Who carries the burden of climate change? Heterogeneous impact of droughts in sub-Saharan Africa*

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Abstract

Droughts can dramatically affect economic activities, especially in developing countries where more than half the labor force is in the agricultural sector. This paper highlights the causal impact of drought on income inequality using a new methodology known as the quantile treatment effect on the treated under the copula stability assumption. This method generalizes the difference-in-differences framework to the entire distribution. The methodology is applied to a geo-referenced and nationally representative household survey of two sub-Saharan African countries: Ethiopia and Malawi. The results show that droughts worsen income inequality in both countries. Lower-income quantiles are subject to a higher decrease in per capita income, up to 40% for the lowest-income quantile. In contrast, higher-income quantiles are largely unaffected or appear to benefit from the drought. These results are robust to several specifications and offer quantitative insights into how extreme weather conditions affect inequality dynamics in developing countries. Inequality formation is driven by differences in the ability to cope with droughts. The results show that wealthier households have a higher capacity to find alternative sources of income to prevent a welfare drop. In contrast, the most vulnerable households, particularly those that are low in assets, remote, or headed by females or older individuals, are most seriously harmed. Finally, consumption-smoothing behaviors and asset depletion strategies in middle-income households are also observed.

Keywords: Inequality, Drought, Adaptation, Africa

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1 Introduction

The increase in frequency and intensity of weather shocks provoked by climate change is a significant threat for sub-Saharan African countries, mainly because of their dependence on rain-fed agriculture and their lack of infrastructure (Tol 2018; Trisos et al. 2022). Extreme weather events strongly impact agricultural production on the continent, endangering food security and limiting its capacity for development (Tol 2018). While the literature has documented the average effect of weather shocks on various development outcomes, how these shocks differentially affect households' income remains unclear (Hallegatte and Rozenberg 2017). However, this differential effect is important since the overall level of inequality could rise due to the more frequent and intense shocks that sub-Saharan Africa is expected to experience in the future (Ranasinghe et al. 2021).

This paper explores the relationship between weather shocks and inequality in sub-Saharan Africa. Exploiting the severe drought of 2015 in Ethiopia and 2016 in Malawi, it uncovers how weather shocks impact real wages at different levels of the income distribution. For this purpose, it uses a new empirical causal inference methodology known as the quantile treatment effect on the treated (QTT) under the copula stability assumption. This methodology generalizes the difference-in-differences method to the entire outcome distribution and allows a measure of the unconditional quantile treatment effect on the treated (Callaway and Li 2019). When dealing with inequality, it is important as the focus is on unconditionally poor or rich households, and not highly educated households with relatively low or high wages, for example (Frölich and Melly 2013).

This new method is applied to three waves of geo-referenced and representative household panel data from LSMS-ISA, combined with a high-resolution statistical drought index: the Standardized Precipitation and Evaporation Index (SPEI) (Vicente-Serrano, Beguería, and López-Moreno 2010; Peng et al. 2020). Relative to other measures, this index presents the advantage of integrating the precipitation and temperature dimensions of droughts. Formally, the QTT is computed on the real income, consumption, and asset level of households affected by the 2015 drought in Ethiopia and the 2016 drought in Malawi in comparison with those unaffected by the drought. Mechanisms leading to the increase in inequality are then explored by looking at household characteristics that explain heterogeneity in the impact of drought on farm and off-farm income and by exploring the coping strategies used by different household typologies.

The results of this paper show that droughts widen the income distribution. Lower-income quantiles experience a significant decrease in per capita income, up to 40% for the lowest 10% of households. In contrast, the higher-income quantiles benefit from droughts in Ethiopia and are not impacted in Malawi. These results are robust in both countries for many empirical choices, namely those that (1) control for the socio-economic characteristics of households, (2) use alternative indexes to measure drought events, (3) consider potential spatial spillovers, and (4) remove threshold effects. Inequality formation is driven by wealthier households' greater ability to find alternative sources of revenue in Ethiopia's off-farm sector and Malawi's farm sector. Specifically, there is evidence of a sectoral reallocation of wealthy household activities in Ethiopia. These households take advantage of the higher productivity of the off-farm sector and benefit from the drought. The results also emphasize the high vulnerability of drought-affected households that are remote or headed by females or older individuals.

These findings represent a step forward in understanding the relationship between weather shocks and inequality. First, the use of counterfactual distribution allows the impact on inequality to be quantified. The result is strong and corresponds to an increase in the Gini coefficient of about 20% in both countries. Second, the methodology allows the observation of the impact on both sides of the distribution. To the best of my knowledge, this is the first study documenting how the sectoral reallocation provoked by the drought allows the highest-income households to benefit from a bad weather event. Finally, the results show how the difference in household coping strategies leads to different income structures and higher levels of inequality.

This study focuses on two strands of literature related to climate justice. The first explores how extreme weather conditions differentially impact households (Arslan et al. 2016; Sesmero, Ricker-Gilbert, and Cook 2018; Letta, Montalbano, and Tol 2018; Amare et al. 2021; Aggarwal 2021). They highlight climate variability's heterogeneous impact, mainly affecting vulnerable households. For example, Arslan et al. (2016) used Tanzanian smallholder data and calculated the income elasticity with respect to the last 10-year average of precipitation over income quantiles. They observed that lower-income households were more affected by rainfall deficits. Sesmero, Ricker-Gilbert, and Cook (2018) used panel data from Malawi collected between 2002 and 2009 to compute the income elasticity related to the growing season rainfall conditions over household assets' quantile level. They provide evidence that weather conditions affected low-asset households more because of their low capacity for income diversification. Whereas most former studies used panel fixed-effect models (Arslan et al. 2016; Sesmero, Ricker-Gilbert, and Cook 2018; Letta, Montalbano, and Tol 2018; Amare et al. 2021; Aggarwal 2021), this study instead uses an extension of the difference-in-differences method to estimate the causal impact of a drought on the whole outcome distribution. The main advantage of using the method of Callaway and Li (2019) is to consider the dynamic trend of inequalities in exploiting two pre-treatment periods to infer how inequality would have changed if there were no drought. Moreover, it measures the unconditional QTT, which is more relevant when dealing with overall inequality.[1] Lastly, the causal identification is non-parametric and relies on clear and realistic assumptions, and the counterfactual distribution is clearly identified.

The second line of inquiry examines the impact of weather anomalies on inequalities (Thiede 2014; Keerthiratne and Tol 2018; Paglialunga, Coveri, and Zanfei 2022; Palagi et al. 2022). Paglialunga, Coveri, and Zanfei (2022) has analyzed the effect of temperature and precipitation variations on the Gini coefficient in 150 countries. Their findings suggest that warmer temperatures and lower precipitation significantly drive income inequality, particularly in countries with high levels of agricultural activity. Similarly, in a cross-country analysis, Palagi et al. (2022) estimated the impact of precipitation on the bottom 50% income share. They show that extreme precipitation levels exacerbate income inequality in countries that are highly dependent on agriculture. While previous studies only relied on cross-country or cross-community comparisons and descriptive analyses (Thiede 2014; Keerthiratne and Tol 2018; Paglialunga, Coveri, and Zanfei 2022; Palagi et al. 2022), this study provides micro-level causal evidence of how a drought impacts inequality. Inequality is also measured by analyzing overall income distribution, which offers more comprehensive information than analyses using a single index, such as the Gini coefficient (Paglialunga, Coveri, and Zanfei 2022), the Theil index (Thiede 2014; Keerthiratne and Tol 2018), and the bottom 50% share of national income (Palagi et al. 2022).

This study also advances our understanding of other issues related to weather-shock-induced inequalities. First, the way in which heterogeneity in accessing coping strategies leads to increased inequality is analyzed by looking at the impact of droughts on farm and off-farm income and the heterogeneity of coping strategies used by different types of households. This analysis complements Sesmero, Ricker-Gilbert, and Cook (2018), who argue that the wealthiest households are more diversified by considering the dynamic of the diversification triggered by the shock. Second, the use of a single index

1. Quantile regression and panel fixed-effect models (used by (Arslan et al. 2016; Sesmero, Ricker-Gilbert, and Cook 2018; Letta, Montalbano, and Tol 2018; Aggarwal 2021)) estimate conditional QTT, which correspond to the treatment effect for given covariates. For example, controlling for education means looking at quantiles within each education class (see (Frölich and Melly 2013)). In studying inequality, the focus is on unconditionally poor or rich households, not highly educated households with relatively low or high wages, for example.

including both the temperature and precipitation dimensions of drought provides a more intuitive and easier-to-interpret representation of the impacts of droughts compared to most of the previous studies that considered diverse climate and weather measures with heterogeneous impacts on crop growth (Arslan et al. 2016; Sesmero, Ricker-Gilbert, and Cook 2018; Letta, Montalbano, and Tol 2018; Aggarwal 2021). Third, the use of real income as the outcome, in addition to consumption, helps to overcome two main biases identified in previous studies (Letta, Montalbano, and Tol 2018; Aggarwal 2021; Amare et al. 2021): namely, (i) overestimation of the impact of a shock on higher-income households due to the decrease in the proportion of income available for consumption as income levels fall (see figure A3), and (ii) neglect of auto-consumption, which is a non-negligible and unevenly distributed part of household income (De Magalhães and Santaeulàlia-Llopis 2018). Finally, the analysis focuses on two countries with different growth and inequality dynamics. This focus enhances external validity and sheds light on how structural dynamics shape access to coping strategies.

The article is organized as follows. Section 2 presents a literature review of the impact of drought in sub-Saharan Africa. Section 3 presents the data from Ethiopia and Malawi. Section 4 then describes the empirical model used. Section 5 presents the results. Section 6 concludes the paper by discussing the results, their policy implications, and future research paths.

2 Background

2.1 The multidimensional impact of drought

The World Meteorological Organization defines droughts as prolonged dry spells in the climate cycle caused by a lack of rainfall. According to the latest Intergovernmental Panel on Climate Change (IPCC) report, droughts are the main climate hazards impacting African livelihoods and well-being, and their impacts are multi-dimensional (Trisos et al. 2022). The key impacts include the reduction of economic output, especially agricultural production, and economic input, such as water and energy (Trisos et al. 2022). Droughts are classified into meteorological (precipitation deficits), agricultural (soil moisture deficits), ecological (plant water stress), and hydrological droughts (water shortages in streams or reservoirs), depending on the systems impacted. This study focuses on agricultural and ecological droughts, which cause the greatest socio-economic harm in rural Africa (Caretta et al. 2022). The latest IPCC report highlights the fact that with climate change, the current rise in temperature is accompanied by an increase in the frequency and intensity of extreme heat, which is likely to increase the occurrence of agricultural and ecological droughts in southwestern and southeastern Africa and Madagascar (Ranasinghe et al. 2021). In particular, agricultural and ecological drought occurrence will increase at two degrees warming in southwestern Africa at high confidence levels and in southeastern Africa and Madagascar at medium confidence levels (Ranasinghe et al. 2021). In that context, the consequences of such events must be addressed to develop effective public policies to mitigate poverty and inequality.

The socio-economic impacts of droughts are multi-dimensional. First, agricultural production is severely affected, mainly because over 95% of crops are rainfed in sub-Saharan Africa (FAO 2021). For example, in Malawi, the drought of 2016 caused yield declines of 32% to 34% (McCarthy et al. 2021). The decline in agricultural production reduces agricultural income and food auto-consumption for agricultural households, as well as food consumption of all households through the increase in prices for agricultural commodities and food scarcity (Baez, Caruso, and Niu 2020). Droughts also impact deforestation and forest development, leading to a decline in ecosystem services and a reduction of income based on forest products, considered a safety net for vulnerable households (Leblois 2021; Vaglietti, Delacote, and Leblois

2022; Meyer 2023). Additionally, they impact the availability and quality of water, causing health and conflict problems, as well as excessive mortality among livestock (Gautier, Denis, and Locatelli 2016). Considering that most of the population relies on smallholder agriculture and pastoralism, the drop in agricultural production indirectly impacts a large part of the economy, such as non-farm income (Wineman et al. 2017), nutrition (Tirado et al. 2015) and migration (Cai et al. 2016).

2.2 Household coping strategies and social inequality

Households use many strategies to anticipate risks (ex-ante) or cope with drought-related problems (ex-post). These strategies range from agricultural practices (crop diversification, livestock management) to household-level resource-smoothing strategies such as income diversification, migration, or financial tools (insurance or credit, for example) (Dercon 2002). There is a large body of literature studying the effectiveness and drivers of individual coping strategies, but few authors explore the links, synergies, and substitution between them (Gao and Mills 2018).

Implementing these strategies relies on the capital endowment of the households, whether it is social, human, financial, physical, or natural (Bailey, McCleery, and Barnes 2019; Paumgarten et al. 2020). For example, social networks, education, access to credit, livestock endowment, and proximity to common pool resources could allow access to diversified income sources. An extensive range of endowments to cope with weather shocks has been studied in the literature. For example, the livestock endowment is used as a buffer stock and acts as a self-insurance mechanism to cope with shocks (Fafchamps, Udry, and Czukas 1998). Considering natural capital, Noack, Riekhof, and Di Falco (2019) find that the ecosystem services provided by the biodiversity endowment allow crops to better resist weather shocks. Similarly, belonging to informal associations, a component of the social capital endowment, provides better access to credit and thus limits the depletion of household assets (Efobi, Atata, and Ajefu 2020). A capital endowment can help mitigate the risk of reduced consumption and incentivize farmers to adopt riskier technologies, such as increasing fertilizer use. (Dercon and Christiaensen 2011).

Following these observations, the most vulnerable households, which have barriers to the ownership of such capital, may not be able to cope with droughts and may thus be more affected, aggravating poverty and inequality. Regarding the direct effect on agricultural production, on the one hand, wealthier households have access to better agrarian assets, technologies, and soil quality, making them less vulnerable to weather shocks (Letta, Montalbano, and Tol 2018; Arslan, Belotti, and Lipper 2017). On the other hand, educated and high-income households may be more specialized in agriculture to focus on high-return activities despite the risk involved (Wuepper, Yesigat Ayenew, and Sauer 2018; Asfaw et al. 2019). Agriculture is often the most profitable activity in rural sub-Saharan Africa, and the wealthiest households are more prone to risky choices (Dercon and Christiaensen 2011; Asfaw et al. 2019). They may thus focus on agricultural activity and be strongly impacted by weather shocks, at least in the short run (Little et al. 2006; Gautier, Denis, and Locatelli 2016).

3 Data

This study uses three waves of geo-referenced and representative household panel data from LSMS-ISA, combined with a high-resolution drought index: the Standardized Precipitation and Evaporation Index (SPEI). This section describes the construction of the main variables and some contextual elements relating to Ethiopia and Malawi.

3.1 Context

Figures A6a and A6b show the number of people affected by agricultural droughts in Ethiopia and Malawi over 15 years up to the year of treatment. Both countries experienced only minor droughts between the year before the first wave of panel data and the second wave of panel data (2011 to 2014 in Ethiopia and 2010 to 2015 in Malawi) and experienced a drought that affected almost half of the households in the year of the third wave of panel data (2015 in Ethiopia and 2016 in Malawi). This drought pattern makes Ethiopia and Malawi ideal candidates for the empirical method described in the following section and is the primary reason for selecting these countries. Moreover, some other features make the analysis of these two countries of prime interest.

Both countries have characteristics that make them particularly vulnerable to climate variability. The agricultural sector is dominated by smallholder and rain-fed farms. Agriculture is the backbone of their economies, accounting for 31% and 22% of GDP and employing 67% and 77% of their total workforce, respectively (Ethiopia first throughout this paragraph) (World Bank 2018). The high poverty levels and low levels of education in these countries further amplify their vulnerability, as noted in the recent IPCC report (Trisos et al. 2022). 31% and 69% of the population lived below the poverty line in 2015 and 2016, respectively, and 14% and 52% of the population suffered from severe food insecurity in 2018, while only 52% and 62% of adults were literate, respectively (World Bank 2018).

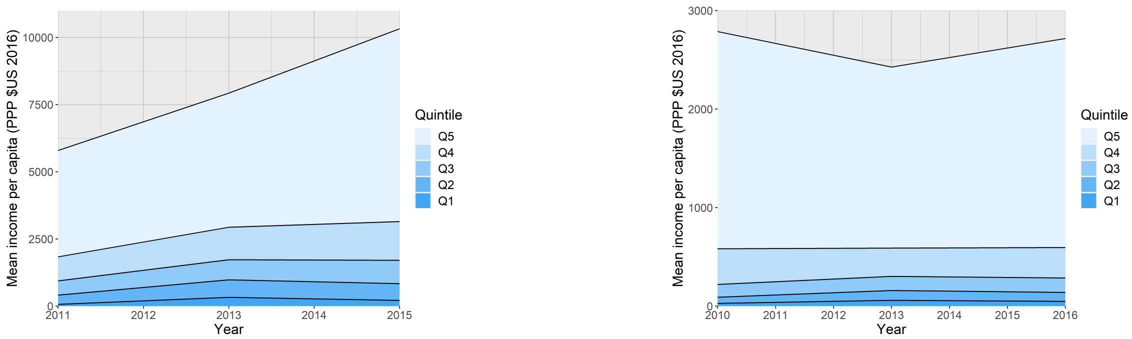
Both countries are representative of the low-income and mainly agricultural countries of sub-Saharan Africa. They both lie in around 30$^{\text{th}}$ place in terms of GDP per capita and Human Development Index out of 48 countries (World Bank data[2]).

However, there are some notable differences between the two countries. Ethiopia experienced growth in GDP per capita of 5–10% per annum between 2010 and 2016, while Malawi's GDP per capita remained relatively constant. Malawi's level of inequality and poverty is higher than Ethiopia's despite similar national incomes (World Inequality Lab data[3]). Figure 1 illustrates these differences in depicting the evolution of per capita income among household quintiles in the two countries.

Figure 1

Evolution of each quintile of per-capita income in Ethiopia and Malawi

(a) Ethiopia (LSMS) **(b)** Malawi (LSMS)



Note: Per capita income is computed with LSMS-ISA data as described in Section 3.2.

2. https://data.worldbank.org/. Accessed on 05/01/2023.
3. https://wid.world/. Accessed on 05/01/2023.

3.2 Household survey data

The present study uses a nationally representative panel of household surveys from Ethiopia and Malawi, consisting of three waves each, collected in 2011/2013/2015 for Ethiopia and 2010/2013/2016 for Malawi. The dataset was acquired as part of the World Bank's Living Standards Measurement Study-Integrated Surveys on Agriculture (LSMS-ISA) and is known for its quality and accuracy, which has been ensured through advancements in survey methodology, such as GPS measurement of plot size and household location, as well as the use of non-standard units to report agricultural production (Carletto and Gourlay 2019).

Households' agricultural income is calculated using the method proposed by De Magalhães and Santaeulàlia-Llopis (2018). The unsold production value is estimated using farm-gate prices and the World Bank protocol for imputing prices, based on the median value per unit at the smallest geographical level for which there were at least ten observations. This method considers the value of non-permanent and permanent crop production, livestock, and livestock products. The agricultural income equals the total value of agricultural production minus the associated costs, including wages for non-household members, inputs and seeds, rent for plots and materials, and transportation costs to market.

In addition to agricultural income, the study also considers other sources of household income, such as business profits, labor income (wage and ganyu[4]) and non-labor income (remittances, pensions, capital income, inheritance, and lottery winnings).

I have included income from coping strategies in real income for two main reasons. First, the variation in households' access to these strategies is the main mechanism studied which influences the heterogeneity in the impact of drought on income. Second, it is challenging to distinguish between income derived from coping strategies and regular household behavior.[5]

Most studies using LSMS-ISA data focus mainly on consumption data as a proxy for income due to their strong reliability and minimal missing data (Letta, Montalbano, and Tol 2018; Tesfaye and Tirivayi 2020; Diwakar and Lacroix 2021). However, when considering inequality, real income per capita seems more relevant since the share of consumption in income is not uniform across income levels of households and due to consumption-smoothing strategies that could reduce the real impact of drought. Figure A3 highlights the fact that the wealthiest households spend a smaller portion of their income on consumption. Hence, droughts may primarily impact their savings, with limited effects on their consumption. Moreover, it has been observed that consumption-smoothing strategies are prevalent in sub-Saharan Africa, which can hide the fact that households often have to sell assets to maintain their consumption levels, leading to long-term impacts (Carter et al. 2007; Carter and Lybbert 2012; De Magalhães, Koh, and Santaeulàlia-Llopis 2019). As a result, income provides more insight into the impact of drought on inequality, though it is often prone to greater measurement errors. LSMS-ISA employs advanced measurement techniques, especially on agricultural activity, that help minimize these errors and be more confident in the accuracy of income data.

This study leverages the total value of assets reported by households in Malawi to measure households' long-term wealth. However, such data is not available in Ethiopia. Therefore, an asset index is constructed using principal component analysis of housing characteristics, agricultural assets, and durable goods ownership, following the method proposed by Kafle, Jolliffe, and Winter-Nelson (2018).

All income components are winsorized at 1% and 99% to avoid measurement errors to reflect final

4. 'Off own-farm informal piecework labor, usually agricultural in nature, in which payment of food or cash is given' (Kerr 2005). Poorer households mainly use it as a complementary revenue. This revenue exists only in Malawi.

5. For instance, separating the portion of agricultural income that results from irrigation usage from that resulting from standard plot management sounds difficult.

income following De Magalhães and Santaeulàlia-Llopis (2018). Monetary values are expressed in 2016 dollar purchasing power parities (PPP), adjusted for inflation using World Bank data.[6] All outcomes are expressed in logarithms. Negative-income households are excluded from the analysis.[7]

3.3 Weather data

Agricultural drought is a shortage of soil moisture that affects crop growth, reducing crop yields (Chatterjee et al. 2022). Various measures of agricultural drought are used in the literature to capture the effect of weather on agricultural production. They rely either on meteorological data (e.g., Standardized Precipitation Index), on soil moisture data (e.g., Soil Moisture Anomaly Index), on vegetation cover (e.g., Normalized Difference Vegetation Index), or a combination of these sources.

This study uses the Standardized Precipitation and Evapotranspiration Index (SPEI), which evaluates the temporal deviation of the climate water balance, expressed as the difference between precipitation and potential evaporation, compared to the long-term average (Vicente-Serrano, Beguería, and López-Moreno 2010). This index is comparable across regions and includes the temperature component of drought through potential evaporation. Considering water balance allows for better-monitored soil moisture than the indexes considering precipitation anomalies alone. Moreover, this index depends only on meteorological data and, therefore, is independent of local agricultural practices linked to vegetation and soil moisture (Liu et al. 2015). Finally, it is widely used in socio-economic studies of the impacts of agricultural drought in sub-Saharan Africa (Kubik and Maurel 2016; Bozzola and Smale 2020; McCarthy et al. 2021; Defrance, Delesalle, and Gubert 2022; Zappalà 2023; Meyer 2023). Following the method of (Peng et al. 2020), I construct a high-resolution SPEI dataset using precipitation data from the Climate Hazards group InfraRed Precipitation with Station (CHIRPS) (Funk et al. 2015)[8] and evaporation data from the Global Land Evaporation Amsterdam Model (GLEAM) data (Martens et al. 2017).[9] The final SPEI resolution is 0.25 degrees.

As a robustness check, I also use the Standardized Soil Moisture Index (SSMI) during the main crop growing season to capture agricultural droughts. This index has been verified in both the Horn of Africa and East Africa (Agutu et al. 2017; Agutu et al. 2020). The Standardized Soil Moisture Index (SSMI) directly measures the soil moisture deficit, which defines agricultural drought. Soil moisture data is sourced from the Famine Early Warning System Network (FEWS NET) Land Data Assimilation System (FLDAS).[10] These data are calculated through simulations forced by CHIRPS precipitation data and evaporation and runoff data from the Noah model. The Noah model incorporates MODIS land cover data and Food and Agriculture Organization (FAO) soil data and is commonly used in atmospheric and land modeling studies.

As in Agutu et al. (2017) and Agutu et al. (2020), Agnew (2000)'s scale defines the threshold for agricultural drought. When the mean of the 3-month SPEI or 3-month SSMI is less than -0.84 during the growing season, the household experiences a drought. This measure corresponds to the occurrence of a drought every five years. The 3-month SPEI during the growing season is used as the baseline measure of drought. Other measures are used in robustness checks.

Figure A7 presents the distribution of the mean SPEI in the growing season at the period of the

6. https://data.worldbank.org/. Accessed on 05/01/2023.

7. Negative-income households represent fewer than 10% of households in both countries. These data contain measurement errors, mainly due to bad agricultural production reports. Their inclusion only changes the results for the first income decile, leading to a very wide confidence interval. It is common in the literature to remove these households (Arslan et al. 2016; De Magalhães and Santaeulàlia-Llopis 2018).

8. https://www.chc.ucsb.edu/data/chirps accessed on 04/05/2022.

9. https://www.gleam.eu/ accessed on 03/05/2022.

10. https://disc.gsfc.nasa.gov/datasets/FLDAS_NOAH01_C_GL_MA_001/summary accessed on 29/09/2022.

drought in both groups. The intensity of drought in the treated group is relatively homogeneous in both countries. No household experienced an extreme drought ($SPEI \leq -1.65$) and fewer than 25% of households experienced a severe drought ($SPEI \leq -1.28$). The distribution of the SPEI in the control group is relatively homogeneous in both countries. It is centered around -0.2 and -0.5 in Ethiopia and Malawi with a standard deviation of 0.4 and 0.2 respectively. Almost no households experienced an excess of water during the drought year.

3.4 Summary statistics

Table 1
Summary statistic of 2013 for Ethiopia

Drought in 2015		No			Yes		
Variable	N	Mean	SD	N	Mean	SD	Test
Income per capita ($ PPP)	1306	2613.26	3386.5	1616	3101.18	3705.57	T.test <0.01
Consumption per adult eq ($ PPP)	1238	4525.05	3542.91	1584	6224.33	4125.31	T.test <0.01
Asset index	1306	-0.36	1.76	1616	-0.13	2.13	T.test <0.01
Farm income per cap ($ PPP)	1306	1604.87	2042.1	1616	1742.6	2225.26	T.test 0.08
Non-farm income per cap ($ PPP)	1306	1008.4	2991.81	1616	1358.58	3276.82	T.test <0.01
Nb members	1306	5.79	2.56	1616	5.43	2.47	T.test <0.01
Age of the head	1306	44.79	14.9	1616	48.28	15.47	T.test <0.01
Rural household	1306	0.9	0.29	1616	0.9	0.3	T.test 0.49
Female-headed	1306	0.25	0.43	1616	0.28	0.45	T.test 0.04
Access to city (< 200 km)	1306	0.28	0.45	1616	0.44	0.5	T.test <0.01
Years of education	1306	2.31	3.87	1616	1.66	3.39	T.test <0.01

Notes: T.test presents the p-value of a student test of equality of mean in the treatment and the control group.

Table 2
Summary statistic of 2013 for Malawi

Drought in 2016		No			Yes		
Variable	N	Mean	SD	N	Mean	SD	Test
Income per capita ($ PPP)	646	910.68	1410.04	792	558.58	1090.81	T.test <0.01
Consumption per adult eq ($ PPP)	646	1020.4	1319.6	792	740.5	1241.79	T.test <0.01
Asset value per cap ($ PPP)	646	1415.84	3335.19	792	1055.87	2698.33	T.test 0.03
Farm income per cap ($ PPP)	646	284.49	568.73	792	202.07	371.88	T.test <0.01
Non-farm income per cap ($ PPP)	646	626.07	1358.11	792	344.77	1012.52	T.test <0.01
Nb members	646	5.49	2.37	792	5.17	2.11	T.test <0.01
Age of the head	646	45	14.42	792	44.04	15.42	T.test 0.22
Rural household	646	0.64	0.48	792	0.82	0.39	T.test <0.01
Female-headed	646	0.18	0.39	792	0.29	0.45	T.test <0.01
Access to city (< 200 km)	646	0.75	0.43	792	0.76	0.43	T.test 0.56
Years of education	646	6.58	4.42	792	5.42	4.21	T.test <0.01

Notes: T.test presents the p-value of a student test of equality of mean in the treatment and the control group.

Tables 1 and 2 present descriptive statistics of households affected or not by the drought of 2015 in Ethiopia and 2016 in Malawi in the survey wave prior to the drought. In Ethiopia, households that experienced the drought tend to be slightly richer, with the average per capita income respectively equal to 3,101$ PPP and 2,613$ PPP, and the average per capita consumption respectively equal to 5,079$ PPP and 3,679$ PPP. In addition, the heads of these households are older and have fewer years of education.

In Malawi, households that experienced the drought are generally poorer, with the average per capita income respectively equal to 552$ PPP and 911$ PPP and the average per capita consumption respectively equal to 649$ PPP and 904$ PPP. Moreover, the treatment group has a higher proportion of rural households and those headed by females.

The lack of balanced descriptive statistics does not appear to be a problem, as the methodology used only requires changes in outcome distribution to be parallel in the treatment and the control group. Figure A8a and A8b show changes in the distribution of per capita income in the control and treatment groups. As confirmed by the tests made in sections 5.1.1 and 5.2.1, changes in the distribution of per capita income are relatively parallel in the treatment and the control group in the pre-treatment periods. Moreover, I also use a propensity-score method based on household characteristics to improve the comparability of the treatment and control groups.

4 Empirical model

4.1 Estimation of the distributional impact of drought

The identification strategy is based on drought variability over time and space. I use characteristics of two countries that experienced agricultural droughts, which affected about half of the panel households in the year of the third wave of panel data, although those countries experienced only minor droughts from the start of panel data collection until the year before the last wave (see Figure A6). These particularities allow the use of the QTT framework developed by Callaway and Li (2019). The idea is to generalize the difference-in-differences framework to the entire outcome distribution to identify the QTT. The outcome dynamics in non-affected households and past changes in each outcome quantile makes it possible to build the counterfactual distribution. This estimation relies on an assumption of conditional constancy of income mobility in the absence of treatment, which seems reasonable when considering yearly income data (Callaway 2021). The main contribution of this method is to use two pre-treatment periods to infer the inequality dynamic if there were no droughts. In comparison to the quantile regression and panel fixed-effect models, which measure the QTT conditional on covariates and unobserved heterogeneity, it measures the unconditional QTT, corresponding to the difference between treated and untreated quantile outcome, if treated individuals had been chosen randomly (Frölich and Melly 2013). Considering other methods measuring the unconditional QTT (Athey and Imbens 2006; Firpo 2007; Chernozhukov, Fernández-Val, and Melly 2013), the assumptions made are less restrictive and more realistic with respect to the experimental design.[11] Although some studies have already used the difference-in-differences framework to study the impact of droughts (Joshi 2019; Becerra-Valbuena and Millock 2021), to the best of my knowledge, this is the first study to use the distributional difference-in-differences framework on the impact of extreme weather conditions.

Three periods of time (t, $t-1$, and $t-2$) are considered, in which part of the population is affected by a drought (treated group) between periods $t-1$ and t. Households have potential outcomes, either in the treated group ($D=1$) or in the untreated group ($D=0$), Y_{Dt}. The quantile treatment effect on the treated is then equal to:

11. In particular, the assumptions required for the Change-in-Changes method (Athey and Imbens 2006) and the propensity score re-weighting procedure (Firpo 2007) are not verified in the pre-treatment periods. On the one hand, Athey and Imbens (2006) assumes that the distribution of unobservable data does not change over time which is unlikely considering the pre-trend dynamic of income and inequality (see Figure 1). On the other hand, Firpo (2007) assumes that potential outcomes are not influenced by unobservable data whereas they are likely to play a key role in our setting: tables 1 and 2 show that differences in outcomes between groups are unlikely to be explained only by the covariates considered. Considering a difference-in-differences framework seems to be more reasonable to tackle issues related to omitted variable bias. The method used by Chernozhukov, Fernández-Val, and Melly (2013), which also makes more restrictive assumptions, is considered in robustness checks (see Section 5.1.2)

$$QTT(\tau) = F^{-1}_{Y_{1t}|D=1}(\tau) - F^{-1}_{Y_{0t}|D=1}(\tau) \tag{1}$$

With τ in $[0,1]$, and F_W represents the distribution of a random variable W.

The observed distribution of the potential outcome in the treated group estimates the first term. The challenge is to estimate the counterfactual distribution of the potential outcome of the treated group if there were no treatment.

To estimate the counterfactual distribution, Callaway and Li (2019) shows that the standard 'parallel trends' assumption is insufficient. It is necessary to add two assumptions: (1) the distributional difference-in-differences assumption, which generalizes the parallel trend assumption to the entire distribution, and (2) the copula stability assumption, which supposes that the changes in potential outcome in each quantile between t and $t-1$ would have been equivalent to the change observed between $t-1$ and $t-2$ if there were no treatment.

The unconditional distributional difference-in-differences assumption supposes that the distribution of the change in untreated potential incomes is independent of belonging to the treated or the untreated group. The copula stability assumption supposes that the dependence between $(\Delta Y_{0t}|D=1)$ and $(\Delta Y_{0t-1}|D=1)$ is the same as the dependence between $(\Delta Y_{0t-1}|D=1)$ and $(\Delta Y_{0t-2}|D=1)$. They can be respectively written as:

$$\Delta Y_{0t} \perp\!\!\!\perp D \tag{2}$$

$$C_{\Delta Y_{0t}|D=1, \Delta Y_{0t-1}|D=1}(.,.) = C_{\Delta Y_{0t-1}|D=1, \Delta Y_{0t-2}|D=1}(.,.) \tag{3}$$

With C_{W_1,W_2} the copula of the random variables W_1 and W_2.

The independence of ΔY_{0t} and D (2) seems reasonable since I use a standardized measure of drought events, making their occurrence a priori random in the country.[12] This assumption is equivalent to supposing that distributions of the change in per capita income in the treated and the control group would have been equal if there were no drought and could be tested in the pre-treatment period. The copula stability assumption (3) can then be interpreted as the constancy of income mobility over time in the treatment group if there were no treatment, i.e., the correlation between the ranks in the income distribution of the treatment group would not have changed over time if there were no drought. As pointed out by Callaway (2021) in the appendix, the copula stability assumption is likely to be satisfied when dealing with yearly income data without major economic shocks. For example, it is strongly verified in the United States. However, to the best of my knowledge, no study in sub-Saharan Africa has already described changes in long-term income mobility, due to lack of data. Verifying this assumption in the pre-treatment period would have required additional waves of household surveys. Consequently, I test it in the control group, which remains unaffected by the drought, and where income mobility may have changed similarly to the treatment group in the absence of the drought.

Under these assumptions, Callaway and Li (2019) shows that the counterfactual distribution can be estimated by:

$$\hat{F}_{Y_{0t}|D=1}(y) = \frac{1}{n_D} \sum_{i \in \mathcal{D}} \mathbb{1}\{\hat{F}^{-1}_{\Delta Y_t|D=0}(\hat{F}_{\Delta Y_{t-1}|D=1}(\Delta Y_{it-1})) \leq y - \hat{F}^{-1}_{Y_{t-1}|D=1}(\hat{F}_{Y_{t-2}|D=1}(Y_{it-2}))\} \tag{4}$$

With n_D, the number of observations in the treated group, and $\mathcal{D}$, the set of treated individuals.

To increase the likelihood of the distributional difference-in-differences assumption holding, I consider the case in which this assumption holds after conditioning on some covariates, including the

12. The probability of being affected by a drought is the same for all households and is equal to 0.2.

number of household members, the education, sex, and age of the head, and the fact of living in a rural area, all of which are likely to play a part in determining the outcome.

Callaway and Li (2019) shows that under the conditional distributional difference-in-differences assumption,[13] the QTT is well defined and it is possible to estimate the counterfactual distribution by:

$$\hat{F}^{p}_{Y_{0t}|D=1}(y) = \frac{1}{n}\sum_{i=1}^{n}\frac{(1-D_i)}{p}\frac{\hat{p}(X_i)}{(1-\hat{p}(X_i))}\mathbb{1}\{\Delta Y_{t,i} \leq y\} \Big/ \frac{1}{n}\sum_{i=1}^{n}\frac{(1-D_i)}{p}\frac{\hat{p}(X_i)}{(1-\hat{p}(X_i))} \tag{5}$$

With $\hat{p}(x)$ an estimator of the propensity score, p the number of treated individuals, n the number of observations, and D_i a binary for belonging to the treatment group.[14]

Similarly to the common difference-in-differences framework, the main assumptions cannot be directly tested but can be verified in pre-treatment periods. The unconditional distributional difference-in-differences assumption is tested in the pre-treatment period (between $t-1$ and $t-2$), using the Kolmogorov-Smirnov test.[15] However, as we dispose of only two pre-treatment periods for both countries, the copula stability assumption cannot be tested in pre-treatment periods with our panel data. Thus, I test whether this assumption was realistic in both countries' control groups. I do this by looking at changes in the period-over-period income dependence using Spearman's rho, as recommended by Callaway (2021) in their online supplementary appendix on the copula stability assumption.

4.2 Impact of the drought on farm and non-farm income

To understand the impact of the drought on inequality, I measure the causal impact of the drought on different components of household income, according to the household's wealth level. I do this using the semi-parametric difference-in-differences estimator developed by Abadie (2005) to analyze how agricultural droughts impact households differently based on their characteristics. This estimator improves the comparability of the treatment and control groups by re-weighting the average treatment effect on the treated based on the propensity score of being treated, given characteristic X. Assuming the existence of the expectation of the outcome variable, the average treatment effect on the treated (ATT) is equal to:

$$ATT = E[(Y_{1t} - Y_{0t}) * \frac{D - P(D=1|X)}{P(D=1|X) * (1 - P(D=1|X)}]$$

Propensity scores are estimated with the series logit estimator such as:

$$P(\widehat{D=1}|X) = \Lambda(\hat{\alpha_0} + \sum_{k=1}^{K}\hat{\alpha_k}X^k)$$

With Λ, the logistic function, and α_k the estimation parameters.

This method makes it possible to compute a linear least square approximation of the conditional average treatment effect on the treated. Given a set of covariates Z, the conditional average treatment effect on the treated, defined by: $CATT : z \rightarrow E[Y_{1t} - Y_{0t}|D=1, X, Z=z]$, can be linearly approximated by:

$$\theta_0 = \arg\min_{\theta\in\Theta} E[P(D=1|X) * \{\frac{D - P(D=1|X)}{P(D=1|X) * (1 - P(D=1|X)} * (Y_{1t} - Y_{0t}) - Z'\theta\}^2]$$

13. This assumption is similar to Equation 2 after conditioning on covariates: ΔY_{0t} II $D|X$

14. The QTT under the copula stability assumption was computed using the qte R package developed by Callaway and Li (2019)

15. The test is computed using the stat R-package

With $\Theta \subset \mathbb{R}^k$, and k the number of covariates in Z.

These results hold under two assumptions: (1) the conditional parallel trend assumption, $E[Y_{0t} - Y_{0t-1}|D = 1, X] = E[Y_{0t} - Y_{0t-1}|D = 0, X]$ and (2) a support assumption for the propensity score, $P(D = 1) > 0$ and $P(D = 1|X) < 1$ with a probability of 1. The distributional difference-in-differences assumption implies the first assumption (equation 2) and can be tested in the pre-treatment period. The second assumption is verified in the estimation of the propensity score.

I use the semi-parametric difference-in-differences estimator to measure the mean impact of agricultural drought on per capita income, per capita farm income (including self-consumed production and off-own-farm agricultural employment), and per capita non-farm income (including self-employment revenue and capital revenue). Moreover, I measure how the impact of the drought varies with household characteristics, including the household's assets,[16] the gender, education, and age of the household head, and the fact of living in a rural area. The standard errors are computed following (Abadie 2005)'s method and include the errors related to the estimation of the propensity score.[17]

5 Results

This section presents the results of the impact of drought on inequality in Ethiopia and Malawi. For each country, it presents the distributional impacts of the drought, a discussion of the assumptions made, a description of robustness checks, and the mechanisms leading to the increase in inequality. All outcomes are expressed in logarithms. Therefore, the QTT can be interpreted as an elasticity.

5.1 Ethiopia

5.1.1 The distributional impact of drought

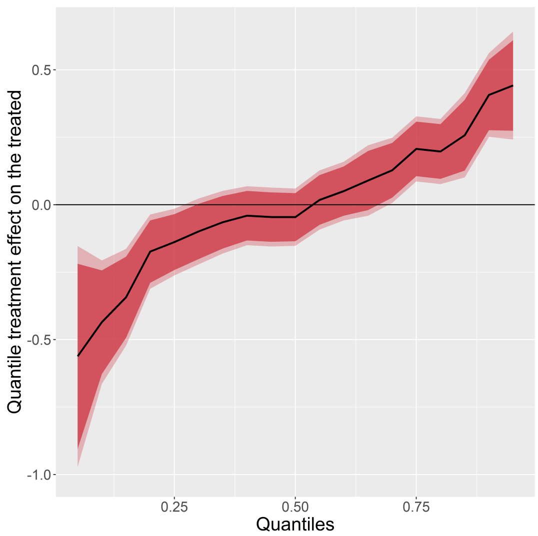
Impact on income, consumption and asset levels. Figure 2 shows the quantile treatment effect on the treated using Callaway and Li (2019)'s method both with and without covariates. As pointed out, the quantile treatment effect on the treated refers to the difference between the actual quantile function of per capita income and the counterfactual quantile function if there were no drought among the treated units. First, the drought episode has a widening effect on income distribution, mainly due to a higher proportion of households becoming poorer. Specifically, the 30% households at the bottom of the income distribution experienced a significant decrease in income, estimated at around 30%. On the other hand, households at the top of the income distribution benefit from the drought. The 25% highest-income households experienced a significant increase in income. These results suggest that the drought exacerbates income inequality and deepens poverty. Compared to the counterfactual distribution, the Gini coefficient rises by 23% in the treated group, going from 0.41 to 0.51. The region impacted by the drought goes from relatively equal to relatively unequal, considering values of the Gini coefficient in other countries of sub-Saharan Africa.[18] The number of people below the 1.90$ poverty line by 38%, increasing from 11% to 15% of the total population.

Results for consumption per adult equivalent[19] do not present the same pattern. The drought only significantly affects the first decile of the consumption distribution, while the rest of the distribution is

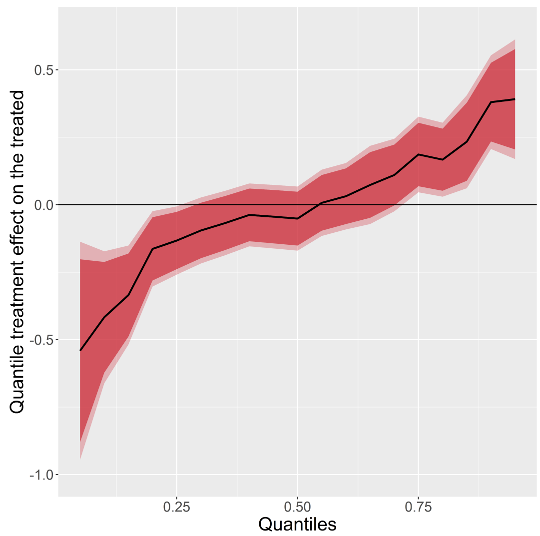
16. Asset index for Ethiopia and Asset value for Malawi
17. Abadie's semi-parametric difference-in-differences estimator is computed using the ASDID Stata package (Houngbedji 2016)
18. The most unequal country is South-Africa with a Gini coefficient of 0.63, and the most equal is Guinea, with a Gini coefficient of 0.3.
19. Consumption per adult equivalent is used as it is considered to be a better measure of household welfare. The results with consumption per capita are very similar.

Figure 2
Quantile Treatment Effect on Copula Stability assumption for Ethiopia

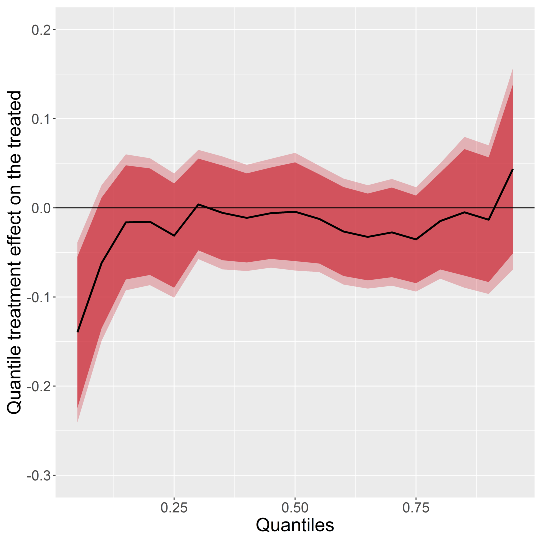
(a) Income per capita (no covariates)



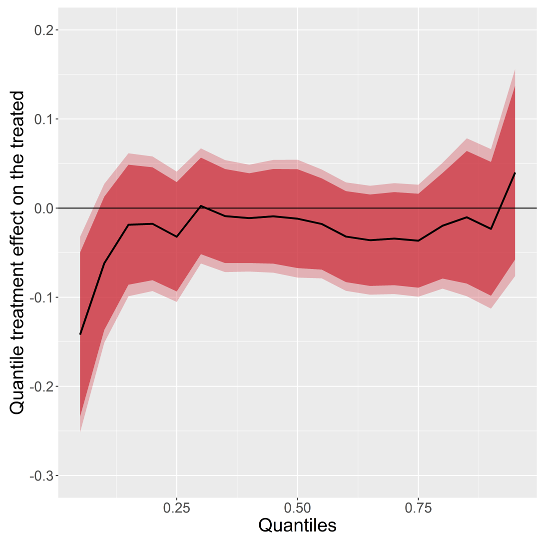
(b) Income per capita (covariates)



(c) Consumption per adult eq (no covariates)



(d) Consumption per adult eq (covariates)



Note: Quantile Treatment Effect on the treated is computed with the method of Callaway and Li (2019) for income per capita (top) and consumption per adult equivalent (bottom), without covariates (left) and with covariates (right), including rural dummy, head education, head age, female-headed household dummy, number of household's members and number of household's adult equivalent. The Quantile Treatment Effect on the treated is estimated for each 0.05 interval for $\tau \in [0.05, 0.95]$. The inclusion of covariates is made through propensity score matching. Symmetric confidence intervals at 0.05 and 0.1 levels are computed with 500 bootstrap iterations.

almost unaffected. These results suggest that, apart from the 10% poorest, households employ effective consumption-smoothing strategies, allowing them to maintain their consumption habits despite the income drop. Moreover, it highlights the importance of using real wages to measure the impact of the drought on the highest-income households. The proportion of income used for consumption decreases with increasing income levels, as shown in figure A3a. Consequently, the increase in income is not directly related to the consumption level and is likely to be saved. It is essential to exercise caution when interpreting this last result. The distributional difference-in-differences assumption may not hold when there is a difference in consumption levels between the treatment and control groups since the level of consumption influences consumption behaviors.

Households may deplete their assets to maintain their consumption levels, which could impact their income in the long term (Little et al. 2006). Figure A11 shows that the impact of the drought on the asset index (including housing characteristics, agricultural assets, and goods) is concentrated in the middle of the asset distribution. Poorer households do not have assets to deplete, while the wealthiest households do not need to deplete their assets to maintain their livelihoods. This result suggests that middle-income households may face a higher long-term impact of the drought. However, this conclusion should be considered cautiously due to the limited information available on households' ability to restore their assets and the potential impact of asset depletion on future income.

Given the correlation between the rankings in income, consumption, and asset distribution,[20] we can draw the following inferences. The least affluent households saw a significant decline in income, which is, to a lesser degree, reflected in their consumption levels. Households of moderate wealth did not experience impacts on income and consumption, but they had to exhaust their assets to sustain their livelihoods, potentially leading to long-term income effects. Conversely, the wealthiest households gained income benefits from the drought and did not need to deplete their assets.

Assumption discussion As explained in Section 4.1, these results hold under two main assumptions: the distributional difference-in-differences assumption (equation 2) and the copula stability assumption (equation 3).

Figure A9 presents the distribution of change in per capita income, per adult equivalent consumption, and asset index between $t-1$ and $t-2$ for the treated and the control group in Ethiopia and table A4 shows the result of the Kolmogorov-Smirnov test for unconditional equality of distribution. They show that the equality of distribution of the treatment and the control group hypothesis cannot be rejected at the 10% level for the per capita income and the asset index. As discussed above, the assumption may not hold for the consumption per adult equivalent, as the level of consumption is not similar in both groups, and consumption behaviors depend on the income level.

Figure A10 shows that changes in period-over-period income dependency in the three waves for the control group is relatively constant over time. Moreover, income mobility is relatively constant in the treatment group, which gives confidence in this assumption. This result aligns with Namirembe-Kavuma and Bbaale (2019)'s observations, who found no variation in income mobility in Uganda between their three waves of panel data. The stability of income mobility depends on the structure of the economy (Dzanku 2020; Mekasha and Tarp 2021). In Ethiopia, the agricultural sector employs most of the population, and the percentage of people working in this sector has not changed much in the last 20 years, dropping slightly from 80% to 76% (World Bank data from 2000 to 2020.[21]) Thus, assuming constant income mobility seems reasonable.

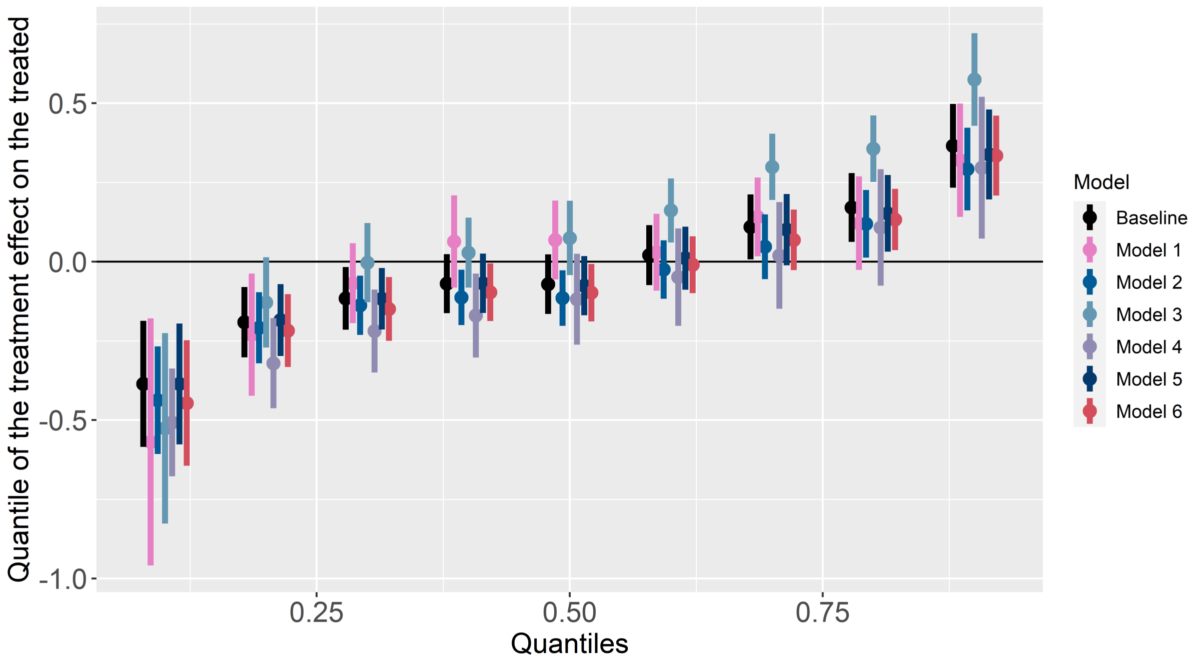
20. Spearmann correlation is equal to 0.4 for per capita consumption and per capita income, and 0.3 for asset index and per capita income

21. https://data.worldbank.org/. accessed on 05/01/2023

5.1.2 Robustness check

Robustness of parameters To assess the robustness of these results, I conducted additional tests by incorporating the following modifications into the model: (1) Using alternative drought indicators such as the 1-month SPEI, the 6-month SPEI, and the 3-month SSMI (Model 1, Model 2, and Model 3, respectively), (2) Using the minimum value of the 6-month SPEI during the growing season instead of the mean value (Model 4), (3) Removing households close to the drought threshold from the control group to prevent threshold effects[22] (Model 5), and (4) Omitting the buffer around the household location when retrieving weather data (Model 6). The results of these modifications are illustrated in Figure 3, which displays the QTT for the baseline model and all other models (Models 1 to 6). Despite slight variations, all models show a similar pattern where the bottom of the income distribution experiences a significant decrease in income while the top benefits from the drought. However, the impact at the top of the distribution varies slightly across models, with the use of the 3-month SSMI exhibiting a more substantial effect than the baseline.

Figure 3
Robustness of the Quantile Treatment Effect under Copula Stability assumption and diverse specifications



Note: The Quantile Treatment Effect on the treated is computed with the method of Callaway and Li (2019) under the following specifications: (1) use of 1-month SPEI (Model 1), (2) use of 6-month SPEI (Model 2), (3) use of 3-month SSMI (Model 3), (4) use of the minimum of SPEI (Model 4), (5) remove untreated units next to SPEI threshold (Model 5), and (6) remove buffer to compute SPEI (Model 6). The Quantile Treatment Effect on the treated is estimated for each 0.05 interval for $\tau \in [0.05, 0.95]$. Symmetric confidence intervals at 0.05 levels are computed with 500 bootstrap iterations.

Spatial spillovers and threshold effect Reducing drought events to a binary variable poses the potential risk of a threshold problem. Some households in the control group may experience droughts nearly

22. All households with a mean value for the 3-month SPEI of between -0.84 and -0.75 are excluded from the control group, as they may have been impacted.

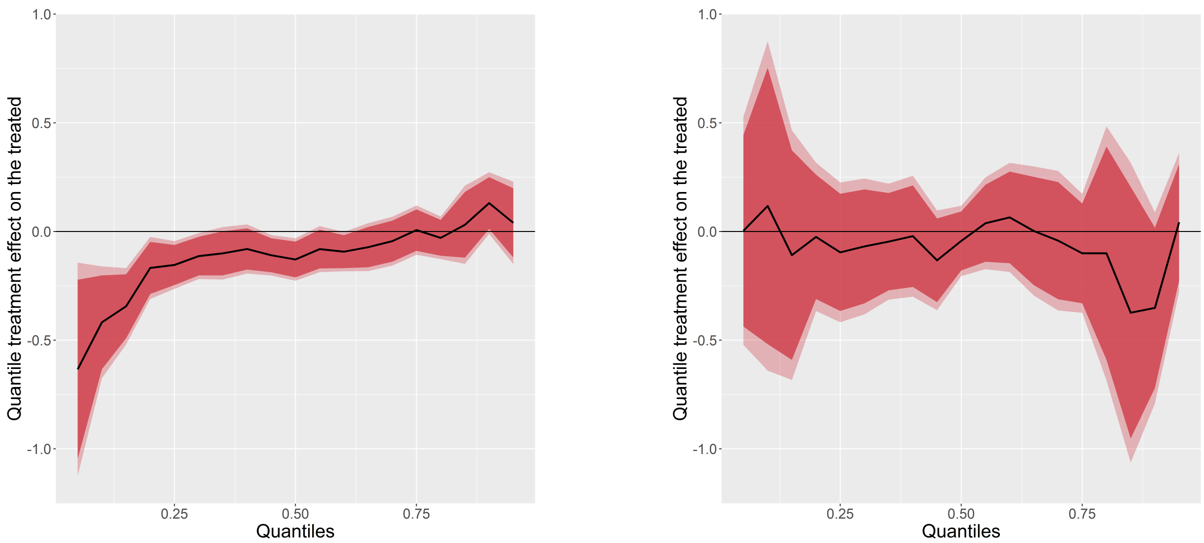
as intense as those in the treatment group. Additionally, droughts in a specific region of a country can also affect other areas through local food markets (Brown and Kshirsagar 2015), migration (Becerra-Valbuena and Millock 2021), and energy production[23] (Nhamo et al. 2018), among other factors. As a result, the effects measured using the distributional difference-in-differences method could be underestimated since the drought also impacts the control group. To address this limitation, I use the method developed by Chernozhukov, Fernández-Val, and Melly (2013), which consists of building the counterfactual distribution of the outcome in the treatment group using a model based on previous observations from the treatment group. Detailed information about this method is available in Appendix B.1.

Figure 4a shows the quantile treatment effect on the treated using a model on the pre-treatment period to infer the effect of the treatment, using distribution regression. These results are consistent with those obtained from the previous method. Droughts widen the distribution of income.

Figure 4
Counterfactual analysis to build Quantile Treatment Effect of income per capita of Ethiopia

(a) QTE on treatment group

(b) QTE on control group



Note: The Quantile Treatment Effect on the treated is computed with the method of Chernozhukov, Fernández-Val, and Melly (2013) (see section B.1). The covariates used to model the per-capita income include human capital (education), natural capital (local crop suitability index, forest cover, and water proximity), social capital (female household head, number of household members), and physical capital (rural household, market access). The Quantile Treatment Effect on the treated is estimated for each 0.05 interval for $\tau \in [0.05, 0.95]$.

To assess the quality of the predictive distribution regression model, I applied the previous method to the untreated units. Figure 4b shows that the difference between the counterfactual distribution and the actual distribution is not significantly different from 0 in all quantiles at the 10% level. This result indicates that the treatment does not impact the control group at each quantile of the distribution and supports the initial model's validity and the negligible effect of spillovers. However, the confidence interval is wide, suggesting some imprecision.

23. In Ethiopia and Malawi, most of the electrical energy production comes from hydroelectric power generation

5.1.3 Mechanisms

The QTT, either using the copula stability assumption or with counterfactual inference, shows that agricultural droughts widen the income distribution. However, it does not provide information on which households are the most affected by the drought, as households can move in the income distribution. This part aims to explore the mechanism behind the results. It examines the characteristics of the most affected households, the drought impacts on the different components of household income (farm and off-farm), and the household coping strategies used according to their wealth level.

Table 3
Conditionnal average treatment effect on the treated

ATT	Total income		Farm income		Non-farm income	
	(1)	(2)	(3)	(4)	(5)	(6)
Drought	0.03	0.06	−0.22*	−0.21*	0.13	0.16
	(0.07)	(0.07)	(0.13)	(0.12)	(0.16)	(0.16)
Asset index		0.08**		−0.17		0.24***
		(0.04)		(0.11)		(0.08)
Age of the head		−0.02***		−0.01		−0.01
		(0.00)		(0.01)		(0.01)
Female headed		−0.34**		−0.24		−0.45
		(0.17)		(0.32)		(0.35)
Rural household		0.17		−0.54		1.56***
		(0.35)		(0.69)		(0.57)
Observations	2922	2922	2922	2922	2922	2922

Note: Abadie's semi-parametric difference-in-differences estimator for per capita income (1,2), farm per capita income (3,4), and non-farm per capita income (5,6). The propensity score is computed with a logistic model including covariates for living in rural areas, having access to a city (living at less than 400 kilometers of a city of 50,000 inhabitants), the age of the household head, the number of household members, and being a female-headed household. All variables are centered. Standard errors including errors related to the propensity score estimation following Abadie2005 are in parentheses. I denoted significance at 10% with *, 5% with **, and 1% with ***

Non-farm and farm income Table 3 shows Abadie's semi-parametric difference-in-differences estimator presented in section 4.2 and applied to per capita income (1, 2), per capita farm income (3, 4), and per capita non-farm income (5, 6) for the ATT (1, 3, 5) and the linear approximation of the conditional ATT (2, 4, 6). The conditional ATT measures how the treatment effect on the treated varies with some covariates. Relying on a long-term measure of wealth (the asset index), the objective is to assess how farm and non-farm income are impacted by the drought, whether these impacts are different for poor and rich households, and what are the other household characteristics linked to a more pronounced impact on those incomes.

Considering per capita income, the ATT is non-significant, in line with the results found with the QTT. The conditional ATT shows that the drought impact is significantly higher for households with low assets or headed by females or older individuals. For example, if the head is a female, the impact of the drought is 34% greater than for those with a male head, all other things being equal.

Farm and non-farm income analysis further highlights the heterogeneous effects on households. On average, households experience a significant decrease in per capita farm income of 22%, which is unsurprising as agricultural drought primarily impacts farm production. However, no characteristics considered are linked to a mitigation of the impact of droughts on farm income. The main driver of heterogeneity between households concerns per capita non-farm income. High-asset households significantly increase their non-farm per capita income when facing droughts compared with other households. This increase in non-farm income is mainly concentrated in rural areas.

The results suggest that during agricultural droughts, rural households attempt to compensate for their agricultural production losses by finding alternative sources of revenue. Households possessing more assets tend to be more successful in identifying alternative income streams within the non-farm sector. In contrast, the most vulnerable households, which include those with limited assets, led by females or older individuals, lack the same capacity. As a result, these households experience a more pronounced impact, contributing to a rise in inequality.

Coping strategies In Appendix B.3, I provide evidence of the use of some strategies to cope with the drought. Table 4 reports a summary of the results of this analysis.

Households affected by the drought make ex-post adjustments to their agricultural practices.[24] They are more likely to adopt irrigation and increase their use of inorganic fertilizers. While these practices are associated with higher crop income, they mitigate the impact of the drought only on an extensive margin (more people adopting strategies linked to higher income) and not on the intensive margin (irrigation and fertilizers being more effective for people impacted by the drought.[25]) Crop diversification leads to higher crop income and stronger resilience to drought impacts. However, households do not diversify their crops when facing droughts, probably due to the time required for implementation. These results align with the literature on agricultural practice adoption (Aker and Jack 2021; McCarthy et al. 2021), which shows how agricultural practices can offset the impact of weather shocks.

Irrigation, use of fertilizers and diversification can also be seen as ex-ante strategies. Households implement them before the drought as risk management strategies. The fact that these practices are linked to higher crop income shows that these practices are efficient.

Concerning non-agricultural practices, I find evidence that households, especially the wealthiest, significantly increase the time dedicated to off-farm labor and are more likely to experience the migration of a household member for work purposes. Additionally, the wealthiest households experience an increase in the remittances received. Their higher work opportunities and remittances drive the impact of the drought on inequality.

Better-off households The results suggest that the increase in per capita non-farm income for asset-rich households exceeds their per capita farm income loss, leading to an overall benefit from the drought. Several mechanisms could explain this fact.

The main explanation for the increase in the wealthiest households' income is linked to the drought-triggered reallocation from the farm to the non-farm sector. As shown in table A6, non-farm activities exhibit significantly higher labor productivity than farm activities in Ethiopia. When facing the drought, the wealthiest households decrease the time devoted to farm labor in favor of off-farm labor. As a result, they benefit from higher labor productivity, reflected in higher global income. Such observations align with the productivity gap measured by Gollin, Lagakos, and Waugh (2014), which finds that output per worker in non-agricultural activities was at least twice as high as in agriculture, controlling for hours worked and human capital differences. Thus, moving out of agriculture should bring significant income gains.

24. Ex-post is used as we observe some differences in implementation between the treatment and the control group at the time of the drought.

25. This result can sound counter-intuitive for irrigation, but can be explained by the difference in the propensity to adopt being linked to greater efficiency of adoption.

Table 4
Summary table of coping strategies used by households

Coping strategy	Country	Poor households	Rich households	Confidendence	Efficiency	References
Agricultural strategy						
Irrigation	Ethiopia	Yes	Yes	High	+++	Tables B1 and B3
	Malawi	Yes	Yes	Low	0	Tables B2 and B4
Diversification	Ethiopia	No	No	High	+++	Tables B1 and B3
	Malawi	No	No	High	++	Tables B2 and B4
Increase of the use of intrants	Ethiopia	Yes	No	High	++	Tables B1 and B3
	Malawi	No	No	High	+	Tables B2 and B4
Increase livestock income	Ethiopia	No	No	Low	NA	Table B1
	Malawi	No	Yes	High	+++	Table B2
Non agricultural strategy						
Temporal migration of a household member	Ethiopia	Yes	Yes (+)	High	+	Table B5
	Malawi	No	No	High	NA	Table B6
Increase off-farm work hours	Ethiopia	Yes	Yes	High	+++	Table B5
	Malawi	No	No	Medium	NA	Table B6
Remitances	Ethiopia	No	Yes	High	++	Table B5
	Malawi	No	No	High	NA	Table B6

Note: This table reports findings developped on the Appendix B.3. For each country, I measure the use of some major strategies to cope with the drought, as well as their efficiency in providing higher specific income.

The remaining question is why households did not transition away from agriculture prior to the drought, given that the productivity gap was already present, as shown in Table A6. Recent literature tries to understand the movement frictions explaining the weak labor reallocation occurring despite this productivity gap (review in Gollin (2023)). Some of these frictions can be relaxed when a drought occurs explaining the drought-induced labor reallocation.

Individual Preferences: Households might have a preference for agricultural activities even if these are less productive compared to off-farm work under normal conditions. Those preferences can be related to cultural practices, work-leisure trade-offs, or bequest motives. Those non-income-related motivations may be altered by the drought in favor of income-related motivations.

Information Asymmetry: Households may not be fully aware of the productivity gains from off-farm activities when not facing a drought. For example, Baseler (2023) shows in a field experiment that rural people underestimate urban wages by half. The stress of a drought could force them to reallocate their activities and discover these gains.

Property rights: The link between land use and land rights is a source of friction for mobility between sectors (Janvry et al. 2015) because households fear the expropriation of their land. By disturbing the land market (Tabetando et al. 2023), a drought can relax this constraint on households.

This reallocation is mainly observed for wealthier households both because they may have more opportunities thanks to their different types of capital: better education, market integration, productive assets and network integration, and also because they may be better able to afford to bear the cost of migration or sectoral reallocation.

To a lesser extent, some other mechanisms could explain why some households benefit from the drought. General equilibrium effects could benefit households better connected to the agricultural market. In particular, as a preliminary illustration, I find evidence that the price of maize[26] increases with the drought, using a simple difference-in-differences model on local prices at the village level (see Appendix B.2). This result is in line with Brown and Kshirsagar (2015), who find that weather shocks increase crop prices in local markets. This price increase mitigates the impact of drought on farm income. Households with higher wealth, enhanced agricultural technologies, and improved market access may gain more from the rise in crop prices.

26. Maize is the main crop product in both Ethiopia and Malawi.

Finally, some parts of the non-farm income may not be correlated with the loss at the household level. For example, remittances tend to increase for the wealthiest households. Still, due to information asymmetry between givers and receivers, the remittance increase may exceed the household's damage (Joseph, Nyarko, and Wang 2018).

5.2 Malawi

5.2.1 The distributional impact of drought

Impact on income, consumption and asset levels Figure 5 shows the quantile treatment effect on the treated using the method of Callaway and Li (2019) with and without covariates. As for Ethiopia, drought episodes widen the income distribution. However, in the case of Malawi, the increase in inequality is mainly driven by the poorest households becoming poorer. When conditioning the QTT on covariates, the richest households are not significantly affected by drought at the 5% level. At the same time, the 50% poorest households experienced a significant (apart from the 10^{th} percentile) decrease in income per capita of approximately 30% at the 5% level. Compared to the counterfactual distribution, the Gini coefficient rises by 21%. As 80% of the population lives under the 1.90$ poverty line, the poverty level does not change with the drought.[27] Nevertheless, already poor households experienced an income drop, reaching 40%.

As observed in Ethiopia, the impact on the distribution of consumption per adult equivalent is minor compared to income per capita. Only the poorest 20% of households experienced a significant decrease in consumption at the 5% level without covariates and at the 10% level when conditioning on covariates. The rest of the distribution is not significantly impacted. Once again, this result may be due to consumption-smoothing strategies used by households to prevent shocks from affecting their livelihoods.

Figure A12 shows that the impact of the drought on the value of per capita assets is concentrated in medium-wealth households. Households situated between the 30^{th} and the 60^{th} percentile of the wealth distribution experience a significant decrease in the value of their assets (almost 30%) while the impact on the value of assets is not significant for the remaining households.

Assumption discussion These results hold under two main assumptions: the distributional difference-in-differences assumption (equation 2) and the copula stability assumption (equation 3).

The main challenge with the Malawi case study is that the north experienced a good rainy season in 2010, as depicted in figure A5. Farm income was high in that part of the country, where most households belong to the control group.[28] As a consequence, the pre-treatment parallel trends are not verified. Table A2 shows that, in the pre-treatment period, farm income difference is significantly higher in the treatment group, leading to a higher per capita income. When removing households with an SPEI greater than 0.84 in 2010,[29] parallel trends hold (table A3). Moreover, as depicted in table A2, the effect does not depend on the household's assets and, thus, does not represent a problem for the copula stability assumption to hold.

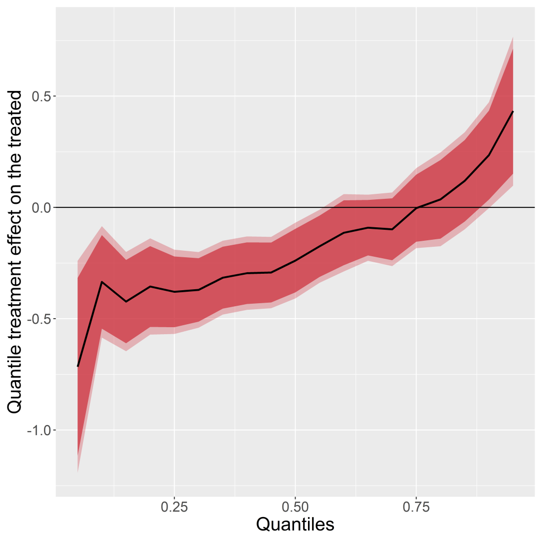
Arguments similar to those applying to Ethiopia can then be used to justify the reliability of the copula stability assumption. Malawi's economy is mainly agricultural and has hardly changed in the last 20 years. The GDP per capita has been relatively constant, and agricultural employment fell from 81% to

27. The drought does not impact the 20% richest households.
28. The correlation between rainy-season mean SPEI in 2010 and the dummy of belonging to the treatment group is equal to -0.74.
29. The 421 households which experienced good rainfall conditions in 2010.

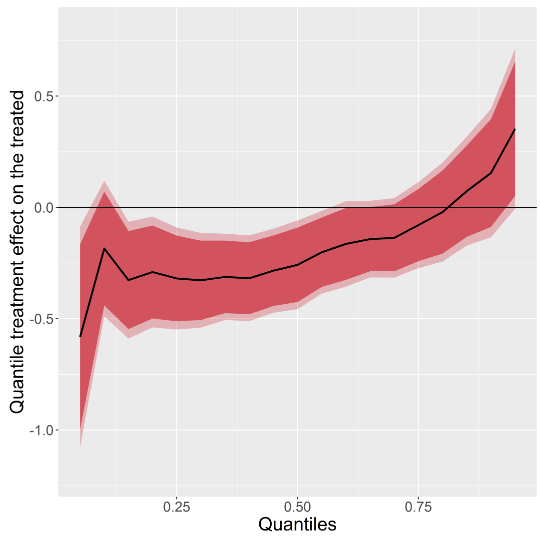
Figure 5

Quantile Treatment Effect on Copula Stability assumption for Malawi

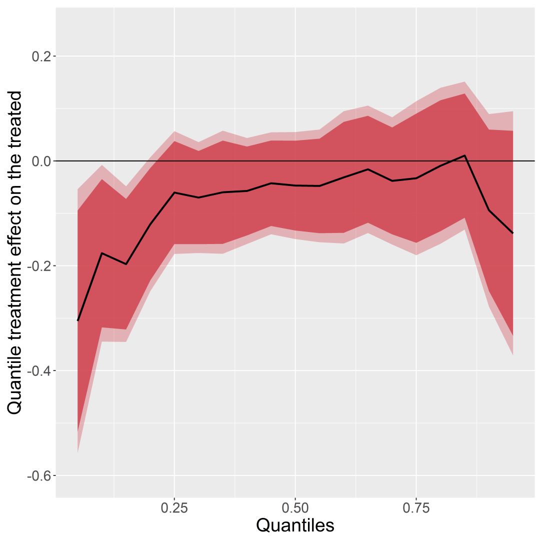
(a) Income per capita (no covariates)



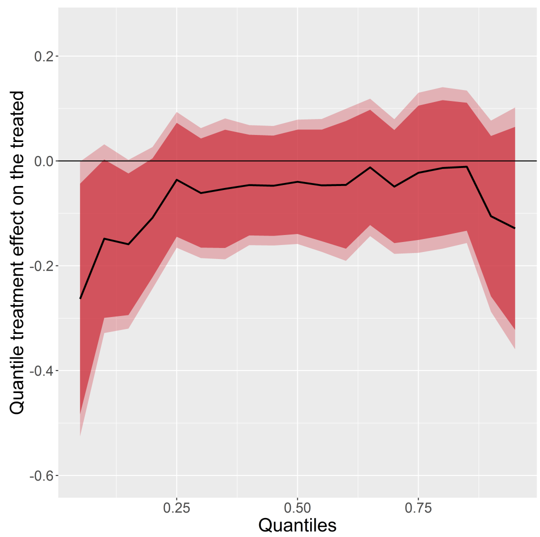
(b) Income per capita (covariates)



(c) Consumption per adult eq (covariates)



(d) Consumption per adult eq (no covariates)



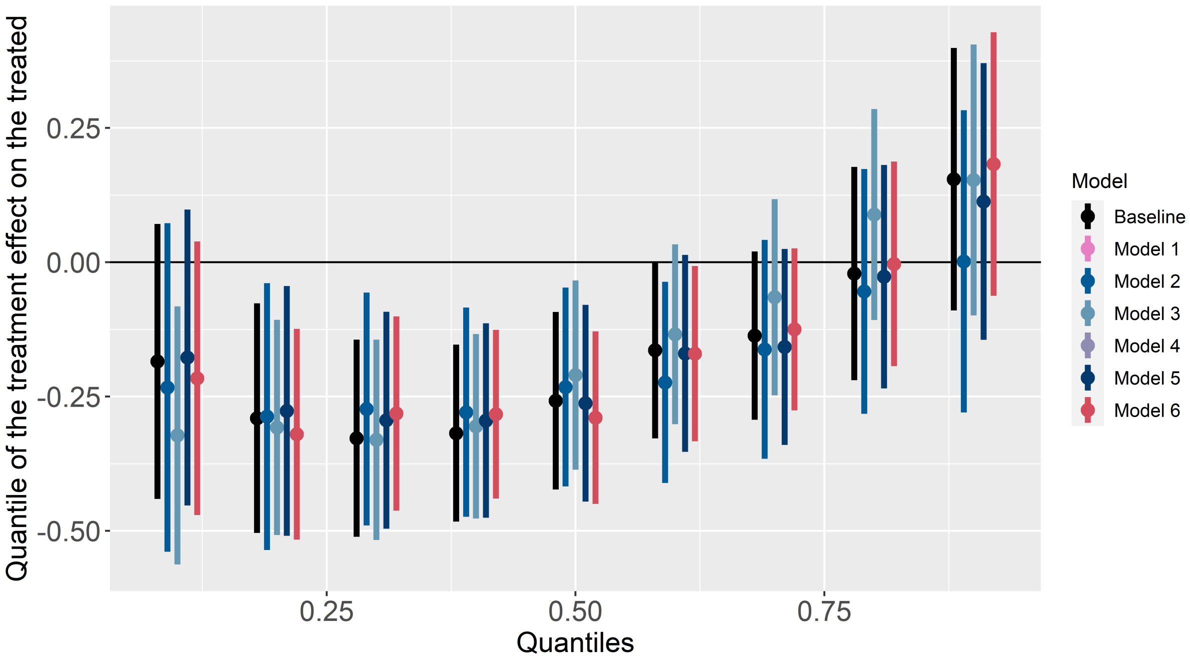
Note: Quantile Treatment Effect on the treated is computed with the method of Callaway and Li (2019) for income per capita (top) and consumption per adult equivalent (bottom), without covariates (left) and with covariates (right), including rural dummy, head education, head age, female-headed household dummy, number of household's members and number of household's adult equivalent. The inclusion of covariates is made through propensity score matching. The Quantile Treatment Effect on the treated is estimated for each 0.05 interval for $\tau \in [0.05, 0.95]$. Symmetric confidence intervals at 0.05 and 0.1 levels are computed with 500 bootstrap iterations.

76% from 2000 to 2019 (World Bank data[30]). Thus, income mobility is likely to be constant during the study period. Figure A10 shows changes in period-over-period income dependency in the treatment and control groups' three waves. The value is relatively constant in both groups.

5.2.2 Robustness check

Robustness of parameters The same robustness models were used as for Ethiopia.[31] Nevertheless, Models 1 and 4 are removed from the analysis due to the small group size (88 households in the treatment group and 40 in the control group, respectively). Results for these models are shown in figure 6 and stay robust to new specifications.

Figure 6
Robustness of the Quantile Treatment Effect under Copula Stability assumption and diverse specifications



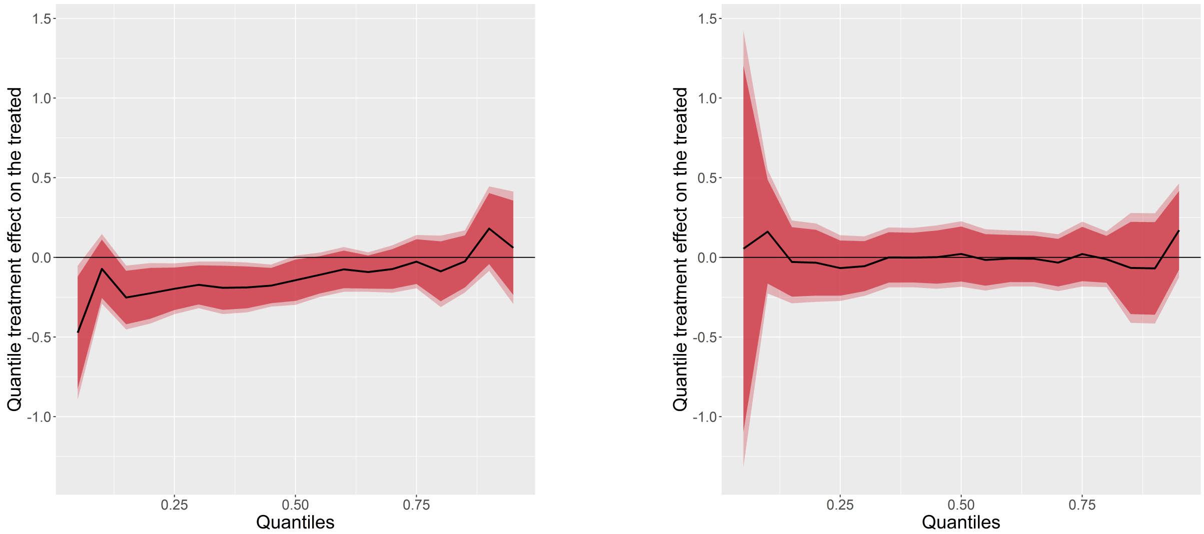
Note: The Quantile Treatment Effect on the treated is computed with the method of Callaway and Li (2019) under the following specifications: (1) use of 1-month SPEI (Model 1), (2) use of 6-month SPEI (Model 2), (3) use of 3-month SSMI (Model 3), (4) use of the minimum of SPEI (Model 4), (5) remove untreated units next to SPEI threshold (Model 5), and (6) remove buffer to compute SPEI (Model 6). Model 1 and model 4 are not displayed because of tiny groups (88 households in the treatment group and 40 in the control group, respectively). The Quantile Treatment Effect on the treated is estimated for each 0.05 interval for $\tau \in [0.05, 0.95]$. Symmetric confidence intervals at 0.05 levels are computed with 500 bootstrap iterations.

Spatial spillovers and threshold effect Figure 4a shows the quantile treatment effect on the treated using a model on the pre-treatment period to infer the effect of the treatment, using distribution regression. Results are very similar to those observed with the previous method. Droughts widen income distribution.

30. https://data.worldbank.org/. accessed on 05/01/2023.
31. (1) I use alternative drought indicators such as the 1-month SPEI and the 6-month SPEI as well as the 3-month SSMI (respectively Model 1, Model 2, and Model 3), (2) I use the minimum value of the 6-month SPEI during the growing season rather than the mean value (Model 4), (3) I remove households near the drought threshold from the control group to avoid threshold effects (Model 5) and (4) I do not use a buffer around the household location to retrieve geographical data (Model 6).

Figure 7
Counterfactual analysis to build Quantile Treatment Effect of income per capita of Ethiopia

(a) QTE on treatment group **(b)** QTE on control group



Note: The Quantile Treatment Effect on the treated is computed with the method of Chernozhukov, Fernández-Val, and Melly (2013) (see section B.1). The covariates used to model the per-capita income include human capital (education), natural capital (local crop suitability index, forest cover, and water proximity), social capital (female household head, number of household members), and physical capital (rural household, market access). The Quantile Treatment Effect on the treated is estimated for each 0.05 interval for $\tau \in [0.05, 0.95]$.

To test the quality of the predictive distribution regression model, I applied the previous model to the untreated units. Figure 4b shows that the difference between the counterfactual distribution and the actual distribution is not significantly different from 0 at all quantiles at the 10% level. This result suggests that the treatment does not impact the control group at each quantile of the distribution. It validates the first model's pertinence as spillovers are negligible.

5.2.3 Mechanisms

Non-farm and farm income Table 5 shows Abadie's semi-parametric difference-in-differences estimator applied to per capita income (1, 2), per capita farm income (3, 4), and per capita non-farm income (5, 6) for the ATT (1, 3, 5) and linear approximation of conditional ATT (2, 4, 6). The drought significantly impacts per capita income, reducing it by by 20%.

Farm income[32] is significantly impacted by the drought and decreases by 40% on average. The heterogeneity in the impact of the drought comes from the farm income, for which the wealthiest households are significantly less impacted. At the same time, non-farm income is globally non-impacted by the drought, even if households with female heads are significantly more impacted.

Coping strategies Table 4 shows that households affected by the drought are more likely to adopt irrigation, a practice linked to higher crop income but not to a reduction in drought impact. Moreover, the wealthiest households increase their livestock income mainly by selling more livestock units and, to a lesser extent, by increasing output of livestock-related products (mainly milk and eggs). This increase in

32. Including crop income, livestock income, agricultural-wage income, and ganyu.

Table 5
Conditionnal average treatment effect on the treated

ATT	Total income		Farm income		Non-farm income	
	(1)	(2)	(3)	(4)	(5)	(6)
Drought	−0.15*	−0.14*	−0.35**	−0.45***	−0.08	−0.02
	(0.09)	(0.08)	(0.17)	(0.17)	(0.17)	(0.16)
Asset value (k)		−0.00		0.03**		−0.02
		(0.01)		(0.02)		(0.01)
Female headed		0.11		0.69*		−0.67*
		(0.24)		(0.41)		(0.41)
Age of the head		−0.00		−0.01		0.00
		(0.01)		(0.01)		(0.01)
Rural household		−0.22		1.09**		−0.47
		(0.20)		(0.47)		(0.33)
Observations	1438	1438	1438	1438	1438	1438

Note: Abadie's semi-parametric difference-in-differences estimator for per capita income (1,2), farm per capita income (3,4), and non-farm per capita income (5,6). The propensity score is computed with a logistic model including covariates for living in rural areas, the age of the household head, the number of household members, and being a female-headed household. All variables are centered. Standard errors including errors related to the propensity score estimation following Abadie2005 are in parentheses. I denoted significance at 10% with *, 5% with **, and 1% with ***

livestock income is the primary explanation for the increase in inequality in this country. I do not find evidence of the use of non-agricultural coping strategies in Malawi.

Finally, ganyu, widely used by poorer households in reaction to the drought, does not give them a sufficient livelihood alternative to prevent an increase in inequality. Thus, it supports the idea that ganyu acts more like a survival strategy than an effective coping strategy (Kerr 2005).

Long-lasting impact of the drought Is this increase in inequality temporary or did it last over time? To answer this question, I apply the previous methodology replacing the post-treatment period with the 2019 wave of data (three years after the drought).[33]

Figure A13 shows the results of this exercise. The impact of the drought on income inequality seems to persist slightly over time even if it is particularly imprecise. When taking into account covariates, the impact is not significant at the 10% level in almost all quantiles. The increase in the Gini coefficient is mitigated to 8% compared to the 21% observed in the short term.

As depicted in Figure A5, the 2019 rainy season was particularly wet in Malawi. The median of the SPEI was respectively equal to 1.65 and 1.05 in the control and treatment groups. This strong weather anomaly is likely to bias the results and explain their imprecision. Predicting the bias direction is challenging because while a wet season can enhance crop yields, an excessively wet season is harmful. The 2019 flood was mainly provoked by Cyclone Idai, which caused a significant loss of crop production (Government of Malawi 2019). As the control group was more impacted, the bias might have lowered the long-term impact of the 2016 drought.

33. This exercise cannot be applied to Ethiopian data as the 2018 wave uses a new panel.

5.3 Comparison between countries

The results regarding per capita income, consumption per adult equivalent, and asset value are similar for both countries. The drought widens the income distribution, resulting in a higher level of inequality. The impact on consumption is restricted to the first decile of households, while other households succeed in smoothing their consumption level. Finally, medium-wealth households significantly deplete their assets when faced with drought.

Given the correlation between the rankings in income, consumption, and asset distribution,[34] we can draw the following inferences. The poorest households saw a significant decline in income, which, to a lesser extent, is reflected in their consumption levels. Medium-wealth households did not experience impacts on income and consumption, but they had to deplete their assets to sustain their livelihoods, potentially leading to long-term impacts on income. Conversely, the richest households gained income benefits from the drought and did not need to deplete their assets.

The main difference between the two countries is that the 20% richest Ethiopian households benefit from the drought.[35] In Ethiopia, richer households compensate for their farm income loss with a significant increase in non-farm income, while in Malawi, the compensation goes through farm income, especially livestock income. In Ethiopia, households' coping strategies focus on diversifying their activity to the non-farm sector, while in Malawi, such diversification is not observed. These observations are consistent with the results presented in section 5.1.3, i.e., Ethiopian households benefit from a productivity gap due to sectoral reallocation from the farm sector to the non-farm sector.

Why is sectoral reallocation not observed in Malawi? This question is beyond the scope of this paper. Ethiopia's high growth in GDP and poverty reduction since 2010 contrasts with Malawi's stagnant GDP and poverty ratio and may have provided the former's richest households with more opportunities in the non-farm sector. The service and manufacturing sectors are more attractive in Ethiopia than in Malawi, which may explain this difference between the two countries.

6 Conclusion

This article investigates how droughts impact inequalities using a distributional difference-in-differences framework applied to Ethiopia and Malawi. Our main results are similar in both countries regarding income, consumption, and assets: droughts increase inequality. The 10% poorest households experience a decrease in per capita income of about 40%, while the richest households benefit from the drought in Ethiopia and are not impacted in Malawi. In terms of consumption, the impact is alleviated, providing evidence of smoothing consumption behaviors. The impact on assets is restricted to medium-wealth households. These results are robust for several specifications, including (1) a propensity score matching approach, (2) the use of alternative drought indexes, (3) the consideration of spatial spillovers, and (4) the removal of a potential threshold effect.

While impacts are similar in the two countries, underlying mechanisms vary from one case to the other. In Ethiopia, the increase in inequality is explained by the greater ability of the wealthiest households to find alternative sources of income in the non-farm sector. Evidence shows that the drought led to a sectoral reallocation of the wealthiest households' workforce. They increase the time devoted to non-farm activities at the expense of farm activities. The productivity gap between the farm and the non-farm sector allows these households to benefit from the drought. In Malawi, rich households rely on

34. The Spearmann correlation is equal to 0.5 in Ethiopia and 0.6 in Malawi for per adult equivalent consumption and per capita income, and 0.3 for asset value and per capita income in both countries.

35. See figure 2 and 5.

their livestock income to reduce drought drawbacks, and are therefore not significantly impacted by the drought.

The results shed light on the high risk that climate change will exacerbate inequality and on the need to take local contexts into account. First, the critical objective of adaptation policies must be the reduction of poorer households' vulnerability to extreme weather conditions. *Ex-ante* policies could support poorer households' development of resilience by (1) creating income diversification opportunities to reduce the exposure to climate risk, (2) favoring the acquisition of assets that can represent safety nets in the case of hardship, and (3) promoting the shift to crops and agricultural practices that increase resilience to climate variability and require less water. *Ex-post* climate aid could be targeted toward poorer households, especially those with low levels of assets. Aid must also be triggered before damage assessment to limit asset depletion, which is often necessary to allow consumption-smoothing strategies. Second, the results show that the coping strategies implemented by households depend on local characteristics. Consequently, there is no one-size-fits-all intervention, and policymakers should carefully consider the context in which households find themselves. In particular, essential policy concerns should include supporting women's integration into the job market and opening up of remote areas.

The framework proposed in this article concentrates on the short-term impact of a particular drought that affects only about half the population. Although the framework does not consider spatial extent and intensity, these two parameters may limit households' strategies - even the richest ones - and lead to different distributional impacts. Such extensions go beyond the scope of this article, but to include intensity considerations, the methodology used in this article could be extended via a continuous treatment specification Callaway and Huang (2020). In addition, the method of Chernozhukov, Fernández-Val, and Melly (2013), presented in the appendix B.1, can cover the case of droughts that impact the entire country. Still, no placebo test can be made in that case. Finally, despite drought episodes becoming more frequent in the coming years, the repetition of shocks has not been studied in the literature. Multiple droughts may foster poverty traps and reinforce the increase in inequality. Nevertheless, they may also enhance households' ability to adapt their behaviors through new agricultural practices or diversification, thus increasing their resilience (Leichenko and Silva 2014; Wuepper, Yesigat Ayenew, and Sauer 2018). Future work should focus on such extensions.

Overall, this paper underlines the need for a joint approach to the sustainable development goals (SDGs) developed by the United Nations. The reduction of inequality (SDG 10) and poverty (SDG 1) also requires ambitious climate policies (SDG 13), both in terms of mitigation and adaptation, to address the disproportionate impacts of climate change on the most vulnerable populations.

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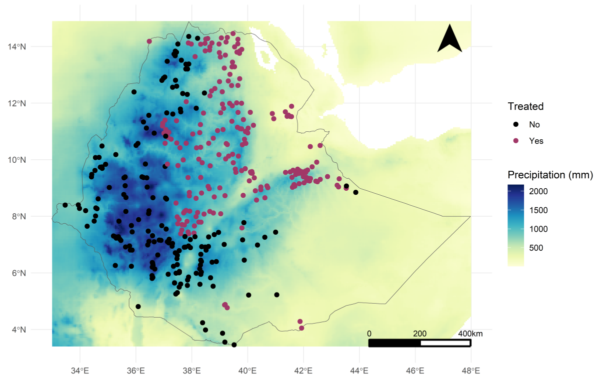
A Appendix Figures and Tables

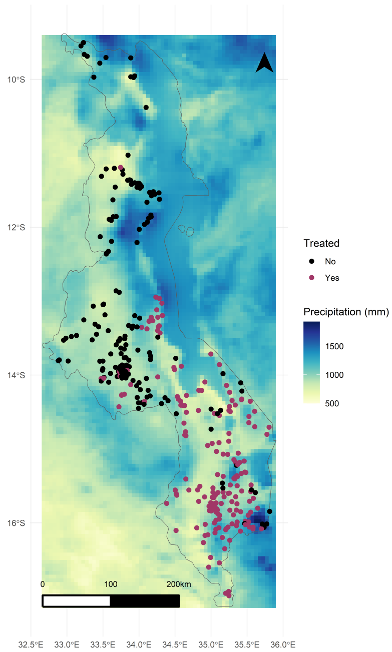
A.1 Appendix figures

Figure A1
Yearly long-term mean precipitations (1981-2020) and location of households affected by the drought (Ethiopia)



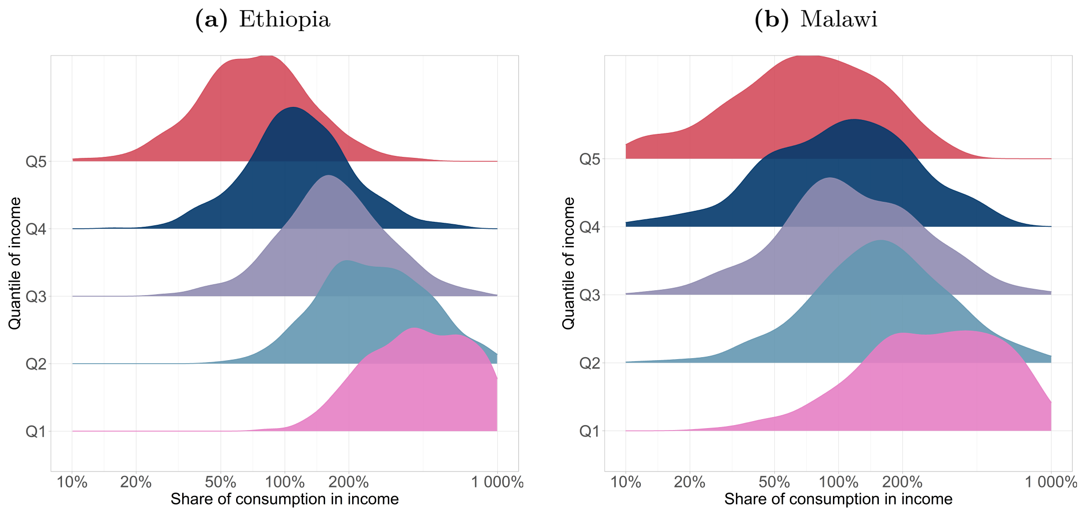
Note: Precipitations are measured in millimeters per year. Precipitation data are CHIRPS

Figure A2
Yearly long-term mean precipitations (1981-2020) and location of households affected by the drought (Malawi))



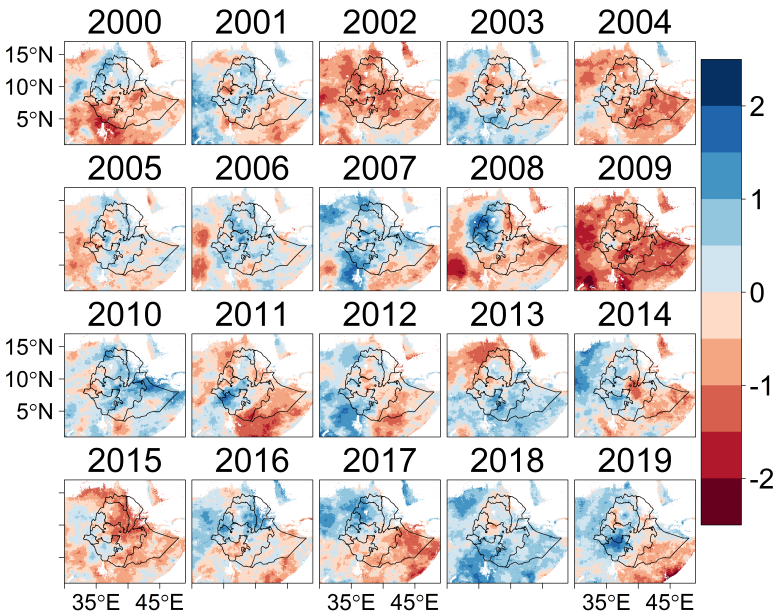
Note: Precipitations are measured in millimeters per year. Precipitation data are CHIRPS

Figure A3
Share of the consumption in income according to the household income quintile in 2013 for Ethiopia and Malawi



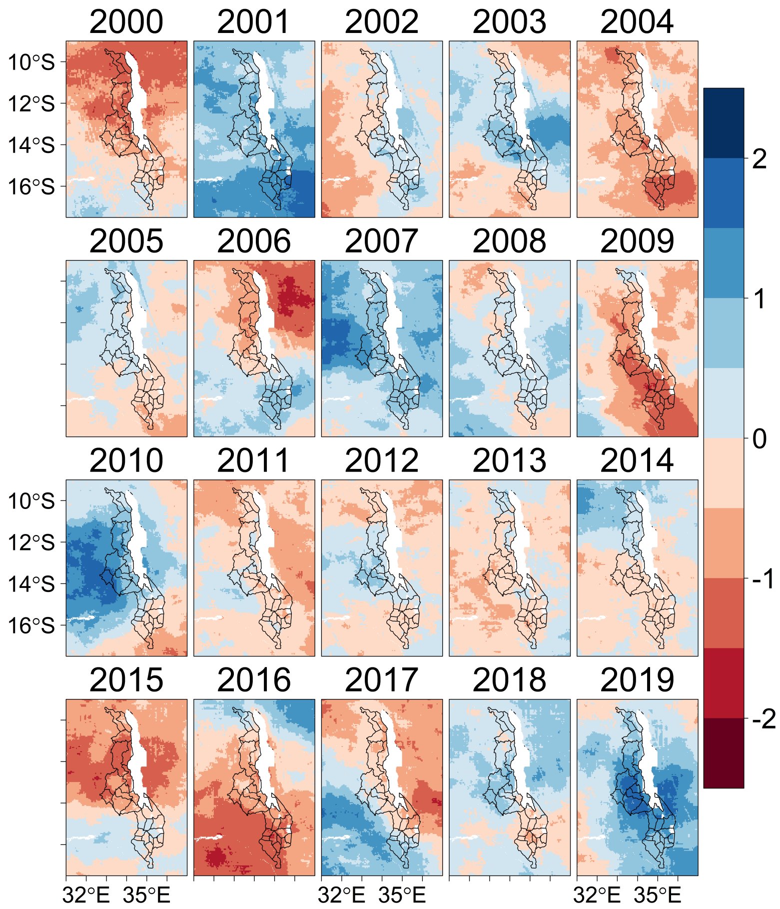
Note: Share of consumption in income is equal to the total consumption divided by the total income of households. A logarithmic scale is used. Value can be superior to 100%, as the computation methodology of consumption and income are very different: yearly consumption is estimated from one week multiplied by 52 (with potential seasonal bias), while income is estimated yearly.

Figure A4
Mean of the 3-month SPEI during the agricultural season of the main crop from 2000 to 2019 in Ethiopia



Note: The Standardized Precipitation and Evaporation Index (SPEI) is a measure of rainfall deficit. It is computed using CHIRPS precipitation data and GLEAM evaporation data and masked with land cover data from MODIS to remove non-applicable areas.

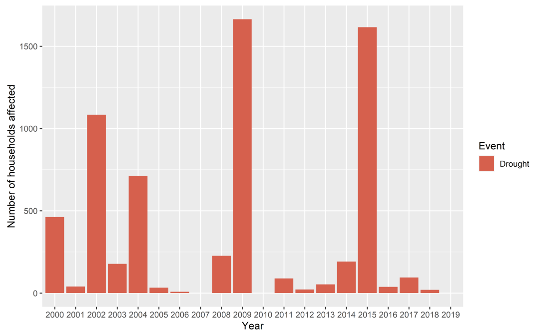
Figure A5
Mean of the 3-month SPEI during the agricultural season of the main crop from 2000 to 2019 in Malawi



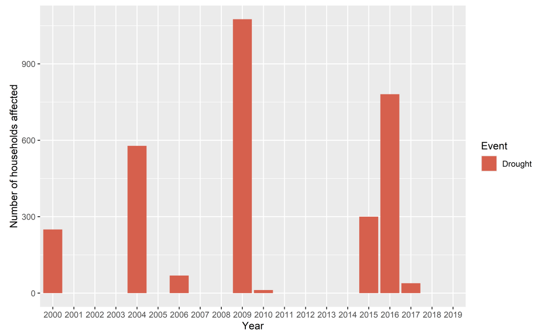
Note: The Standardized Precipitation and Evaporation Index (SPEI) is a measure of rainfall deficit. It is computed using CHIRPS precipitation data and GLEAM evaporation data and masked with land cover data from MODIS to remove non-applicable areas.

Figure A6
Number of households affected by drought and flood over time in Ethiopia and Malawi

(a) Ethiopia (3596 households)



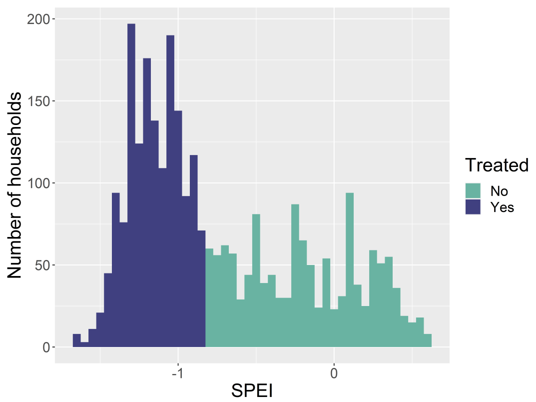
(b) Malawi (1491 households)



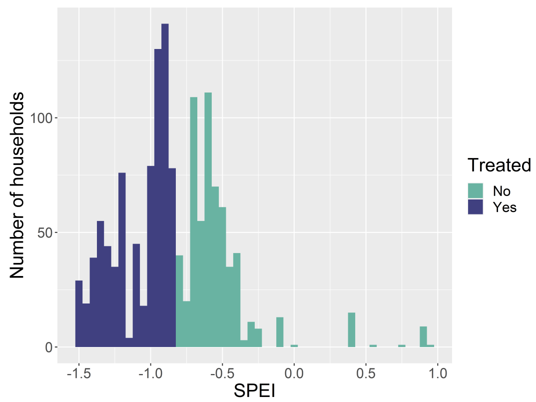
Note: A household is considered to be affected by drought if the mean of the 3-month SPEI during the growing season of the main crop is less than -0.84.

Figure A7
Distribution of the SPEI in the control and treatment group, in Ethiopia and Malawi

(a) Ethiopia (2015)

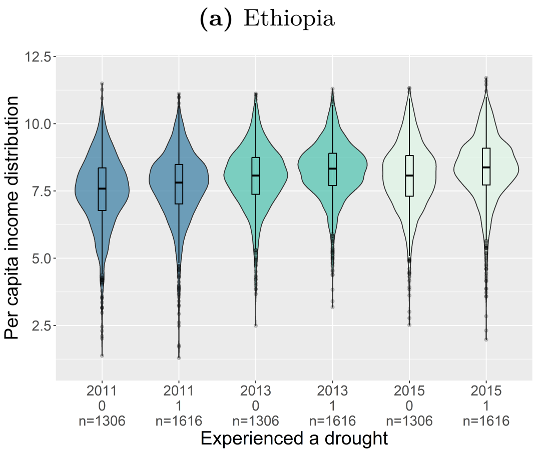


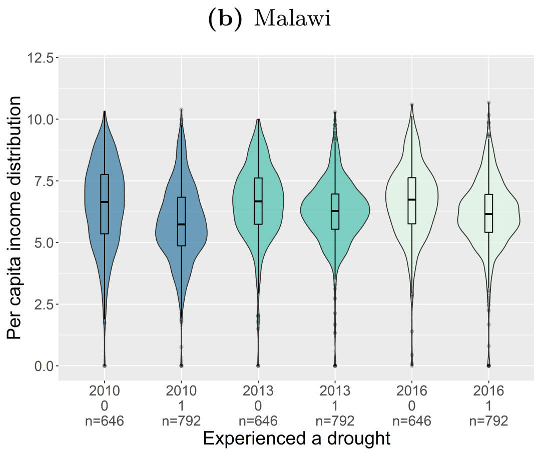
(b) Malawi (2016)



Note: Distribution of the mean of the 3-month SPEI during the growing season of the main crop in the treated and the control group in the treated year. A household is considered to be affected by the drought if the mean of the 3-month SPEI during the growing season of the main crop is less than -0.84. The Standardized Precipitation and Evaporation Index (SPEI) is a measure of rainfall deficit. It is computed using CHIRPS precipitation data and GLEAM evaporation data.

Figure A8
Distribution of the per capita income (in log) over time in the control (0) and treatment group (1), in Ethiopia and Malawi

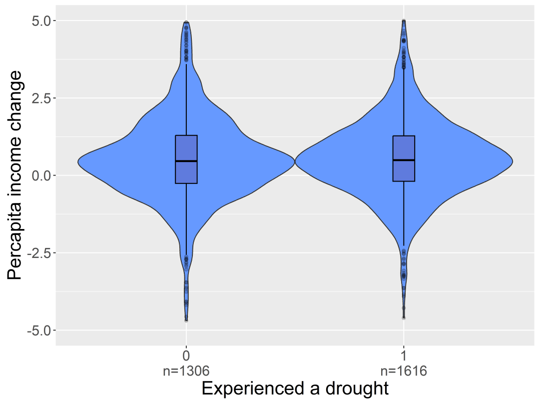




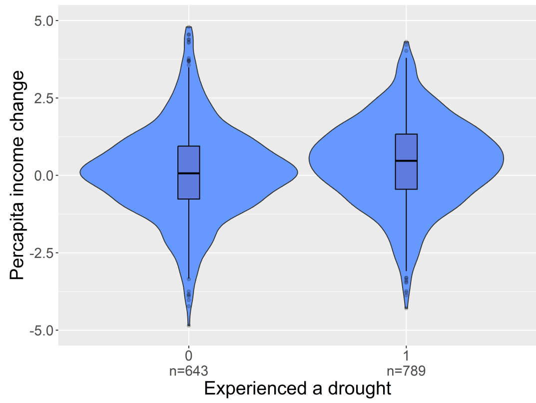
Note: Income distribution is computed with LSMS-ISA data as described in Section 3.2.

Figure A9
Pre-treatment distribution of change of outcomes for the treated and the control group

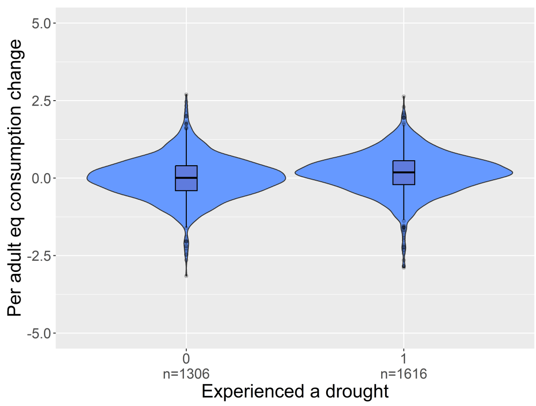
(a) Ethiopia — Per capita income



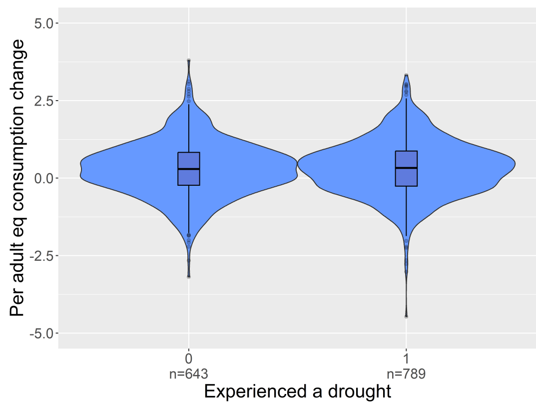
(b) Malawi — Per capita income



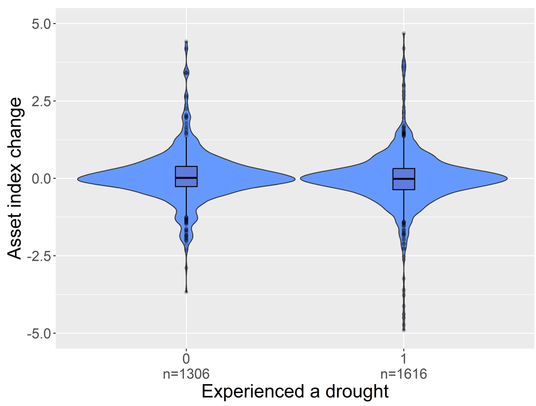
(c) Ethiopia — Per adult eq consumption



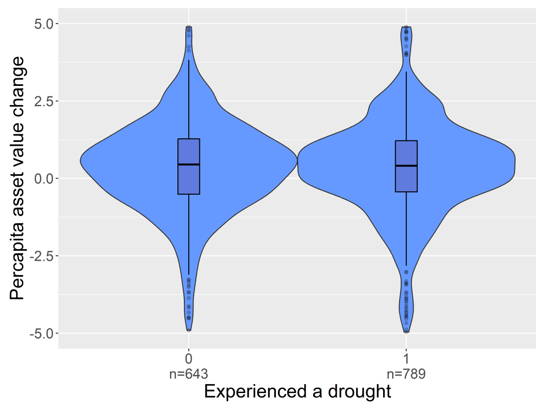
(d) Malawi — Per adult eq consumption



(e) Ethiopia — Asset index



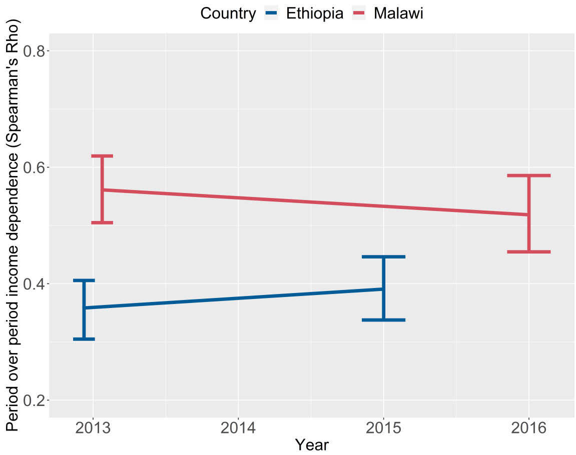
(f) Malawi — Asset value



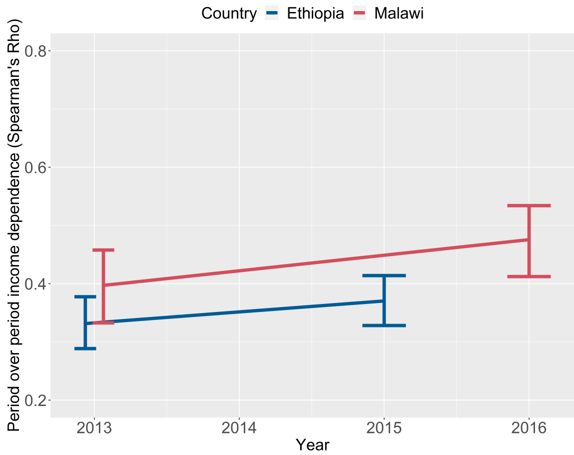
Note: Distribution of change of different outcomes in pre-treatment period for Ethiopia (left) and Malawi (right) for the control group and the treatment group. The unconditional distributional difference-in-differences assumption supposes the equality of treatment and control group outcome distribution if there were no drought (see Equation 2) and can be tested in the pre-treatment period.

Figure A10
Evolution of the year over year income dependence (Spearman's rho) in Ethiopia and Malawi for the control and treatment group in all panel waves

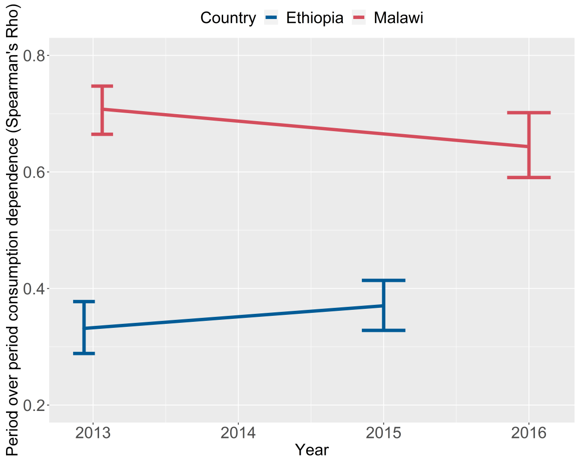
(a) Control group — Per capita income



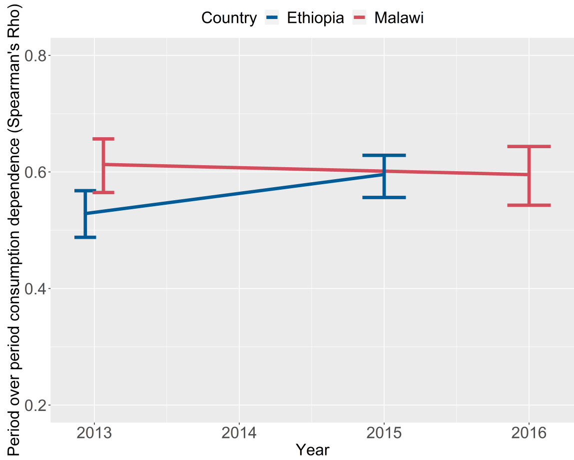
(b) Treatment group — Per capita income



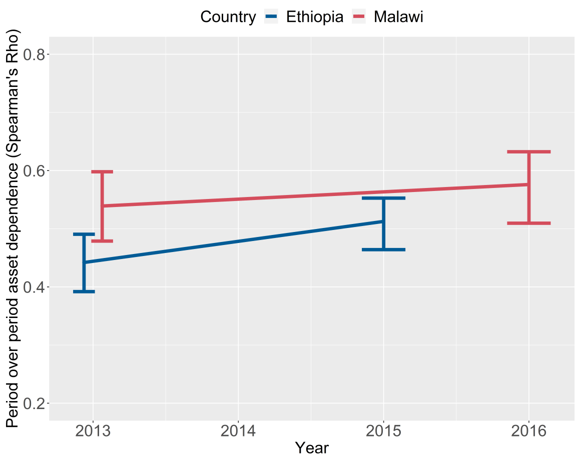
(c) Control group — Consumption per adult eq



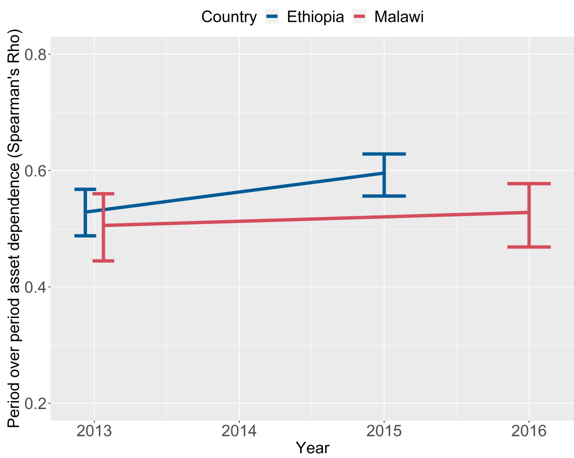
(d) Treatment group — Consumption per adult eq



(e) Control group — Asset value/index

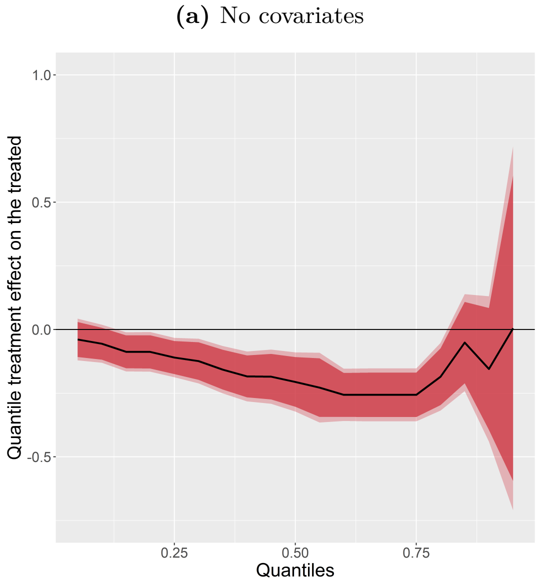


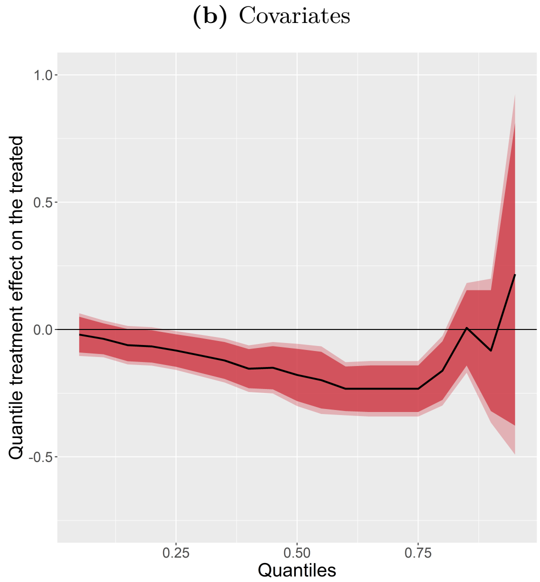
(f) Treatment group — Asset value/index



Note: Spearman'rho evolution for income per capita (a, b), consumption per adult equivalent (c, d) and asset value for Malawi and asset index for Ethiopia (e,f), in the control group (a, c, e) and the treatment group (b, d, f). Spearman'rho is equal to the correlation between the rank of the household in the income distribution in period t and t-1, divided by the product of the standard deviations of the rank variables.

Figure A11
Quantile Treatment Effect on Copula Stability assumption for asset index in Ethiopia



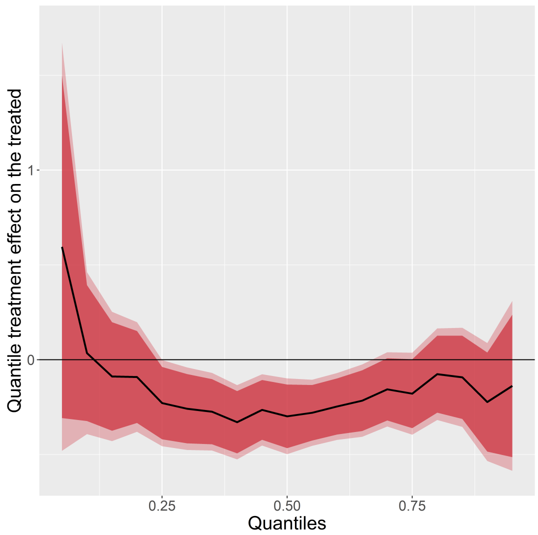


Note: Quantile Treatment Effect on the treated is computed with the method of Callaway and Li (2019) for asset index without covariates (left) and with covariates (right), including rural dummy, head education, head age, female-headed household dummy, number of household's members and number of household's adult equivalent. The Quantile Treatment Effect on the treated is estimated for each 0.05 interval for $\tau \in [0.05, 0.95]$. The inclusion of covariates is made through propensity score matching. The asset index is computed through principal component analysis of variables, including agricultural assets (livestock, machinery, and lands), durable goods, and housing characteristics. Symmetric confidence intervals at 0.05 and 0.1 levels are computed with 500 bootstrap iterations.

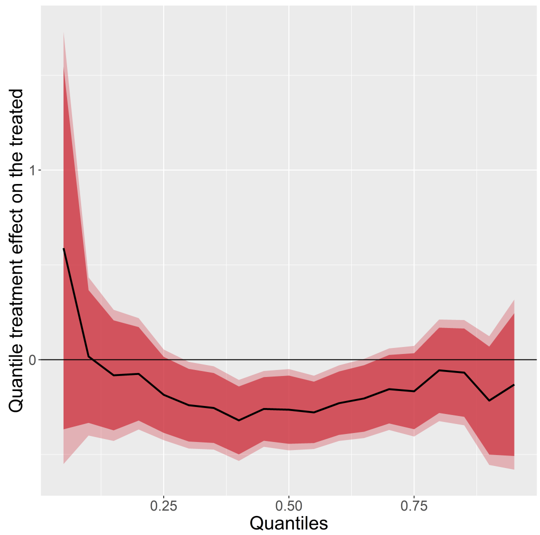
Figure A12

Quantile Treatment Effect on Copula Stability assumption for the value of assets owned by the household in Malawi

(a) No covariates



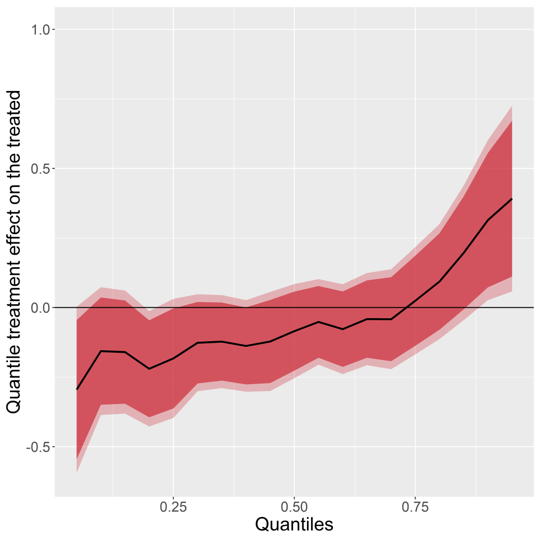
(b) Covariates



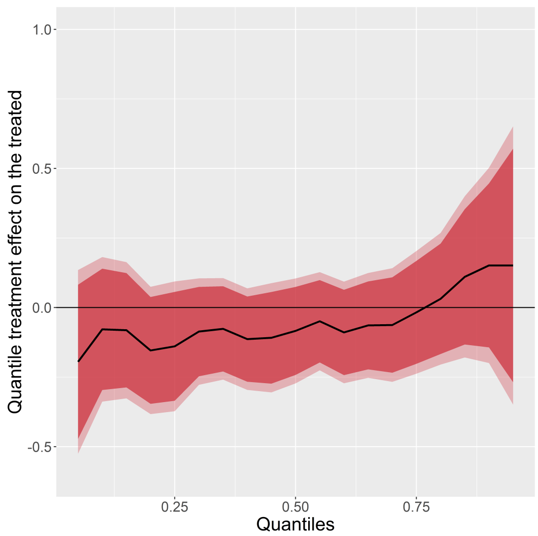
Note: Quantile Treatment Effect on the treated is computed with the method of Callaway and Li (2019) for the value of assets owned by the households without covariates (left) and with covariates (right), including rural dummy, head education, head age, female-headed household dummy, number of household's members and number of household's adult equivalent. The inclusion of covariates is made through propensity score matching. Assets include housing characteristics and durable goods. The Quantile Treatment Effect on the treated is estimated for each 0.05 interval for $\tau \in [0.05, 0.95]$. Symmetric confidence intervals at 0.05 and 0.1 levels are computed with 500 bootstrap iterations.

Figure A13
Long-term Quantile Treatment Effect

(a) No covariates



(b) Covariates



Note: To measure long-term impact, I apply the same method as the baseline but replace the post-treatment period data (2016 wave) with the data of the 2019 wave. The Quantile Treatment Effect on the treated is computed with the method of Callaway and Li (2019) for asset index without covariates (left) and with covariates (right), including rural dummy, head education, head age, female-headed household dummy, number of household's members and number of household's adult equivalent. The Quantile Treatment Effect on the treated is estimated for each 0.05 interval for $\tau \in [0.05, 0.95]$. The inclusion of covariates is made through propensity score matching. Symmetric confidence intervals at 0.05 and 0.1 levels are computed with 500 bootstrap iterations.

A.2 Appendix tables

Table A1
Conditionnal average treatment effect on the treated in the pre-treatment period

ATT	Total income		Farm income		Non-farm income	
	(1)	(2)	(3)	(4)	(5)	(6)
Drought	−0.03	−0.04	0.03	0.03	−0.04	−0.03
	(0.08)	(0.08)	(0.13)	(0.13)	(0.15)	(0.15)
Asset index		0.04		0.01		0.08
		(0.03)		(0.08)		(0.06)
Age of the head		0.01		−0.00		−0.01
		(0.01)		(0.01)		(0.01)
Female headed		0.31		0.43		0.42
		(0.20)		(0.33)		(0.34)
Rural household		−0.03		0.37		−0.41
		(0.32)		(0.59)		(0.48)
Observations	2922	2922	2922	2922	2922	2922

Note: Abadie's semi-parametric difference-in-differences estimator for per capita income (1,2), farm per capita income (3,4), and non-farm per capita income (5,6). The propensity score is computed with a logistic model including covariates for living in rural areas, having access to a city (living at less than 400 kilometers of a city of 50,000 inhabitants), the age of the household head, the number of household members, and being a female-headed household. All variables are centered. Standard errors including errors related to the propensity score estimation following Abadie2005 are in parentheses. I denoted significance at 10% with *, 5% with **, and 1% with ***

Table A2
Conditionnal average treatment effect on the treated in the pre-treatment periods

ATT	Total income		Farm income		Non-farm income	
	(1)	(2)	(3)	(4)	(5)	(6)
Drought	0.32***	0.31***	0.42***	0.46***	0.23	0.19
	(0.09)	(0.09)	(0.15)	(0.16)	(0.17)	(0.17)
Asset value (k)		−0.01		−0.05*		−0.04
		(0.01)		(0.03)		(0.03)
Female headed		−0.22		−0.44		0.44
		(0.25)		(0.32)		(0.43)
Age of the head		−0.00		−0.01		−0.00
		(0.01)		(0.01)		(0.01)
Rural household		0.17		−0.57		0.07
		(0.23)		(0.44)		(0.37)
Observations	1438	1438	1438	1438	1438	1438

Note: Abadie's semi-parametric difference-in-differences estimator for per capita income (1,2), farm per capita income (3,4), and non-farm per capita income (5,6). The propensity score is computed with a logistic model including covariates for living in rural areas, the age of the household head, the number of household members, having access to a city and being a female-headed household. All variables are centered. Standard errors including errors related to the propensity score estimation following Abadie2005 are in parentheses. I denoted significance at 10% with *, 5% with **, and 1% with ***

Table A3
Conditionnal average treatment effect on the treated in the pre-treatment periods excluding flooded areas in 2010

ATT	Total income		Farm income		Non-farm income	
	(1)	(2)	(3)	(4)	(5)	(6)
Drought	0.11	0.15	0.23	0.29	0.21	0.19
	(0.12)	(0.12)	(0.20)	(0.22)	(0.21)	(0.21)
Asset value (k)		−0.02		−0.09		0.00
		(0.03)		(0.06)		(0.06)
Female headed		−0.47		−0.35		0.21
		(0.33)		(0.43)		(0.50)
Age of the head		0.00		−0.01		−0.01
		(0.01)		(0.01)		(0.01)
Rural household		−0.41		−1.30*		0.03
		(0.34)		(0.68)		(0.52)
Observations	1017	1017	1017	1017	1017	1017

Note: Abadie's semi-parametric difference-in-differences estimator for per capita income (1,2), farm per capita income (3,4), and non-farm per capita income (5,6). The propensity score is computed with a logistic model including covariates for living in rural areas, the age of the household head, the number of household members, having access to a city and being a female-headed household. All variables are centered. Standard errors including errors related to the propensity score estimation following Abadie2005 are in parentheses. I denoted significance at 10% with *, 5% with **, and 1% with ***

Table A4
Test of unconditional distribution equality in Ethiopia

Outcome	**Test**	**P-value**
Per capita income	Kolmogorov-Smirnov	0.57
Per adult eq consumption	Kolmogorov-Smirnov	0.00
Asset index	Kolmogorov-Smirnov	0.25

Note: The Kolmogorov-Smirnov test is used to verify the hypothesis that the distribution of change in outcome is equal in the control and treatment groups. A p-value $> \alpha$ indicates that the equality of distribution cannot be rejected at the α level.

Table A5
Test of unconditional distribution equality in Malawi

Outcome	**Test**	**P-value**
Per capita income	Kolmogorov-Smirnov	0.000
Per adult eq consumption	Kolmogorov-Smirnov	0.803
Asset value	Kolmogorov-Smirnov	0.473

Note: The Kolmogorov-Smirnov test is used to verify the hypothesis that the distribution of change in outcome is equal in the control and treatment groups. A p-value $> \alpha$ indicates that the equality of distribution cannot be rejected at the α level.

Table A6
Agricultural and non-agricultural productivity by level of asset in treatment group (Ethiopia)

Variable	N	Mean	SD	N	Mean	SD	Diff
Panel A: Year = 2013							
Level of asset (2013)		Poor			Rich		
Farm productivity	685	5.65	7.27	565	5.84	6.75	0.19
Non-farm productivity	48	22.27	57.9	113	17.86	27.2	-4.41
Time spent on agricultural work	866	195.18	237.8	750	270.97	342.01	75.79***
Time spent on non-agricultural work	866	75.32	398.46	750	300.06	904.76	224.74***
Panel B: Year = 2015							
Level of asset (2013)		Poor			Rich		
Farm productivity	652	8.35	14.24	550	9.11	11.43	0.76
Non-farm productivity	54	23.5	33.87	127	45.66	134.22	22.15*
Time spent on agricultural work	866	154.11	187.36	750	203.4	245.99	49.29***
Time spent on non-agricultural work	866	77.39	411.34	750	343.86	1092.21	266.47***

Note: Level of labor productivity (total value added divided by total labor hours) and labor hours spent on agricultural and non-agricultural work for households in the treated group, above or below the median of the level of assets in pre-treatment period. I denoted significance at 10% with *, 5% with **, and 1% with ***

Table A7
Agricultural and non-agricultural productivity by level of asset in treatment group (Malawi)

Variable	N	Mean	SD	N	Mean	SD	Diff
Panel A: Year = 2013							
Level of asset (2013)		Poor			Rich		
Farm productivity	315	2.17	5.74	351	2.7	9.44	0.53
Non-farm productivity	11	3.87	7.01	10	7.68	11.06	3.81
Time spent on agricultural work	396	57.31	62.24	396	97.69	89.18	40.38^{***}
Time spent on non-agricultural work	396	37.29	244.73	396	21.58	172.83	-15.71
Panel B: Year = 2016							
Level of asset (2013)		Poor			Rich		
Farm productivity	280	1.63	3.69	320	3.83	14.46	2.19^{***}
Non-farm productivity	16	3.77	6.75	12	6.27	9.14	2.5
Time spent on agricultural work	396	66.62	81.78	396	101.21	112.71	34.59^{***}
Time spent on non-agricultural work	396	42.95	269.01	396	21.74	172.9	-21.21

Note: Level of labor productivity (total value added divided by total labor hours) and labor hours spent on agricultural and non-agricultural work for households in the treated group, above or below the median of the level of assets in pre-treatment period. I denoted significance at 10% with *, 5% with **, and 1% with ***

B Appendix

B.1 QTE with counterfactual inference

Going back to the definition of the quantile treatment effect on the treated (Equation 1) and considering that the outcome can be explained by some covariates X_t, I now consider the following equation to model the counterfactual distribution of the outcome:

$$F_{Y_{0t}|X_t,D=1}(y) = \int_{(0,1)} 1\{Q_{Y_{0t}|X_t,D=1}(u) \leq y\}du \tag{6}$$

With Q_W the quantile function of the random variable W. A distribution regression is then used to estimate this counterfactual distribution such as:

$$\hat{F}_{Y_{0t}|X_t,D=1}(y) = \Lambda(X_t'\hat{\beta}(y)) \tag{7}$$

With $\hat{\beta}(y)$, the distribution regression estimator obtained in the previous wave of panel data, and Λ the standard normal distribution function. Distribution regression is very similar to quantile regression (Koenker and Bassett 1978), but empirical evidence suggests a better fit to income distribution (Redmond, Doorley, and McGuinness 2021).

In practice, the idea is to run a set of probit equations that estimate $P(Y_{1t-1} \leq w)$ on a fine grid covering possible income levels w:

$$P(Y_{1t-1} \leq w|D=1) = \Phi(\beta_0(w) + \beta_1(w)X_{t-1}) \tag{8}$$

With Φ the cumulative distribution function of the standard normal distribution. The covariates X_{1t-1} used to model the per-capita income include human capital (education), natural capital (local crop suitability index, forest cover, and water proximity), social capital (female household head, number of household members), and physical capital (rural household, market access). The choice of these variables relies on the fact they are practically unaffected by the drought because of their long-term definition.

This model is then used to predict $\hat{F}_{Y_{0t}|D=1}(w) = P(Y_{0t}|D = 1 \leq w)$, the counterfactual distribution of outcome, from the value of Y_{1t-1} and X_t. With equation 1, it is possible to estimate the quantile treatment effect on the treated by making the difference between the actual distribution of income and the counterfactual distribution computed as described above[36]. A placebo test is performed by applying the model to the control group.

36. The counterfactual distribution is computed with the counterfactual R package developed by Chen et al. (2017)

B.2 Drought impact on crop prices

The household income computation uses the World Bank protocol to estimate the local price of crops: the price is fixed at the smallest geographical scale with more than ten observations. The most cultivated crop in Ethiopia and Malawi is maize. Thus, each enumeration area has a particular maize price (more than ten observations by enumeration area).

As a simple illustration of the impact of drought on maize prices, I use a simple difference-in-differences method at the enumeration area level to observe how the drought of 2015 in Ethiopia and 2016 in Malawi impacted the price of maize. Following Sant'Anna and Zhao (2020), I compute the average treatment effect under an unconditional parallel trend equal to:

$$\hat{ATT}_{UPT} = \frac{\sum D_i(Y_{i,t} - Y_{i,t-1})}{\sum D_i} - \frac{\sum (1-D_i)(Y_{i,t} - Y_{i,t-1})}{\sum (1-D_i)} \tag{9}$$

With $Y_{i,t}$, the price of maize in the enumeration area i, at time t, and D_i, a binary variable equal to 1 if the enumeration area i was affected by the drought.

This estimation is causal under the unconditional parallel trend assumption: the treatment and the control would have changed in parallel if there had been no drought:

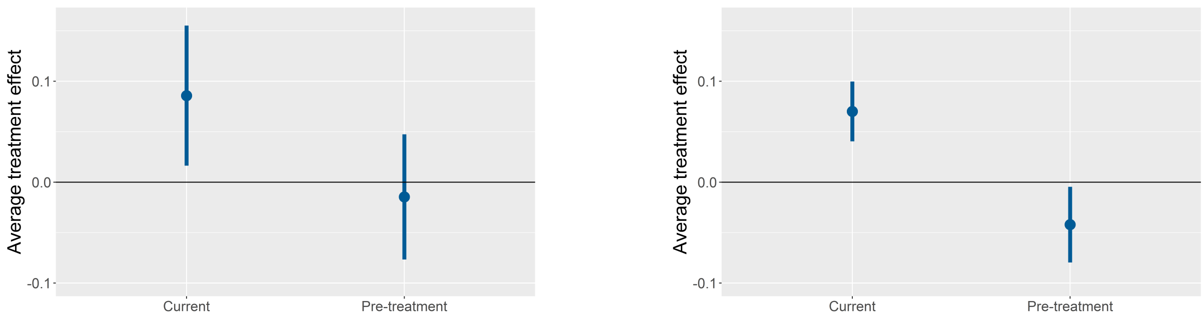
$$E[Y_t(0) - Y_{t-1}(0)|D = 0] = E[Y_t(0) - Y_{t-1}(0)|D = 1] \tag{10}$$

This assumption can not be directly tested. To test its likelihood, I verify whether the assumption was verified in the pre-treatment period by computing $\hat{ATT}_{UPT}$ between 2011 and 2013 in Ethiopia and 2010 and 2013 in Malawi.

Figure B1

Average treatment effect on maize prices at the enumeration level

(a) Ethiopia **(b)** Malawi



Note: Unconditional ATT defines in equation 9 of drought impact on local maize prices, in the current and pre-treatment periods. Estimation is made at the level of the enumeration area. Bootstrap standard errors at 0.1 level are computed with 500 iterations.

Figure B1 shows the unconditional average treatment effect of the drought on maize prices at the enumeration area level. The drought significantly increased local maize prices by 10% in Ethiopia and 7% in Malawi. The unconditional parallel trend is verified in the pre-treatment periods in Ethiopia, but it is not verified in Malawi. The fact that the rainy season was good in northern Malawi in 2010 must explain the price reduction observed between 2010 and 2013, as explained in section 5.1.1.

B.3 Coping strategies

This appendix explores some strategies households use to cope with the drought and their efficiency. Strategies are divided into agricultural-income-related and non-agricultural-income-related. Table 4 summarizes the main findings of this section.

B.3.1 Methodology

To test the use of some coping strategies by households, I consider how changes in an indicator relative to the use of a specific coping strategy differ between the treatment and the control group, with heterogeneity with respect to the pre-treatment level of the household's assets. Formally, I consider the following model between the pre-treatment period $(t-1)$ and the treatment period (t):

$$Strat_{it} = Post_t * Treat_i * Asset_i + X_{it} + \gamma_i + \lambda_t + \epsilon_{it} \tag{11}$$

With $Strat_{it}$ the outcome relative to the use of a coping strategy, $Post_t$ a dummy for the second period, $Treat_i$ a dummy for belonging to the treatment group, $Asset_i$ the level of assets in the pre-treatment period, and X_{it} some controls including being a rural household, the number of members in the household and the educational level, age and gender of the household head. γ_i are household fixed-effects, λ_t time fixed-effects, and ϵ_{it} the time-varying error term, which is assumed to follow a normal distribution. Error terms are clustered at the enumeration area level. When $Strat_{it}$ is a dummy variable, the model is estimated with a probit regression model without including fixed effects. When y_{it} is observed only in the post-treatment period, the following simplified model is considered:

$$Strat_i = Treat_i * Asset_i + X_i + \epsilon_i \tag{12}$$

These models are not strictly causal, as I do not verify perfect parallel trends for all indicators conditional on the pre-treatment level of the asset. The last model is in fact only a correlation between an indicator and the fact that it belongs to the treatment group, according to the pre-treatment level of the asset.

To test the effectiveness of such strategies, I consider the difference in the revenue that is supposed to be allocated between the treatment and the control group due to the fact they have implemented a particular strategy. Formally, I consider the following model:

$$y_i = Treat_i * Strat_i + X_i + \epsilon_i \tag{13}$$

Where y_i is a specific part of the revenue.

This model only measures the correlation between household income and the implementation of a coping strategy, conditional on having been affected by a drought. Consequently, it does not claim causality.

B.3.2 Agricultural strategies

According to the data available, six agricultural strategies are taken into account: (1) irrigation use, (2) crop diversification, (3) reduction in inorganic fertilizer levels, (4) increased income from livestock, (5) reduction in on-farm hired labor, and (5) reduction of on-farm hired labor wage. For the last two strategies, data are only available for Ethiopia. The implementation of irrigation is measured by a dummy equal to one if the households do not use irrigation in the pre-treatment period and use irrigation in the treatment period. This variable is observed only during the treatment period. The diversification is

Table B1

Agricultural strategies used by households according to their wealth levels (Ethiopia)

Dependent variables:	Irrigation take-up	Diversification index (log)	Inorganic fertilizer rate (log)	Livestock income (log)	Hired farm labor (log)	Wage farm labor (log)
Model:	(1)	(2)	(3)	(4)	(5)	(6)
	Logit	OLS	OLS	OLS	OLS	OLS
Variables						
Drought	0.7683***					
	(0.2090)					
Asset index	-0.0719					
	(0.1370)					
Drought × Asset index	-0.0452					
	(0.1429)					
Drought × Post		-0.1440***	0.1918***	0.0343	-0.0715	0.0809
		(0.0294)	(0.0323)	(0.1832)	(0.0833)	(0.1169)
Post × Asset index		0.0099	0.0010	0.1483*	-0.0654	0.0483
		(0.0201)	(0.0128)	(0.0868)	(0.0523)	(0.0469)
Drought × Post × Asset index		-0.0215	-0.0225	-0.0475	0.0392	0.0066
		(0.0262)	(0.0194)	(0.1156)	(0.0642)	(0.0527)
Controls:	Yes	Yes	Yes	Yes	Yes	Yes
Fixed-effects						
Year		Yes	Yes	Yes	Yes	Yes
Household		Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	2,731	4,882	4,884	5,844	4,884	1,453
R^2		0.85542	0.58819	0.65586	0.75317	0.88407
Within Adjusted R^2		0.01637	0.01256	0.00260	0.00094	-0.00626
Pseudo R^2	0.02864	0.79458	0.50091	0.18782	0.35108	0.63806

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Note: Regression of irrigation take up (no irrigation in $t-1$ and irrigation in t), diversification index (log), inorganic fertilizer rate (log), livestock income per capita (livestock revenue minus cost) on the fact to be affected by the drought and according to the asset level. For irrigation take-up, a probit model is used. The level of the asset is equal to the value of the asset index in the pre-treatment period. Controls include living in rural areas, the age of the household head, the education of the household head, the number of household members, and being a female-headed household. Year and household fixed-effect are used.

Table B2
Agricultural strategies used by households according to their wealth levels (Malawi)

Dependent variables: Model:	Irrigation take-up (1) Logit	Diversification index (log) (2) OLS	Inorganic fertilizer rate (log) (3) OLS	Livestock income (log) (4) OLS
Variables				
Drought	1.184			
	(0.7298)			
Asset value	-0.0145			
	(0.0470)			
Drought × Asset value	-0.1274			
	(0.1267)			
Drought × Post		-0.0072	-0.0081	-0.1601
		(0.0183)	(0.0101)	(0.1230)
Post × Asset value		-0.0007	-0.0002	-0.0136***
		(0.0008)	(0.0006)	(0.0048)
Drought × Post × Asset value		-0.0026*	0.0001	0.0237**
		(0.0016)	(0.0008)	(0.0110)
Controls:	Yes	Yes	Yes	Yes
Fixed-effects				
Year		Yes	Yes	Yes
Household		Yes	Yes	Yes
Fit statistics				
Observations	1,113	2,194	2,876	2,876
R^2		0.73142	0.65081	0.60808
Within Adjusted R^2		0.02270	-0.00314	0.00256
Pseudo R^2	0.09286	-68.349	-1.0873	0.23538

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Note: Regression of irrigation take up (no irrigation in $t-1$ and irrigation in t), diversification index (log), inorganic fertilizer rate (log), livestock income per capita (livestock revenue minus cost) on the fact to be affected by the drought and according to the asset level. For irrigation take-up, a logit model is used. The asset level is equal to the value of the assets (in k$ PPP eq) in the pre-treatment period. Controls include living in rural areas, the age of the household head, the education of the household head, the number of household members, and being a female-headed household. Year and household fixed-effect are used.

measured by the composite entropy index of crops grown by the household[37]. This indicator is equal to:

$$D = -\sum_{i=1}^{N} \rho_i \log(\rho_i) \left(1 - \frac{1}{N}\right) \tag{14}$$

Where D is the effective number of crops, N is the number of crops grown by the household, and ρ_i is the relative proportion of land devoted to crop i. This indicator measures the proportional abundance and evenness and is widely used in the diversification literature (Bozzola and Smale 2020; Tesfaye and Tirivayi 2020). The level of inputs is measured by the inorganic fertilizer rate (in kg/ha). The increase in livestock income is measured by the livestock income, which is equal to livestock sold and products issued from livestock sold (milk, eggs, etc.), minus the cost relative to livestock purchase and care.

Tables B1 and B2 explore the results of implementing agricultural strategies according to the pre-treatment asset level for Ethiopia and Malawi. Tables B3 and B4 explores the relationship between those strategies and the crop income per capita.

The results show that irrigation take-up is higher for households affected by the drought, even if the number of households concerned is low (respectively 5% and 1% of the total number of households). Regarding efficiency, irrigation allows households to have higher crop income in Ethiopia, but the increase in crop income is independent of being affected by the drought.

No evidence of adaptation through crop diversification is found in either country. The results suggest that crop diversification is strongly positive for crop income and reduces the impact of drought in Ethiopia.

Results also indicate that households do not significantly alter the amount of labor they hire or the wages they pay.

In Ethiopia, drought-affected households significantly increase their inorganic fertilizer use, allowing them to reduce the impact of the drought.

Finally, in Malawi, the wealthiest households affected by the drought increase their livestock income mainly by selling more livestock units and, to a lesser extent, by increasing on-farm livestock production (mainly milk and eggs).

B.3.3 Non-agricultural strategies

I focus on three main non-agricultural strategies: increasing the time dedicated to off-farm labor, migrating at least one household member for work purposes, and increasing remittances. The indicators used are the hours of off-farm labor per capita, a dummy for the migration of a member of the households for work purposes, and the amount of money received from relatives and friends.

Tables B5 and B6 show the results of the implementation of such strategies by households according to their level of assets.

The results show that there is no evidence that these strategies are being used in Malawi. In Ethiopia, the results show an increase in the time dedicated to off-farm activities. This increase concerns all households but is significantly greater for high-asset households. The probability of the migration of a household member for work purposes is globally higher for the wealthier households and higher for all households affected by the drought. Finally, the wealthiest households received significantly more remittances when affected by the drought.

37. Modified version of the Shannon-Weaver index enables comparison of crop diversity across different locations (Tesfaye and Tirivayi 2020)

Table B3
Efficiency of agricultural strategies used by households (Ethiopia)

Dependent variables:	Crop income per capita (log)			
Model:	(1)	(2)	(3)	(4)
Variables				
Drought	-0.7501***	-1.107***	-0.3522**	-1.042***
	(0.1475)	(0.2907)	(0.1412)	(0.2916)
Irrigation take up	1.347***			0.8903***
	(0.3403)			(0.3008)
Drought × Irrigation take up	-0.2975			-0.9876**
	(0.5306)			(0.4970)
Diversification index		0.3560***		0.3482***
		(0.0582)		(0.0572)
Drought × Diversification index		0.4841***		0.4514***
		(0.0876)		(0.0872)
Inorganic fertilizer rate			-0.0199	-0.0261
			(0.0287)	(0.0297)
Drought × Inorganic fertilizer rate			0.0819***	0.0503
			(0.0311)	(0.0318)
Controls:	Yes	Yes	Yes	Yes
Fit statistics				
Observations	2,731	2,442	2,442	2,409
R^2	0.12961	0.12102	0.04870	0.11282

Clustered (Household) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Note: Regression of the crop income per capita (value of crop production minus costs) on agricultural practices and the fact to be affected by the drought. Irrigation take-up corresponds to households not using irrigation in $t-1$ and using irrigation in t, the diversification index is the entropy composite index, and the inorganic fertilizer rate is measured in tonnes per hectare. Controls include living in rural areas, the age of the household head, the education of the household head, the number of household members, and being a female-headed household.

Table B4
Efficiency of agricultural strategies used by households (Malawi)

Dependent variables:	Crop income per capita (log)			
Model:	(1)	(2)	(3)	(4)
Variables				
Drought	-1.071***	-0.6825***	-0.6717***	-0.7023**
	(0.2038)	(0.2329)	(0.2106)	(0.3121)
Irrigation take up	-0.3571			-1.286
	(2.512)			(2.289)
Drought $\times$ Irrigation take up	-0.3399			-0.1031
	(2.805)			(2.595)
Diversification index		3.028***		3.038***
		(0.5002)		(0.5273)
Drought $\times$ Diversification index		-0.9148		-0.7102
		(0.7485)		(0.7723)
Inorganic fertilizer rate			2.641*	-0.5397
			(1.576)	(1.702)
Drought $\times$ Inorganic fertilizer rate			-0.9722	0.2282
			(2.021)	(2.120)
Controls:	Yes	Yes	Yes	Yes
Fit statistics				
Observations	1,113	1,105	1,438	1,061
R^2	0.04943	0.08915	0.13517	0.08803

Clustered (Household) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Note: Regression of the crop income per capita (value of crop production minus costs) on agricultural practices and the fact to be affected by the drought. Irrigation take-up corresponds to households not using irrigation in $t-1$ and using irrigation in t, the diversification index is the entropy composite index, and the inorganic fertilizer rate is measured in tonnes per hectare. Controls include living in rural areas, the age of the household head, the education of the household head, the number of household members, and being a female-headed household.

Table B5
Non-agricultural strategies used by households according to their wealth levels (Ethiopia)

Dependent variables:	Off-farm labour per capita (log)	Migration for work	Remittances (log)
Model:	(1)	(2)	(3)
	OLS	Logit	OLS
Variables			
Drought × Post	0.1695**		-0.0013
	(0.0737)		(0.0242)
Post × Asset index	0.1218***		0.0238**
	(0.0463)		(0.0116)
Drought × Post × Asset index	-0.1014*		-0.0386***
	(0.0605)		(0.0149)
Drought		0.4157***	
		(0.0962)	
Asset index		-0.1509***	
		(0.0471)	
Drought × Asset index		-0.0115	
		(0.0528)	
Controls:	Yes	Yes	Yes
Fixed-effects			
Year	Yes		Yes
Household	Yes		Yes
Fit statistics			
Observations	5,844	2,922	5,844
R^2	0.76247		0.69141
Within Adjusted R^2	0.00635		0.01340
Pseudo R^2	0.35099	0.07985	0.65883

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Note: Regression of off-farm labor per capita (log), migration for work of at least one member of the household, income from remittances (log) on the fact to be affected by the drought and according to the asset level. For migration for work, a logit model is used. The level of the asset is equal to the value of the asset index in the pre-treatment period. Controls include living in rural areas, the age of the household head, the education of the household head, the number of household members, and being a female-headed household. Year and household fixed-effect are used.

Table B6
Non-agricultural strategies used by households according to their wealth levels (Malawi)

Dependent variables:	Off-farm labour per capita (log)	Migration for work	Remittances
Model:	(1)	(2)	(3)
	OLS	Logit	OLS
Variables			
Drought × Post	-0.0603		-0.0493
	(0.0804)		(0.0306)
Post × Asset value	-0.0013		0.0002
	(0.0037)		(0.0007)
Drought × Post × Asset value	0.0039		-0.0015
	(0.0061)		(0.0024)
Drought		-0.3277	
		(0.2000)	
Asset value		0.0012	
		(0.0067)	
Drought × Asset value		0.0042	
		(0.0126)	
Controls:	Yes	Yes	Yes
Fixed-effects			
Year	Yes		Yes
Household	Yes		Yes
Fit statistics			
Observations	2,876	1,438	2,876
R^2	0.54067		0.63203
Within Adjusted R^2	-5.99×10^{-5}		0.00444
Pseudo R^2	0.27534	0.05076	0.82986

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Note: Regression of off-farm labor per capita (log), migration for work of at least one member of the household, income from remittances (log) on the fact to be affected by the drought and according to the asset level. For migration for work, a logit model is used. The asset level is equal to the value of the assets (in k$ PPP eq) in the pre-treatment period. Controls include living in rural areas, the age of the household head, the education of the household head, the number of household members, and being a female-headed household. Year and household fixed-effect are used.