in 2004, households experienced regular rainfall patterns. Around 74% of households experienced a drought in 2014 and 69% of households experienced a drought in 2015, as shown in table 1. Among farmers who experienced a drought in 2015, around 83% also experienced a drought in 2014, which corresponds to around 57% of our sample receiving consecutive droughts. We do not find instead evidence of such poor rainfall in earlier years.

By regressing respectively the 2014 and 2015 revenues difference with the baseline (2004) against the droughts we compare the revenue of households who experienced the drought shocks to those who did not. We find that after the first drought, there is no significant difference in the revenue of the farmers who experienced a drought, as compared to those who did not. However, there is a loss in revenue after the second drought, specifically for those farmers that are endowed with less wealth.[2] This result can be interpreted as evidence of limited adaptive success for the latter. Current adaptation measures may thus fail in case of successive extreme events, a scenario that is likely to occur more frequently in the future (Coumou and Rahmstorf, 2012;

[2]Poverty is assessed in terms of wealth, which in turn is measured using the non-farm assets of households from the previous year, such as the value of jewelry, cooking pans, beds, radios, refrigerators, cars, residences and stoves.

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IPCC, 2012). We further investigate the role of wealth in adaptation. Wealthier farmers have resources to make on-farm investments during droughts. Among inputs used in the production process, we find no difference in the quantity of seeds, manure, and fertilizers based on wealth. However, we find that wealthier farmers employ more labor during the second drought. They are also more likely to use different crop varieties, which are suitable during extreme weather events. However, we find no differences in the implementation of soil and water conservation measures based on wealth. We also find that wealthier farmers have more access to credit and own more livestock. One might argue that the cause is not farmers' insufficient adaptation to climate change, but rather the their expectations for future agricultural production. Unfortunately, we did not elicit expectations of the impact of the consecutive droughts on future values. This should be, therefore, considered a limitation of our study.

While collecting 2004 survey data, around 54% of the households reported that they noticed changes in climate over their lifetime. This number rose to 96% in 2015. Changes in climatic conditions are becoming more prominent and noticeable. We can document the increase in adaptive capacity during the study period by exploring the data at hand. During our household surveys, we actually asked whether households use any adaptation methods. We present the results in figures 1a,b. We plot the percentage of farmers using adaptation methods at the *woreda* level in these figures. We can observe that over the years more farmers are using various adaptation methods. In 2015, all the *woredas* had at least 87% of the sample population using adaptation methods. In 2004, *Woredas* such as Kersa, Gesha Deka, Wenbera and Kemashi (all marked as red in figure 1a) had at most 29 % of the households (based on our sample) using adaptation methods. In 2004, 63% of our sample used some adaptation techniques. This number rose to 96% in 2014 and 97% in 2015. These figures present suggestive evidence that the use of adaptation methods has increased over time, whether these strategies are sufficient for extreme weather events, such as multi-year droughts, is a different question.

Our results are robust to the inclusion of a battery of controls and other important checks. We run our empirical specification using revenue constructed from current prices, and other alternative prices. We also present a specification using profit as the dependent variable. While an important caveat[3] applies in this situation, we find that results are largely consistent. The extent of the damages also depends on the wealth of the households.This shows the heterogeneous impact of drought due to pre-existing wealth. Finally, we have other robustness checks like an alternative cutoff to identify droughts, and using temperature and past shocks as the control variables to inspect for all possible situations.

The results of this paper relate and contribute to the economic literature on adaptation to climate change (Mendelsohn *et al.*, 1994; Di Falco *et al.*, 2011; Burke and Emerick, 2016; Aragón *et al.*, 2021) in two ways. First, by providing novel evidence of the effect of subsequent extremes. Second, by highlighting the crucial role that wealth plays in supporting adaptive capacity in the context of a developing economy. The remainder of the paper is organized as follows: In section 2, we discuss our data sources, while section 3 describes our empirical strategy, and section 4 illustrates our results. Section 5 provides

[3]The calculation of profit in the context of developing country is notoriously noisy because of the lack of available data on all the relevant costs during production. We have data for some inputs such as the amount of fertilizers, manure, seeds, temperature, and labor used during production, but we do not have complete information for unit-costs associated with these inputs. Using sample averages to replace missing values for unit-costs associated with inputs, we obtain profits for our sample.

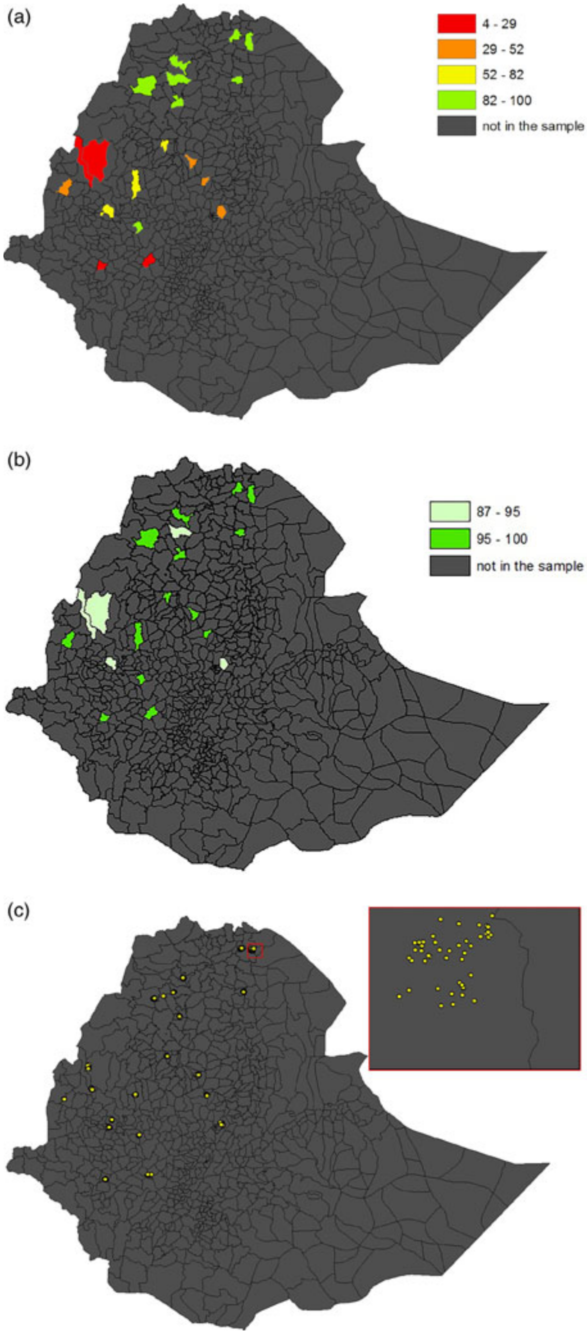

Figure 1. Panel (a) and (b) show a map of Ethiopia with the percentage of farmers adapting at woreda level. The household survey was conducted in 20 woredas shown above. Panel (c) shows the zoomed-in magnified view of the sampled households residing in Atsbi Wenberta.(a) Percentage of farmers adapting at woreda level – 2004, (b) Percentage of farmers adapting at woreda level – 2015, (c) Spatial distribution of our sample in Ethiopia.

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various robustness checks for our results. Section 6 and section 7 provide the mechanism, and the discussion and conclusion of our findings, respectively.

2. Data sources

2.1 Household survey data

The first household survey was carried out in the Nile River Basin, Ethiopia in 2005. The household sampling frame ensures representation of the Nile River Basin at the *woreda* (an administrative division equivalent to a district) level, taking into account the level of rainfall patterns in terms of both annual total and variation. The survey considers the traditional typology of agro-ecological zones in the country, percent of cultivated land, degree of irrigation activity, average annual rainfall, rainfall variability, and the number of food aid-dependent population. The sampling frame selects the *woredas* in such a way that each stratum in the sample matches the proportions for each stratum in the entire Nile basin. The procedure results in the inclusion of twenty *woredas*. Random sampling is then used to select households from each *woreda*. The survey is comprehensive and collects information on agricultural practices and production, costs, investments, and revenues as well as tenure security, past shocks, and access to credit. Detailed production data is available at different production stages (i.e. land preparation, planting, weeding, harvesting, and post-harvest processing). We revisit these households in 2015 and 2016. Figure 1c shows the spatial distribution of households in the survey. Before starting the discussion on rainfall data, it is important to clarify that the household survey collected information on the previous year. For example, 2015 survey, includes information from January 2014 – December 2014. For consistency, hereafter we refer to the year as the year preceding the survey. For example, if the survey is conducted in 2015, we refer to the year as 2014. This notation is consistent throughout the paper. This leads to a panel of around 800 households over three rounds (2004, 2014 and 2015).

2.2 Rainfall data

We use rainfall data to create our main explanatory variable. The importance of rainfall for economic growth in agrarian economies, and in Africa in particular, is widely documented in the literature (see for example, Barrios *et al.*, 2010; Lanzafame, 2014). Miguel *et al.* (2004), for instance, estimate the impact of economic growth on the likelihood of civil conflict using the rainfall variation as an instrument. Almer *et al.* (2017) explore the link between water shocks and rioting in Sub-Saharan Africa. Moreover, the economic impacts of rainfall on the Ethiopian economy are well established (e.g., Dercon and Krishnan, 2000; Dercon and Porter, 2014).

We obtain rainfall data from the Climate Hazards Group (CHG). CHG provides Climate Hazards Group InfraRed Precipitation with Station (CHIRPS) data (Peterson *et al.*, 2015), which uses satellite imagery and station data to create a grid of rainfall time series with a resolution of 0.05°. Using CHIRPS data, we create a drought indicator, which is our key independent variable. We first calculate the rainfall received during *Meher* season (main rainfall season) by summing up the total rainfall in the months of June, July, and August. We generate a historical mean and standard deviation using yearly rainfall received in *Meher* season from 1981 to 2003.[4] We then normalize the rainfall

[4] 2003 is chosen as the final year for historical rainfall because the first survey was conducted in 2005 and rainfall for 2004 is used to analyze the data.

using the historical mean and standard deviation. Droughts are identified as a "−1" standard deviation away from the historical mean rainfall and are then coded as a binary dummy variable (=1 if the household experienced drought at time t and 0 otherwise). Precipitation anomaly directly measures the shortage of rainfall, and is the difference between the observation and the long-term (climate) mean. This anomaly is a primitive index of drought, as discussed by Keyantash and Dracup (2002). Similarly, a rainfall decile-based system for monitoring meteorological drought was suggested by Gibbs and Maher (1967). Furthermore, the Rainfall Anomaly Index (RAI) was developed by van Rooy (1965), and incorporates a ranking procedure to assign magnitudes to positive and negative precipitation anomalies. Finally, Foley (1957), explicitly introduced such a technique that tallies the deviations of monthly measurements of rainfall from long-term monthly averages. This clearly depicts the aggregate amount and duration of water surplus or deficit, but the relative importance of the cumulative precipitation anomaly depends upon the magnitude of the anomaly in relation to normal conditions. As generally accepted in the related literature this metrics discretizes a countinuous variable. We nevertheless check for the robustness of the results when the chosen threshold value is changed.

In summary, we first created the normalized rainfall variable, $z_{i,t}$, where:

$$z_{i,t} = \frac{r_{i,t} - \mu_i}{\sigma_i}$$

Variable $r_{i,t}$ is the rainfall received by a household i at time t during the *Meher* season, μ_i and σ_i are the mean and standard deviation of the historical *Meher* rainfall for household i.

Figure 2a shows the distribution of $z_{i,t}$ in 2004, 2014 and 2015. We notice that in 2004, households received rainfall close to the average historical rainfall. In 2014 and 2015, we observe that average rainfall is much less than the average historical rainfall, which is not true for the other years between 2004 and 2014, as can be substantiated by figure 3. Thus, it appears that Ethiopia experienced important droughts during 2014 and 2015. Households, having $z_{i,t} < -1$, are identified to have experienced a drought. We also present the distribution of normalized rainfall of the years preceding 2014 in figure 2b. Vertical yellow lines in figure 2b at normalized rainfall variable value of 1, denote the cutoff of drought events. Comparing figures 2a,b, we can clearly see that the years 2014 and 2015 received exceptionally poor rainfall; earlier years did not witness such droughts.[5] The consecutive years of poor rainfall may be related to the exceptionally strong El Niño event in 2014–2016.[6] Wolde-Georgis (1997) show consistent association of El Niño years with drought and famine periods in Ethiopia. The distribution of our sample is presened in *Panel a* of table 1 with respect to whether they experienced a drought for 2004, 2014 and 2015. The results for earlier years (2011, 2012 and 2013) are presented as well, in *Panel b* of table 1. It is observed that, in 2004, none of the households in our sample received poor rainfall, however 74% experienced poor rainfall in 2014, and 68% experienced a drought in 2015. This confirms the conclusions drawn from figure 2a. Moreover,

[5]We also looked at the rainfall between 2004 and 2014, we found that none of the years received such exceptionally poor rainfall. Moreover, 2014 and 2015 were particularly bad events as they were consecutive years of poor rainfall.

[6]Rupic *et al.* (2018) state that "*The 2014–2016 El Niño was one of the strongest events on record. It was similar to previous strong events such as the ones in 1982/83 and 1997/98, however, the intensity of the physical forcings and the extent of the social impacts were unprecedented.*"

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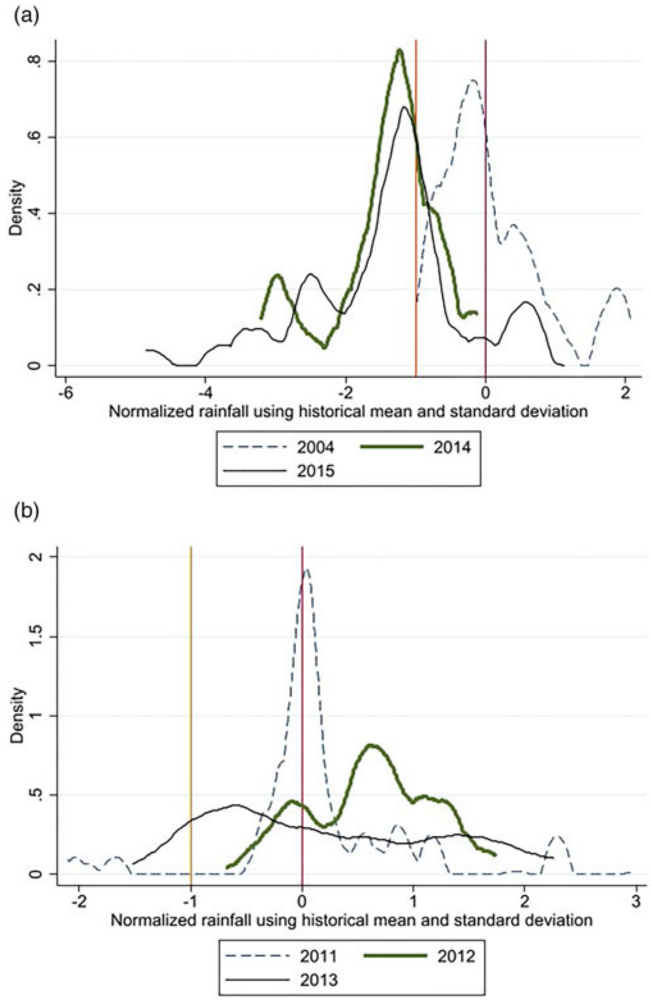

Figure 2. The red line at 0 is a marker which shows the historical mean rainfall. Panel (a) shows that households received poor rainfall in 2014 and 2015, whereas they received normal rainfall in 2004. Panel (b) shows that households did not receive poor rainfall in 2011, 2012 and 2013, as was the case in later years.(a) Distribution of normalized rainfall for 2004, 2014 and 2015, (b) Distribution of normalized rainfall for 2011, 2012 and 2013.

83% of the households who experienced a drought in 2015, also experienced a drought in 2014, which corresponds to around 57% of our sample receiving consecutive droughts. We exploit this variation in rainfall, to estimate whether the households have adapted to droughts in the long run (with the ten-years framework that we have). *Panel b* of table 1 presents further evidence that 2014 and 2015 received exceptionally poor rainfall compared to previous years. Section 2 will explain our approach in detail.

2.3 Temperature data

We use temperature as part of the input control variable. The temperature dataset (Fan and van den Dool, 2008) is developed at the Climate Prediction Center, National Centers

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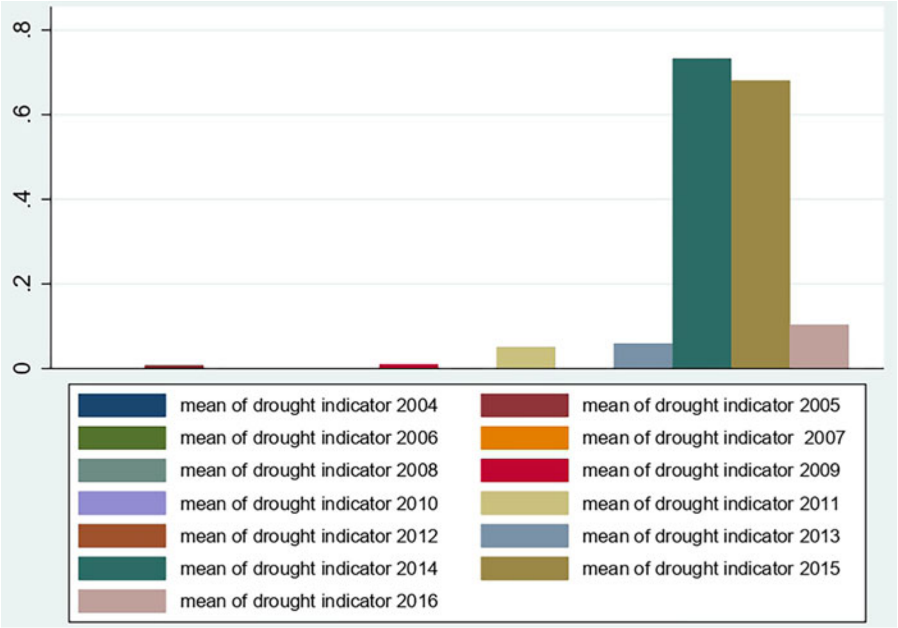

Figure 3. Mean of drought indices from the years 2004 until 2015. It shows, considering 2004 as the baseline year, shocks only occured in 2014 and 2015, and not in the years in between. In these years the average rainfall was much less than the historical rainfall.

for Environmental Prediction.[7] The dataset provides monthly mean surface air temperature at a resolution of 0.5°. It combines two large datasets of station observations collected from the Global Historical Climatology Network version 2 and the Climate Anomaly Monitoring System (GHCN + CAMS).

3. Empirical analysis

We begin with the the following equation:

$$\log(Revenue_{i,2014}) - \log(Revenue_{i,2004}) = \beta(Drought_{i,2014} - Drought_{i,2004}) + \gamma(X_{i,2014} - X_{i,2004}) + (\varepsilon_{i,2014} - \varepsilon_{i,2004})$$

that can be rewritten as:

$$\begin{aligned} &\Delta_{2014}\log(Revenue_i) = \beta\Delta_{2014}Drought_i + \gamma\Delta_{2014}X_i + \Delta_{2014}\varepsilon_i \\ \Longrightarrow\ &\Delta_{2014}\log(Revenue_i) = \beta Drought_{i,2014} + \gamma\Delta_{2014}X_i + \Delta_{2014}\varepsilon_i \end{aligned} \tag{1}$$

Similar approach can be carried out also for the year 2015.

$$\Delta_{2015}\log(Revenue_i) = \beta Drought_{i,2015} + \gamma\Delta_{2015}X_i + \Delta_{2015}\varepsilon_i \tag{2}$$

[7]GHCN Gridded V2 data is provided by the NOAA/OAR/ESRL PSD, Boulder, Colorado, USA, from their Web site at https://www.esrl.noaa.gov/psd/

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In equation (1), we use differences in all variables in 2014 and 2004. Similarly, in equation (2) we use survey data from 2015 and 2004. The baseline year in both equations is 2004. We now describe the variables used for the year 2014 in equation (1). Similarly, the same variables for the other year, 2015 are used in equation (2). The dependent variable of our specification is the difference in log of revenue per hectare of household i between 2004 and 2014. We add a subscript to emphasize the year used in the analysis. $Drought_{i,2014}$ is a dummy variable indicating whether household i experienced a drought in the year 2014, similarly $Drought_{i,2004}$ is a dummy variable, which takes the value 1 if the household experienced a drought in 2004. Since the households did not experience any drought in 2004 we can rewrite $\Delta_{2014}Drought_i$ as $Drought_{i,2014}$. $\Delta_{2014}X_i$ is the difference in time-varying characteristics between 2004 and 2014. These controls are household characteristics, agricultural inputs (such as fertilizers, manure, seeds, labor, and temperature), information sources, and soil quality variables. $\Delta_{2014}\varepsilon_i$ is the change in the idiosyncratic error term. This specification controls for the household fixed effects, and the time-invariant effects.

Household surveys provide information on yields of primary food crops, which are wheat, barley, maize, sorghum, millet, and teff. Using the yields for these crops during the *Meher* season, we construct revenue using national-level prices in 2001. We obtain retail prices for crops at zonal level[8] and then average these prices across various zones to obtain national-level prices.[9] In this way, our estimates will not be influenced by changes in micro-level crop prices. Revenue constructed using this procedure can be thought of as the weighted sum of production data and remove problems associated with variables, such as profits, or actual revenue constructed using current prices. The important months for the growth of these food grains in terms of rainfall are June, July, and August, known as the *Meher* season. For that reason we create the variable for rainfall shocks using the rainfall in *Meher* season. There is another small rainy season from March to May, however, compared to the *Meher* season, little is grown during these months and hence this season will not be discussed. Table 2 presents the descriptive statistics for the most important variables used in the analysis. Furthermore, these variables are defined in table A1 of the appendix.[10] To estimate our regressions we control for household characteristics, inputs, information sources, and soil variables. We measure the per hectare usage of inputs for our analysis. Respondents provide details on information sources, which are also used as controls. The survey included questions regarding fertility and erosion of the soil. Highly fertile soil is coded as 1 with 3 being that of lowest fertility. Similarly, no erosion is coded as 1 while severe erosion is coded as 3. In addition, table A2 provides a comparison between the households which experienced a drought and those that did not experience a drought in 2014 and 2015. We regress various characteristics on the drought indicator and present the coefficients and p-values in table A2. Primarily we find that there is a significant difference among households in inputs usage and other variables (such as, livestock, change crop variety and water and soil conservation), which may be in response to droughts. We discuss it in detail in section 5.

Table 1 and table 2 state that our sample did not experience any droughts in 2004. Our parameter of interest in equation (1) is β. Since none of the households experienced a

[8] Administratively, zones are second-level subdivision of Ethiopia just above *woredas*.

[9] The earliest price data is available for the year 2001, and hence these prices are chosen, as they are assumed to be orthogonal to district level prices of the later years.

[10] All tables and figures with prefix "A", e.g. "A1, A2,. . ." and so on, refer to the appendix (supplementary materials).

Table 2. Descriptive statistics for main variables – 2004, 2014 and 2015

	2004	2014	2015
Revenue	919.66 (777.28)	1730.64 (3343.75)	1891.26 (4868.52)
Climatic Variable			
Drought	0 (0)	0.736 (0.441)	0.687 (0.464)
Household Characteristics			
Household size	6.371 (2.181)	6.387 (2.239)	6.390 (2.231)
Age	45.16 (13.13)	51.38 (12.95)	52.17 (12.75)
Male	0.910 (0.286)	0.854 (0.353)	0.882 (0.323)
Married	0.915 (0.279)	0.871 (0.335)	0.886 (0.319)
Literacy	0.476 (0.500)	0.477 (0.500)	0.433 (0.496)
Wealth	2520.49 (4558.78)	25398.48 (47110.97)	31394.48 (87350.87)
Inputs			
Fertilizers	194.1 (538.1)	476.8 (1041.1)	487.5 (1276.3)
Manure	166.7 (584.0)	423.9 (1074.7)	352.7 (694.5)
Seed	167.7 (246.4)	155.3 (215.1)	153.6 (187.7)
Temperature	18.43 (2.73)	19.09 (2.55)	20.30 (2.53)
Male labor	93.52 (109.6)	198.6 (367.3)	253.5 (286.4)
Female labor	46.51 (72.52)	27.75 (59.45)	87.75 (163.0)
Information Sources			
Extension Workers	0.571 (0.495)	0.512 (0.500)	0.572 (0.495)
Radio and tv information	0.269 (0.444)	0.375 (0.484)	0.407 (0.492)
Climate information	0.390 (0.488)	0.761 (0.427)	0.788 (0.409)
Soil Variables			
Soil erosion	1.584 (0.507)	1.583 (0.434)	1.518 (0.470)
Soil fertility	1.874 (0.506)	1.807 (0.521)	1.815 (0.490)

Continued.

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Table 2. Continued

	2004	2014	2015
Other Variables			
Livestock	2.553 (1.957)	3.191 (2.542)	2.879 (2.271)
Access to credit	0.505 (0.500)	0.868 (0.338)	0.858 (0.349)
Change crop variety	0.382 (0.486)	0.395 (0.489)	0.496 (0.500)
Water and soil conservation	0.382 (0.486)	0.395 (0.489)	0.496 (0.500)

Notes: This table presents the descriptive statistics for the main variables used in the regressions. Mean of the variable is presented along with its standard deviation in parenthesis.

drought in 2004, we interpret β as a comparison between households who experienced a drought in 2014 with those who did not. Depending on the sign of β we can state whether the farming households have adapted to the droughts over the long run (ten years window in our case). We interpret β as the sustained (could be interpreted as the long-run) response to drought because the outcomes are compared over 2004 and 2014. Our reasoning is that this ten-year period provides farmers with sufficient time to make changes in their agricultural practices in response to the changing climate. If β is negative and statistically significant, the revenue in 2014 has reduced for farmers who received a poor rainfall in 2014, compared to the ones that received normal rainfall, using the revenue of 2004 (which was a year with normal rainfall) as reference. Otherwise, adaptation strategies have worked and there are no significant differences in revenue for farmers receiving poor rainfall. This is a crucial aspect of our study, where we elicit the impact of adaptive strategies from the responses of the farmers. This entire exercise is repeated for the data collected in 2015.

4. Results

4.1 Basic results

Panel a of table 3 presents the results of estimating equation (1). We then estimate equation (2) to measure the impact of the drought in 2015 on the revenue of our households. In column (1), we add no additional control variables while in columns (2)–(5) we make use of different sets of control variables as indicated at the bottom of the table. IPCC (2012) states that climate change will increase the probability of extreme events. Our setup enables us to analyze whether farmers are adapting to the possibility of multiple years of consecutive drought. We can observe in *Panel a* that the coefficient associated with $Drought_{2014}$ is negative and insignificant. Column 1 presents results without any covariates. As we add different sets of control variables in columns (2)–(5), the coefficient stabilizes. These results state that although there is a reduction in the revenue of farmers receiving poor rainfall, this reduction is not significantly different from zero. Fundamentally, there is no significant difference in revenue between households who experienced a drought and the ones who did not. This indicates that adaptation has indeed taken place over the years and helped reduce the impact of droughts. We also observe the results from equation (2) for the year 2015, which are provided in *Panel*

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Table 3. Impact of drought on revenue

	(1)	(2)	(3)	(4)	(5)
Panel a					
$Drought_{2014}$	−0.144 (0.175)	−0.144 (0.165)	−0.145 (0.163)	−0.139 (0.162)	−0.144 (0.165)
Observations	811	811	811	811	811
Panel b					
$Drought_{2015}$	−0.279 (0.207)	−0.263 (0.182)	−0.276 (0.183)	−0.270 (0.189)	−0.274 (0.186)
Observations	794	794	794	794	794
Inputs	No	Yes	Yes	Yes	Yes
Household Characteristics	No	No	Yes	Yes	Yes
Information Sources	No	No	No	Yes	Yes
Soil Variables	No	No	No	No	Yes

Standard errors are clustered on the level at which we measure the rainfall, resulting in 65 clusters. Households characteristics include household size, age and gender of the household's head, whether the household's head is literate and married. Inputs include temperature, seeds, fertilizers and manure in kgs per hectare, and male and female labor in person days per hectare. Information sources include government extension officers, information from radio and television and climate information. Soil variables include average soil erosion and soil fertility of the farms. Dependent variable in all the columns is the change in log of revenue per hectare between the base year, 2004 and comparison years, 2014 and 2015.

b of table 3. Similar to the results discussed earlier, these coefficients are negative and statistically insignificant. However, the coefficients in *Panel b* are greater in magnitude and less insignificant as compared to their *Panel a* counterparts. For example, in column 5, *Panel b* of table 3, the coefficient associated with $Drought_{2015}$ has a p value of 0.116. Results from *Panel b* point towards the tentative existence of heterogeneity. To further support our claim that the first drought in 2014 had less effect on agricultural revenues and that the second drought shock in 2015 reduced the revenues compared to the base year 2004 – we run a statistical difference test on the regression coefficients of the two years (shown in A3). It is observed that the result is consistent with our intuition. These results are the total impact of drought on households.

It is possible that there is a heterogeneous impact of drought based on wealth. Estimating equation (1) provides the average impact of the drought and does not provide a complete picture concerning individual heterogeneity. We estimate equation (1) and equation (2) again, adding interactions of wealth with the drought indicator. These interactions are added to explore potential heterogeneities as they convey whether there is a differential impact of drought based on wealth.

The data is an unbalanced panel, as can be seen from the change in the number of observations across the results from 2014 to 2015. Attrition is a phenomenon where some units of observation leave the sample in subsequent time periods (i.e., during follow-ups) and may be considered to have a selectivity bias with respect to time. It is assumed that as soon as a unit exits the sample, nothing can be observed about them. Hence, attrition is an "absorbing" state. With an unbalanced panel, this factor may arise endogenously- and may lead to non-random/ endogenous attrition biases. In our case, however, the number of observations falls from 811 to 794 as can be observed from the table. This is inherently a small sample, and we can safely assume that the attrition is random; so, as only a few samples become absent in the next year, the data still retains its representative nature.

To further substantiate our results, we also construct a *Drought* variable, now by using rainfall data from other months, such as March to May (before, it was done for *Meher* season, which is from June to August). With this new index, we again see negative but insignificant effect of droughts on the revenues. However, for 2015, the magnitude is very small despite being negative. This can be seen as a Placebo test. Results are reported in the table A10.

4.2 Main results

We create a variable *wealth* to measure the heterogeneous impact of drought. It may be argued that the wealth is endogenous (due to omitted variable bias or simultaneity bias). However, this is not the case due to the following reasons: (i) Wealth is measured in the previous year, so the current revenues have no impact on this variable. (ii) Wealth is measured using the total value of non-farm assets belonging to the households.[11] These non-farm assets measure general wealth levels and do not have a direct impact on farm-revenues. (iii) In the estimation strategy described below, we are interested in the coefficient of interaction between wealth and drought which measures the heterogeneous impact of drought based on wealth. Nizalova and Murtazashvili (2016), have shown both analytically and with simulations that the OLS estimator of the interaction term in this context is still consistent if the (presumably) endogenous variable and the unobserved heterogeneity are jointly independent from the exogenous treatment. In our scenario, this condition is fulfilled due to the random nature of the drought. We estimate the following equation:

$$\begin{aligned}\Delta_{2014}\log(Revenue_i) = {} & \beta(Drought_{i,2014} - Drought_{i,2004}) \\ & + \eta(Drought_{i,2014} * \log(Wealth_{i,2014}) \\ & - Drought_{i,2004} * \log(Wealth_{i,2004})) + \gamma\Delta_{2014}X_i + \Delta_{2014}\varepsilon_i\end{aligned}$$

The new variable added to equations (1) and (2) is wealth, whereas the other variables remain the same as before. As was the case before, none of the households experienced a drought in 2004, so we can rewrite the equation as follows:

$$\begin{aligned}\Delta_{2014}\log(Revenue_i) = {} & \beta Drought_{i,2014} \\ & + \eta Drought_{i,2014} * \log(Wealth_{i,2014}) + \gamma\Delta_{2014}X_i + \Delta_{2014}\varepsilon_i\end{aligned} \tag{3}$$

We also run the same equation for 2015.

$$\begin{aligned}\Delta_{2015}\log(Revenue_i) = {} & \beta Drought_{i,2015} \\ & + \eta Drought_{i,2015} * \log(Wealth_{i,2015}) + \gamma\Delta_{2015}X_i + \Delta_{2015}\varepsilon_i\end{aligned} \tag{4}$$

In the above equations we interact $Drought_{i,2014}$ with $\log(Wealth_{i,2014})$, which enables us to explore the heterogeneous impact of droughts with respect to wealth.

[11] These assets include the value of jewelry, cooking pans, beds, radios, refrigerators, cars, residences and stoves.

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$\Delta_{2014}\log(Wealth_i)$ is included in the time-varying controls. We again estimate our results for 2014 and 2015. η captures the heterogeneous impact of droughts based on wealth. Our hypothesis is that if η is positive and significant, then it is easier for households endowed with higher wealth to adapt to the negative impact of droughts. The total impact of droughts in this specification depends on wealth and is obtained using the household's wealth levels, estimated β, and η.

Panel a and *Panel b* of table 4 presents the results. As in earlier analysis, in column (1), we add no additional control variables while in columns (2)–(5) we make use of different sets of control variables as indicated at the bottom of the table. *Panel a* reports that interaction with wealth does not change our results. Coefficient of $Drought_{2014}$ is negative and non-significant. Its interaction term with wealth is also insignificant. Moreover, the magnitude of the coefficient is close to zero (for example in column 5, *Panel a* of table 4 the estimated coefficient of $Drought_{2014} * \log(Wealth_{2014})$ is 0.019 with a standard error of 0.029). Inherently, our results for 2014 state that drought did not have a differential impact based on wealth, and hence we conclude that farmers were able to adapt to the first drought in 2014. *Panel b* of table 4 presents the results for the drought in 2015. Here, we use the delta method to compute the confidence intervals.[12] We observe in *Panel b* that coefficients associated with $Drought_{2015}$ are negative and significant, while the interaction term of $Drought_{2015}$ and $Log(Wealth_{2015})$ is positive and significant. The results from *Panel b* state that in 2015, households with higher wealth were able to better withstand the impact of drought.[13] In essence, the more wealth a household has the less will be the impact of drought on it.

This can be understood by looking at the coefficients of $Drought_{2015}$ (which is negative in magnitude) and its interaction with wealth (which is positive in magnitude). The marginal impact of drought in 2015 is:

$$\beta + \eta * Log(Wealth_{2015})$$

The positive η coefficient offsets the negative β coefficient. For example, if we use the estimates from column 5 of *Panel b* in table 4, we can state that a household with an average wealth of the sample has a reduction of 24% ($-1.392 + 0.118 \times 9.5 = -0.27$ and $\exp^{-0.27} - 1 = -0.24$) in revenue per hectare due to the drought.[14] This differential impact of the drought is not observed in 2014, when there is no significant difference in revenue, irrespective of the wealth levels. This result can be viewed in figure 4 very prominently. *Panel a* of figure 4 shows that irrespective of wealth, drought does not have an impact on revenues in 2014, whereas during the consecutive drought in 2015, as shown in *Panel b*, the decline in revenue depends on the wealth of the household. This supports the theory of adaptive strategies, engendering the inability of the farmers to tackle subsequent droughts, conditional upon lower wealth level. *Panel c* and *Panel d* of figure 4

[12]The delta method allows us to obtain the appropriate standard errors of any smooth function of the fitted model parameter, by applying a Jacobian matrix to the estimated variance matrix of the fitted model parameters.

[13]We also run a join exclusion Wald test of $\beta = \eta = 0$. The results are presented in, figure A1. We reject the null hypothesis for 2015, the heterogeneous model fits the data better.

[14]We also run a specification by first demeaning $Log(Wealth)$ and then interacting with $Drought_{2015}$, and running our regression. Now, the β coefficient gives us the marginal effect of drought in 2015 for a farmer of average wealth. These results are presented in table A13. The impact of drought in 2015 for a household with average wealth is almost identical to the one mentioned in the main text. The interaction term is positive, which is consistent with our original results, and also statistically significant.

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Table 4. Heterogeneous impact of drought on revenue

	(1)	(2)	(3)	(4)	(5)
Panel a					
$Drought_{2014}$	−0.198 (0.329)	−0.343 (0.316)	−0.353 (0.322)	−0.323 (0.340)	−0.304 (0.333)
$Drought_{2014} * Log(Wealth_{2014})$	0.008 (0.029)	0.024 (0.027)	0.025 (0.028)	0.022 (0.029)	0.019 (0.029)
Observations	811	811	811	811	811
Panel b					
$Drought_{2015}$	−1.493 (0.423)	−1.462 (0.403)	−1.422 (0.407)	−1.411 (0.417)	−1.392 (0.413)
$Drought_{2015} * Log(Wealth_{2015})$	0.127 (0.041)	0.126 (0.038)	0.121 (0.039)	0.120 (0.040)	0.118 (0.040)
Observations	794	794	794	794	794
Panel c					
$C\,Drought_{2015}$	−1.415 (0.436)	−1.404 (0.424)	−1.366 (0.431)	−1.330 (0.443)	−1.335 (0.433)
$C\,Drought_{2015} * Log(Wealth_{2015})$	0.154 (0.042)	0.150 (0.041)	0.147 (0.042)	0.144 (0.043)	0.144 (0.043)
Observations	794	794	794	794	794
Inputs	No	Yes	Yes	Yes	Yes
Household Characteristics	No	No	Yes	Yes	Yes
Information Sources	No	No	No	Yes	Yes
Soil Variables	No	No	No	No	Yes

Standard errors are clustered on the level at which we measure the rainfall, resulting in 65 clusters. Households characteristics include household size, age and gender of the household's head, whether the household's head is literate and married. Inputs include seeds, fertilizers, temperature and manure in kgs per hectare, and male and female labor in person days per hectare. Information sources include government extension officers, information from radio and television and climate information. Soil variables include average soil erosion and soil fertility of the farms. We control for change in log of wealth in all our specifications. Drought is interacted with log of wealth to explore the heterogeneous impact of drought. Dependent variable in all the columns is the change in log of revenue per hectare between the base year, 2004 and comparison years, 2015 and 2014.

exhibit the histogram and CDF of $Log(Wealth_{2015})$, respectively. The Cumulative Distribution Function substantiates our observation that there is a heterogeneous impact of drought based on wealth in 2015, by illustrating the distribution of data at these lower levels of wealth.

We notice that as the wealth of the household increases, the impact of the drought decreases. Among farmers who experienced a drought in 2015, around 83% also experienced a drought in 2014, therefore the results in *Panel b* of table 4 are attributed to successive droughts in 2015. We explicitly show this by creating a binary variable $CDrought_{2015}$, which takes the value 1 if the household experienced a consecutive drought in 2015. We estimate our results using this variable and present them in *Panel c* of table 4, these results are similar to the results in *Panel b*. This substantiates the fact that the households that experienced drought consecutively in 2014 and 2015, incur a loss in revenue in 2015. This means that even those who could fight back in 2014, were less able to do so in 2015, in case of successive droughts. Hence, we conclude with a crucial point

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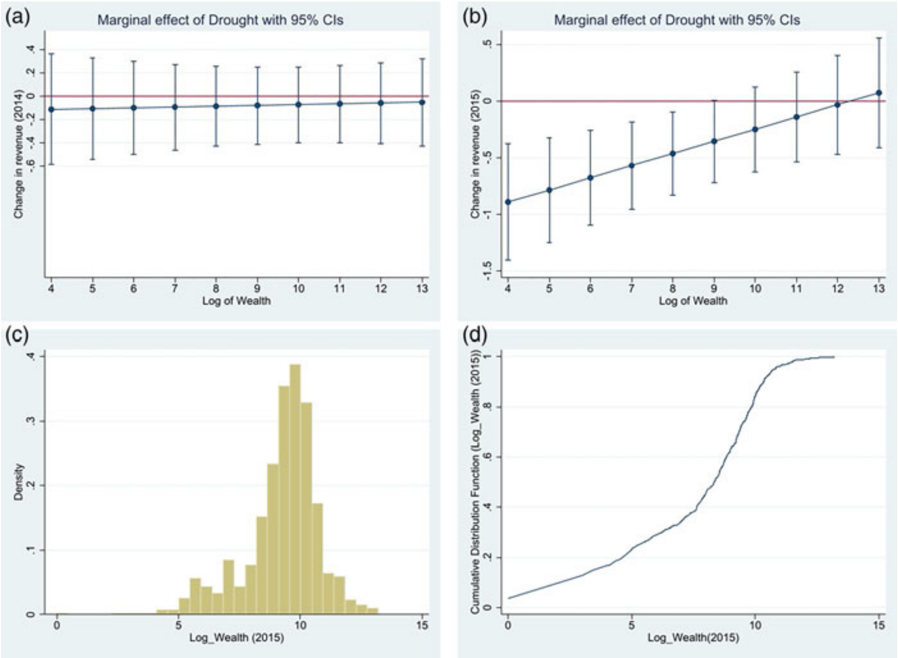

Figure 4. Row 1 shows the comparison of marginal effect of drought in 2014 and 2015 based on the log of wealth of the households. We observe that there is no heterogeneous impact of drought based on wealth in 2014, whereas in 2015 the impact of drought depends on wealth. Row 2 depicts the Cumulative Distribution Function of the wealth of households in 2015. Since we observe a heterogeneous impact of drought based on $Log(Wealth_{2015})$, this figure helps us to see the distribution of data at these lower levels of wealth. (a) Marginal effect of drought in 2014, (b) Marginal effect of drought in 2015, (c) Histogram of $Log(Wealth_{2015})$, (d) CDF of $Log(Wealth_{2015})$.

that farming households in our sample adapted to the first drought in 2014, but did not adapt to the successive drought in 2015.

5. Robustness checks

In this section, we change our specifications and test our assumptions to check whether our results are robust and consistent.

5.1 Alternative prices to construct revenues

Our dependent variable, revenue, is constructed using the price data of various crops at the national level in 2001. The idea behind choosing the year 2001, and constructing the average price at the national level using *woreda* level data, is that these prices are exogenous to the local prices in the later years. Our results primarily rely on this particular choice of prices. It can be argued that the year 2001 may be a special case and our results may vary if another source for prices is chosen. To this end, we construct a different measure of revenue by selecting the average price at the national level using *woreda* level data for 2002, 2003 and average prices over the years 2001 to 2003. We then re-estimate our results for 2014 and 2015 to verify whether these results are consistent. We estimate our results for the average prices over the years 2001, 2002, and 2003. These

Table 5. Robustness check: revenue constructed using average prices from 2001–2003

	(1)	(2)	(3)	(4)	(5)
Panel a					
$Drought_{2014}$	−0.219 (0.329)	−0.388 (0.309)	−0.400 (0.315)	−0.367 (0.334)	−0.350 (0.327)
$Drought_{2014} * Log(Wealth_{2014})$	0.009 (0.029)	0.027 (0.027)	0.028 (0.028)	0.025 (0.029)	0.022 (0.028)
Observations	811	811	811	811	811
Panel b					
$Drought_{2015}$	−1.523 (0.411)	−1.502 (0.390)	−1.466 (0.396)	−1.452 (0.405)	−1.434 (0.401)
$Drought_{2015} * Log(Wealth_{2015})$	0.125 (0.040)	0.126 (0.036)	0.121 (0.038)	0.120 (0.038)	0.118 (0.039)
Observations	794	794	794	794	794
Inputs	No	Yes	Yes	Yes	Yes
Household Characteristics	No	No	Yes	Yes	Yes
Information Sources	No	No	No	Yes	Yes
Soil Variables	No	No	No	No	Yes

Standard errors are clustered on the level at which we measure the rainfall, resulting in 65 clusters. Households characteristics include household size, age and gender of the household's head, whether the household's head is literate and married. Inputs include seeds, fertilizers, temperature and manure in kgs per hectare, and male and female labor in person days per hectare. Information sources include government extension officers, information from radio and television and climate information. Soil variables include average soil erosion and soil fertility of the farms. We control for change in log of wealth in all our specifications. Drought is interacted with log of wealth to explore the heterogeneous impact of drought. Dependent variable in all the columns is the change in log of revenue per hectare between the base year, 2004 and comparison years, 2015 and 2014.

results appear to be consistent with our previous choice of price data. *Panel a* and *Panel b* of table 5 presents the results. The table shows the same estimation results as table 4 but with average national level prices of 2001–2003. The results state that the drought has no differential impact based on wealth in 2014. The differential impact of droughts can be seen in the results for 2015. Table A5 provides results when we use prices from 2002 while table A6 provides results for prices in 2003 to construct the revenue. These tables are presented in the appendix. In addition, we use the revenue constructed using current prices at the zonal level since we do not have prices at the *woreda* level. Administratively, zones are second-level subdivision of Ethiopia just above *woredas*. Additionally, we deflate these values using consumer price index (CPI)[15] to make them comparable across years. The results are presented in table A7 of the appendix. We can observe that the results are consistent with different prices and only change marginally.

5.2 Alternative cutoff to identify droughts

We identify negative rainfall shocks by normalizing current rainfall using the long-term mean and standard deviation; we then identify shocks by using a cutoff of −1 standard deviation. It can be argued that our cutoff does not identify the shocks correctly and it is possible that farmers suffering from the shocks are further away from this cutoff. To

[15]CPI values are obtained from the World Bank database where 2010 is the reference year.

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test this hypothesis we identify our shocks by taking a new cutoff of "−1.25". We re-estimate our results using this new cutoff following the same procedure as before. *Panel a* and *Panel b* of table 6 present results from these estimations. We also provide two more robustness checks with cutoffs "−1.50" and "−1.75", as presented in table 6 in *Panels c & d* and *Panels e & f* respectively. Our results are similar to the previous results, providing the same insights about 2014 and 2015, as shown in the earlier analysis.

5.3 Using profits as the dependent variable

We construct profits (per hectare) by differencing total costs of fertilizers, manure, seeds and labor used in production, from actual revenues constructed using yields of wheat, barley, maize, sorghum, millet, and teff, and the current prices of these crops at zonal level. There are two major issues with using this measure of profits as the dependent variable. The first issue is that we do not have all the relevant costs during production. We use fertilizers, manure, seeds, temperature and labor as the inputs to construct the costs in the production process. A second concern is that we do not have complete information for unit-costs associated with these inputs. We use sample averages during a particular year to replace missing values for unit-costs, wherever we do not have the information. We then deflate these profits using CPI for Ethiopia. We acknowledge that profits constructed using this approach are noisy, however, the results provide important insights on response of profits during droughts. The dependent variable in this specification is profits per hectare therefore, the interpretation of coefficients is different than the earlier results.[16] We show these results in table 7. The sign of the coefficients is consistent with the earlier results and we find no significant difference in profits during the first and second drought. In addition, we find a heterogeneous impact of drought based on wealth. This reaffirms our earlier results.

5.4 Temperature as a control variable

To justify our usage of temperature as part of the inputs, we also control for it separately and check for robustness, taking only fertilizers, manure, seeds, and labor as the inputs. We present our results using temperature as a control variable, notably, the change in temperature in our ten year difference specification, to show that our results are robust. We create this variable using the average temperature during the *Meher* season. We again estimate equation (3) and equation (4) including the change in temperature between the base year 2004 and the year of analysis separately, but removing it from the inputs. The result is consistent, as can be observed in table A4. We find that drought in 2014 had no effect on revenue, whereas a subsequent drought in 2015 had a differential effect on farming households based on household wealth. We conclude from these tests that the earlier results are robust to various specifications.

5.5 Past shocks as a control variable

Woredas that experience regular droughts are different than the ones that do not experience regular droughts, in terms of, their initial level and growth rates of overall economic activity, government services, infrastructure investments, etc. Most of these differences

[16]We chose profits per hectare instead of a log-transformed version of profits because we obtain some instances of negative profits. We also constructed a log-transformed version of profits by adding a constant to profits so that profits become positive. These results are presented in table A8 of the appendix.

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Table 6. Robustness check: drought identified using different cutoffs of standard deviations

	(1)	(2)	(3)	(4)	(5)
Cutoff of −1.25 standard deviation					
Panel a					
$Drought_{2014}$	−0.330 (0.403)	−0.307 (0.386)	−0.325 (0.392)	−0.286 (0.409)	−0.263 (0.404)
$Drought_{2014} * Log(Wealth_{2014})$	0.019 (0.041)	0.020 (0.039)	0.022 (0.040)	0.018 (0.041)	0.015 (0.040)
Observations	811	811	811	811	811
Panel b					
$Drought_{2015}$	−1.403 (0.441)	−1.279 (0.409)	−1.228 (0.406)	−1.201 (0.412)	−1.188 (0.409)
$Drought_{2015} * Log(Wealth_{2015})$	0.128 (0.046)	0.114 (0.042)	0.108 (0.043)	0.106 (0.043)	0.104 (0.043)
Observations	794	794	794	794	794
Cutoff of −1.50 standard deviation					
Panel c					
$Drought_{2014}$	0.322 (0.346)	0.281 (0.333)	0.268 (0.341)	0.358 (0.357)	0.378 (0.356)
$Drought_{2014} * Log(Wealth_{2014})$	−0.034 (0.036)	−0.029 (0.034)	−0.029 (0.036)	−0.037 (0.037)	−0.040 (0.036)
Observations	811	811	811	811	811
Panel d					
$Drought_{2015}$	−1.172 (0.464)	−1.194 (0.442)	−1.167 (0.446)	−1.130 (0.455)	−1.119 (0.450)
$Drought_{2015} * Log(Wealth_{2015})$	0.110 (0.049)	0.113 (0.047)	0.110 (0.048)	0.108 (0.048)	0.108 (0.048)
Observations	794	794	794	794	794
Cutoff of −1.75 standard deviation					
Panel e					
$Drought_{2014}$	0.025 (0.388)	−0.004 (0.381)	−0.021 (0.388)	0.034 (0.414)	0.060 (0.411)
$Drought_{2014} * Log(Wealth_{2014})$	−0.010 (0.040)	−0.007 (0.039)	−0.006 (0.040)	−0.011 (0.042)	−0.014 (0.041)
Observations	811	811	811	811	811
Panel f					
$Drought_{2015}$	−1.280 (0.458)	−1.248 (0.431)	−1.227 (0.433)	−1.190 (0.442)	−1.167 (0.439)
$Drought_{2015} * Log(Wealth_{2015})$	0.119 (0.046)	0.112 (0.044)	0.110 (0.045)	0.107 (0.046)	0.104 (0.046)

Continued.

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Table 6. Continued

	(1)	(2)	(3)	(4)	(5)
Observations	794	794	794	794	794
Inputs	No	Yes	Yes	Yes	Yes
Household Characteristics	No	No	Yes	Yes	Yes
Information Sources	No	No	No	Yes	Yes
Soil Variables	No	No	No	No	Yes

Standard errors are clustered on the level at which we measure the rainfall, resulting in 65 clusters. Households characteristics include household size, age and gender of the household's head, whether the household's head is literate and married. Inputs include seeds, fertilizers, temperature and manure in kgs per hectare, and male and female labor in person days per hectare. Information sources include government extension officers, information from radio and television and climate information. Soil variables include average soil erosion and soil fertility of the farms. We control for change in log of wealth in all our specifications. Drought is interacted with log of wealth to explore the heterogeneous impact of drought. Dependent variable in all the columns is the change in log of revenue per hectare between the base year, 2004 and comparison years, 2015 and 2014.

Table 7. Robustness check: profits as the dependent variable

	(1)	(2)	(3)	(4)
Panel a				
$Drought_{2014}$	−3480.547 (3098.856)	−3703.396 (3228.684)	−3646.261 (3389.444)	−3741.091 (3411.318)
$Drought_{2014} * Log(Wealth_{2014})$	368.597 (332.200)	405.841 (353.192)	410.722 (364.883)	428.062 (369.786)
Observations	811	811	811	811
Panel b				
$Drought_{2015}$	−8647.346 (3449.343)	−8700.543 (3463.223)	−8917.947 (3416.704)	−8820.958 (3466.051)
$Drought_{2015} * Log(Wealth_{2015})$	706.442 (397.301)	730.751 (405.524)	726.478 (399.989)	713.193 (405.135)
Observations	794	794	794	794
Household Characteristics	No	Yes	Yes	Yes
Information Sources	No	No	Yes	Yes
Soil Variables	No	No	No	Yes

Standard errors are clustered on the level at which we measure the rainfall, resulting in 65 clusters. Households characteristics include household size, age and gender of the household's head, whether the household's head is literate and married. Inputs include seeds, fertilizers, temperature and manure in kgs per hectare, and male and female labor in person days per hectare. Information sources include government extension officers, information from radio and television and climate information. Soil variables include average soil erosion and soil fertility of the farms. We control for change in log of wealth in all our specifications. Drought is interacted with log of wealth to explore the heterogeneous impact of drought. Dependent variable in all the columns is the change in profits per hectare between the base year, 2004 and comparison years, 2015 and 2014.

should be controlled due to the ten year difference specification through fixed effects. However, to control for recent past droughts, we create a variable which accounts for the number of droughts received by a household in the past 8 years. To maintain our aforementioned econometric specification we create this variable for each year of our analysis. We then add this variable as an additional control in our empirical specification. The idea is to account for any extreme weather events during the past 8 years, the

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Table 8. Robusness check: past shocks added as a control variable

	(1)	(2)	(3)	(4)	(5)
Panel a					
$Drought_{2014}$	−0.163 (0.316)	−0.313 (0.306)	−0.325 (0.312)	−0.298 (0.331)	−0.275 (0.322)
$Drought_{2014} * Log(Wealth_{2014})$	0.008 (0.028)	0.023 (0.026)	0.024 (0.027)	0.022 (0.029)	0.019 (0.028)
Observations	811	811	811	811	811
Panel b					
$Drought_{2015}$	−1.464 (0.439)	−1.428 (0.424)	−1.386 (0.424)	−1.350 (0.428)	−1.340 (0.425)
$Drought_{2015} * Log(Wealth_{2015})$	0.127 (0.041)	0.126 (0.038)	0.121 (0.038)	0.120 (0.039)	0.118 (0.039)
Observations	794	794	794	794	794
Past Shocks	Yes	Yes	Yes	Yes	Yes
Inputs	No	Yes	Yes	Yes	Yes
Household Characteristics	No	No	Yes	Yes	Yes
Information Sources	No	No	No	Yes	Yes
Soil Variables	No	No	No	No	Yes

Standard errors are clustered on the level at which we measure the rainfall, resulting in 65 clusters. Households characteristics include household size, age and gender of the household's head, whether the household's head is literate and married. Inputs include seeds, fertilizers, temperature and manure in kgs per hectare, and male and female labor in person days per hectare. Information sources include government extension officers, information from radio and television and climate information. Soil variables include average soil erosion and soil fertility of the farms. We control for change in log of wealth in all our specifications. Drought is interacted with log of wealth to explore the heterogeneous impact of drought. Dependent variable in all the columns is the change in log of revenue per hectare between the base year, 2004 and comparison years, 2015 and 2014.

absence of which may bias our results. These results, presented in table 8 do not change by using this specification.

We test out more interactions with past shocks and droughts- to get an even greater interesting look at past shocks being a relevant characteristic in mediating the droughts. The results are presented in A11 and A12.

6. Mechanism

Our results state that adaptive processes set up by the farmers were able to cope with the first drought (in 2014), irrespective of the wealth levels. However, when the second drought took place in 2015, not all households were able to withstand the negative effects of drought. During the drought in 2015, the impact was worse for poor households. We posit that the heterogeneity observed in our results, based on wealth, is due to the difference in investments made by farmers. We start our analysis by focusing on the investments made by households in inputs used during the production process (seeds, manure, fertilizers, temperature, male labor and female labor) and the adaptation strategies (changing crop variety and water and soil conservation measures). These investments are dependent on farmers' financial environment. We, therefore, investigate whether there are credit constraints experienced by farmers, analyzing two variables, 1. access to credit and 2. livestock owned by farmers. These results are presented in table 9. Our aim is to explain the heterogeneity based on wealth, therefore we only present the

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coefficients associated with the interaction of drought and wealth for different outcomes of interest in table 9.[17]

As discussed, we start our analysis by focusing on the inputs used during the production process, seeds, manure, fertilizers, temperature, male labor and female labor. Our outcome variables are input quantities per hectare in logs. We estimate equation (3) and equation (4), using the input quantities as the outcome variables. Our coefficient of interest is the interaction between drought and wealth, and we present this particular coefficient in our results, displayed in table 9. Thus, table 9 presents the information of each dependent variable's coefficient (and standard error)- that are obtained from separate regressions. We find no significant difference for inputs such as seeds, manure and fertilizers. These results are presented in table A9 of the appendix. However, we find that wealthier farmers invest more resources in male and female laborers during the second drought in 2015. We also find significant relation with temperature for the year 2014. Using estimates from column (4) in table 9, we find that a household with an average wealth of our sample increases the male labor by approximately 10% and female labor by approximately 21%, during the second drought; although the marginal effect for female labor is imprecisely calculated.[18]

We now analyze the data regarding the adaptation strategies used by these households. In the context of Ethiopia, Di Falco and Veronesi (2013) find that adaptive methods lead to a significant increase in farm revenue. Due to the limited data available on adaptation strategies in the 2004 survey, we cannot look in-depth at the various different adaptation strategies used by these farming households. However, we can investigate further in two particular adaptation strategies, namely, changing crop variety during farming and using water and soil conservation measures. We have information on households using these adaptation strategies. On the one hand, we do not find any significant difference based on wealth for farmers who used water and soil conservation measures, as you can see in table A9 of the appendix (similar to table 9, obtained from separate regression equations). However, wealthier households are more likely to change crop variety as an adaptation strategy in 2014 and 2015. Results using the binary variable (whether a farmer changes crop variety), as the dependent variable are presented in table 9. The average household is around 10% more likely to use this adaptation strategy in 2015. To summarize our results, we find no differences based on wealth in terms of quantity of inputs (such as manure, fertilizers, temperature, and seeds) and using soil and water conservation measures during drought. However, we find that wealthier farmers use more laborers during the second drought and are more likely to use different crop varieties during both the droughts. In this context, we can safely conclude that wealthier farmers generally make more on-farm investments.

Aragón *et al.* (2021), suggests that, in context with imperfect input markets, negative weather shocks, such as extreme heat, could result in an increase in input use. It is also observed that farmers exposed to negative shocks may need to resort to more intensive use of non-traded inputs, like land and domestic labor, to offset undesirable drops in output and consumption. In this sense, changes in input use are akin to other consumption smoothing mechanisms, such as selling disposable assets or increasing off-farm work, Rosenzweig and Wolpin (1993a) and Kochar (1999). Thus we harmlessly assume that

[17]Complete tables of these results are available on request.

[18]To calculate the marginal impact of drought, we require the coefficients associated with drought and interaction of drought with wealth. Our tables hereafter, only provide the coefficient associates with the interaction of drought with wealth. Complete tables of these results are available on request.

Table 9. Mechanism: coefficients associated with the interaction of drought and log of wealth

	(1)	(2)	(3)	(4)
Panel a: 2014				
Dependent Variable				
Log(*MaleLabor*)	0.046 (0.049)	0.046 (0.048)	0.042 (0.047)	0.043 (0.047)
Log(*FemaleLabor*)	−0.060 (0.070)	−0.045 (0.069)	−0.057 (0.068)	−0.047 (0.064)
CropVariety	0.049 (0.020)	0.049 (0.020)	0.043 (0.019)	0.042 (0.019)
Temperature	−0.044 (0.026)	−0.043 (0.026)	−0.043 (0.023)	−0.039 (0.023)
AccessCredit	0.055 (0.017)	0.054 (0.018)	0.052 (0.018)	0.051 (0.017)
Livestock	0.165 (0.048)	0.158 (0.047)	0.158 (0.046)	0.151 (0.046)
Observations	811	811	811	811
Panel b: 2015				
Dependent Variable				
Log(*MaleLabor*)	0.087 (0.036)	0.085 (0.036)	0.084 (0.033)	0.077 (0.031)
Log(*FemaleLabor*)	0.061 (0.044)	0.080 (0.043)	0.081 (0.043)	0.081 (0.044)
CropVariety	0.053 (0.024)	0.050 (0.023)	0.050 (0.023)	0.051 (0.023)
Temperature	0.059 (0.056)	0.055 (0.056)	0.053 (0.054)	0.056 (0.053)
AccessCredit	0.029 (0.016)	0.027 (0.016)	0.028 (0.016)	0.029 (0.016)
Livestock	0.134 (0.053)	0.135 (0.049)	0.136 (0.047)	0.132 (0.047)
Observations	794	794	794	794
Household Characteristics	No	Yes	Yes	Yes
Information Sources	No	No	Yes	Yes
Soil Variables	No	No	No	Yes

Standard errors are clustered on the level at which we measure the rainfall, resulting in 65 clusters. Households characteristics include household size, age and gender of the household's head, whether the household's head is literate and married. Information sources include government extension officers, information from radio and television and climate information. Soil variables include average soil erosion and soil fertility of the farms. We control for change in log of wealth in all our specifications. For the results in panel a the dependent variable is the change in livestock. Results are presented for each year in different panels. Coefficient associated with the interaction of drought and log of wealth is presented in the table. Dependent variables used are change in, log of male labor and female labor per hectare, average temperature of the Meher months, a binary variable representing whether a household changes crop variety as an adaptation strategy, a binary variable representing whether a member of a households has access to credit and number of livestock owned by the households.

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these were the adaptation strategies taken up by the farmers who received the consecutive shock of droughts. But in this paper, we present a reduced form, so we do not delve deep into each of these adaptive strategies.

The investments decisions of small-holders in developing countries are dependent on their financial ecosystem. Credit market constraints can limit the on-farm investments of these farmers, therefore, we investigate whether there are any credit constraints experienced by them. We create a binary variable (access to credit), if the households borrowed or had the option to borrow credit during the year. We then estimate our regressions using this binary variable as an outcome. We find that in 2014, wealthier farmers were more likely to have access to credit. These results are consistent for 2015, however, the coefficient is smaller in magnitude. The presence of credit constraints makes it difficult for poor farmers to make on-farm investments during droughts. However, there may be other income diversification strategies. Livestock sales are one of the methods discussed in the literature in response to income shocks. Rosenzweig and Wolpin (1993b), find that bullocks in the context of India are not just used as mechanical substitutes for agricultural production but also as a source of consumption smoothing during income shocks. Fafchamps *et al.* (1998), find that livestock sales compensate around 15% to 30% of the income loses during village-level rainfall shocks. However, others in the literature such as Kazianga and Udry (2006), do not find any evidence on using livestock as a consumption smoothing instrument during income shocks. Our survey includes information on livestock in all the years, including the number of cows, oxen, calf, sheep, goat, poultry, donkeys, horses and mules. We prepare an index for livestock using the Regional Livestock units (LSU) coefficients prepared by the Food and Agriculture Organization (FAO) (Upton, 2011), to aggregate information for different types of livestock.[19] We then estimate our empirical specification, using the aggregated livestock variable as our dependent variable. The idea is to investigate whether during the drought there was a differential effect of wealth on the number of livestock owned by the households. These results presented in table 9, indicate that in 2014 and 2015, poor farmers who experienced drought had fewer livestock than the households who owned more wealth, using 2004 as the baseline year. Agriculture requires investments, especially during droughts. These results state that wealthier farmers own more livestock during the drought years in 2014 and 2015. They also suggest that for the same amount of wealth, farmers had fewer livestock in 2015 than in 2014. This reduction in livestock emphasizes the lack of resources during the second drought, especially for poor households. Essentially, our results state that wealthier households make more on-farm investments. This is due to the fact that more resources are available to wealthier farmers such as access to credit or livestock.

7. Discussion and conclusion

We find no difference in revenue during the first drought, irrespective of the wealth levels. During the drought in 2015, the impact was worse for poor households. We conclude that farmers may be adapting to droughts but to a limited extent. We find evidence of increasing awareness about climate change in our data.

Previous empirical studies in economics have focused on studying the detrimental impacts of the increase in temperature on economic growth. Recent studies have also found that climate change will lead to an increase in the frequency and intensity of

[19]The weights denoted are 0.5 for cattle, 0.1 for sheep, 0.1 for goat, 0.01 for poultry, 0.3 for donkey, 0.6 for mule and 0.5 horses.

droughts. Our results adhere to the existing literature, albeit limited, studying the impact of a ten-year difference of drought on farming and crop production under the context of adaptive capacity. To highlight a few works on similar aspects, Adhikari (2018), talk about local site-specific adaptation measures to increase the adaptive capacity of small-holding farmers, in the face of the climate-induced drought scenario. The implications for technology design for drought mitigation and relief in rice production of the rainfed areas of Asia are studied by Pandey *et al.* (2016). Cunado and Ferreira (2014), observe the impact of flood shocks on per capita GDP growth using panel vector autoregression models of large flood events. In a different flavour, D'Arrigo and Wilson (2008), use simple predictive models to generate warning forecasts of drought to mitigate crop failure risk in Indonesia. Banerjee (2010), studies the short and long term impact of floods on agriculture in Bangladesh. Our paper enriches this existing discussion on climatic shocks- adding to the validity of present results, and provides an external outlook from the perspective of Ethiopia.

By using a ten-year difference estimation for data from Ethiopia during the 2014 and 2015 droughts, where the baseline year is 2004, we are able to study whether farmers are adapting to the possibility of a multi-year drought. The advantage of using this approach is that it incorporates adaptive processes undertaken by the farmers in response to the changing climate. We start by constructing household revenue using yields of major food crops. We use national level prices of 2001 to construct revenue, which is our dependent variable. Revenues are constructed using historical prices on the assumption that these prices are orthogonal to the local prices. Using the household survey data collected for 2004, 2014 and 2015, along with the corresponding rainfall data, we explore whether farmers living in the Nile basin of Ethiopia have adapted to droughts in the long run. We find that farmers adapted to the first drought in 2014. Our results state that there is no significant difference in revenue between farmers who experience drought and farmers who did not experience a drought. This result is independent of the wealth levels of farmers. However, a consecutive drought in 2015 led to a reduction in revenue. Farmers who experienced a drought in 2015 had significantly less revenue than those who did not experience the drought. Additionally, the total impact of drought depends on the wealth of the farmers. The loss of revenue is higher for farmers who are less wealthy, which is not the case in 2014. Also, we confirm this result by identifying farmers who received consecutive droughts in 2015 and repeating our analysis which leads to similar results. We argue that this heterogeneity in the impact of the drought is due to more on-farm investments made by wealthier farmers. Wealthier farmers have more resources to make such investments during droughts.

While controlling for the wealth levels, the farmers were able to cope with the first drought but were unable to do so during the second drought. Based on these results, we therefore conclude that over a ten-year period, harmlessly assumed as the long run, households are able to adapt to droughts, but to a limited extent. However, the probability of extreme events such as droughts is expected to increase in the future. In such a scenario, multi-year drought can be encountered more frequently. Our setup enables us to conclude that adaptation strategies may be failing during multi-year droughts, when they are occuring subsequently and when the level of wealth is low for the farmers. Further research is required to study the adaptation strategies which may work in such scenarios.

Supplementary material. The supplementary material for this article can be found at https://doi.org/10.1017/S1355770X23000074

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Competing interest. The authors declare none.

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