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Arnold L. Musungu, Zaneta Kubik, and Matin Qaim

Drought Shocks and Labor Reallocation in Rural Africa: Evidence from Ethiopia

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Zentrum für Entwicklungsforschung (ZEF)
Center for Development Research
Genscherallee 3
D – 53113 Bonn
Germany
Phone: +49-228-73-1861
Fax: +49-228-73-1869
E-Mail: zef@uni-bonn.de
www.zef.de

The authors:
Arnold L. Musungu, Center for Development Research (ZEF), University of Bonn.
Contact: amusungu@uni-bonn.de
Zaneta Kubik, University of Göttingen. Contact: zaneta.kubik@uni-goettingen.de.
Matin Qaim, Center for Development Research (ZEF), and Institute for Food and Resource Economics, University of Bonn; Contact: mqaim@uni-bonn.de .

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Abstract

We study how rural households in Ethiopia adapt to droughts through labor reallocation. By using three waves of panel data and exploiting spatial-temporal variations in drought exposure, we find that households reduce on-farm work and increase off-farm self-employment in response to both short-term and persistent droughts, without abandoning family farming. Diversification into off-farm activities is driven by drought-related productivity declines in agriculture and contributes to consumption smoothing. Households with better access to markets and financial services find it easier to reallocate labor off-farm. Our results highlight the importance of strengthening the rural non-farm economy to enhance rural households' climate resilience.

Keywords: Climate change; labor allocation; labor markets; Africa; Ethiopia.

JEL Codes: Q54, J21, J22, J43, O13

1. Introduction

Extreme weather events – such as droughts – seem to become more frequent with climate change and are known to have negative impacts on farm production and income (Schlenker and Lobell, 2010; Lobell et al., 2011; Chavas et al., 2019; Ortiz-Bobea et al., 2021). Developing countries, particularly in sub-Saharan Africa (SSA) where agriculture is the mainstay of poor people's livelihoods, bear the brunt of these risks. The literature has looked at several ways in which rural households in developing countries can adapt to weather risks, including asset sales, formal and informal insurance, or technology adoption. However, these adaptation strategies are often prohibitively costly, ineffective or unsustainable (Dercon and Krishnan, 2000; Gin´e and Yang, 2009; Karlan and Morduch, 2010; Dercon and Christiaensen, 2011). Much less is known about the extent to which rural households in SSA use labor reallocation for adaptation, especially shifting from farm to off-farm work, and whether such reallocation is effective in protecting household welfare against the negative consequences of weather shocks.

Weather shocks can prompt rural households to reallocate labor in different ways. Households may diversify their income sources or work more, either on-farm or off-farm, in order to make up for lost agricultural revenues. A certain shift from farm work to off-farm work is likely (Branco and F´eres, 2021), as off-farm jobs are typically less affected by weather disruptions. However, off-farm employment depends on local labor markets and their capacity to absorb additional labor during times of weather shocks. If off-farm jobs are not sufficiently available or accessible, self-employment in small non-agricultural businesses can sometimes be an alternative. Yet another alternative would be temporary or permanent migration to regions less affected by weather shocks or with better employment opportunities (Young, 2013).

In this paper, we study labor allocation decisions of rural households as a response to extreme weather shocks in the context of Ethiopia. More specifically, we exploit spatio-temporal variation in exposure to droughts to look at the effects of short-term and persistent drought shocks on the probability of a household to be involved in farm work, off-farm jobs and self-employment as well as the labor time allocated to these employment categories. We also analyze to which extent the labor allocation decisions help households smooth their consumption in the event of a drought shock. Ethiopia provides an interesting context for this study due to several reasons. First, in addition to its high economic vulnerability, Ethiopia is the second most populous country in Africa with 80% of its rural population being employed in agriculture (UN-DESA, 2019). Second, agriculture in Ethiopia is predominantly small-scale farming with widespread poverty and limited access to markets and advanced production technologies. Lastly, Ethiopia has a long history of droughts and an increasing frequency of extreme weather events (Viste et al., 2013; Mekonen et al., 2020).

Our results reveal that an increase in both short-term and persistent droughts has two main effects. First, it reduces the likelihood of households being employed in farm wage jobs and increases their likelihood of self-employment in off-farm jobs. Second, it reduces the labor hours allocated to on-farm wage and self-employment and raises labor allocation to off-farm self-employment. Our results are consistent with droughts causing lower agricultural productivity and frictions in the labor market, leading to lower economic prospects in farm jobs and limited non-agricultural employment opportunities. We confirm the robustness of the findings using various empirical specifications. Finally, we find suggestive evidence that off-farm self-employment is consumption-smoothing

This study is related to an emerging body of literature on labor market and sectoral responses to weather shocks in developing countries. In highlighting the importance of having a robust non-farm rural economy to build resilience against climate change, Jessoe and Taylor (2018) find that local labor markets in Mexico respond to hot years by reducing employment levels in wage work and non-farm jobs. Relatedly, Jaychandran (2006) shows that weather-induced productivity risks hurt poor rural households by significantly driving down wages. On sectoral responses to positive weather shocks, Emerick (2018) estimates that increasing agricultural productivity due to abnormally high rainfall shocks in India leads to an increase in non-agricultural labor share. On the other hand, Colmer (2021) addresses the extent to which labor reallocation can offset the negative economic consequences of weather-driven agricultural productivity shocks in India. In particular, the study finds that temperature-driven reductions in the demand for agricultural labor are correlated with increases in non-agricultural employment. This implies that the capacity of non-agricultural sectors to absorb workers might play a significant role in mitigating the economic impacts of negative agricultural productivity shocks. At the micro level, Branco and F´eres (2021) find that rural farming households in Brazil increase labor supply in non-agricultural sectors during drought episodes.

We contribute to this body of literature in three important ways. First, existing studies have paid little attention to the context of SSA, which is experiencing a unique structural transformation characterized by increasing non-agricultural self-employment without a decrease in on-farm employment (Christiaensen and Maertens, 2022). We address this gap by providing evidence from Ethiopia. Second, we look not only at the effect of short-term droughts (i.e. droughts occurring in the last year or growing season), but also at the effect of persistent droughts (i.e. droughts spanning over the period of the last three years). Third, we explicitly test if the labor reallocation decisions protect household welfare from the negative consequences of drought. Specifically, we analyze if non-farm employment helps households to smooth food and non-food consumption. Existing studies have mostly focused on the direct effects of weather shocks on consumption to infer whether or not households have successfully adapted (e.g., Emerick, 2018; Gao and Mills, 2018; Aggarwal, 2021).

The rest of the paper is organized as follows: The next section describes the conceptual framework, while section 3 discusses the sources of data. We present the empirical strategy and results in sections 4 and 5, respectively, and conclude in section 6.

2. Conceptual Framework

To study household labor allocation decisions, we apply a household production function framework, in which the household is the unit of production, consumption, and decision-making (Udry, 1996). The household maximizes utility by allocating available labor across different activities, such as farming, off-farm work, and leisure, subject to resource constraints and the available production technology. An increase in agricultural productivity implies higher returns to agricultural inputs, thus attracting more labor to the sector (Becker, 1962). In contrast, weather shocks such as drought reduce agricultural productivity, yield and income, and thus lower the returns to agricultural labor, which, in turn, is expected to shift labor away from farm and towards off-farm economic activities (Lewis, 1954; Colmer, 2021).

When faced with reduction of productivity on the own farm, the household may allocate (some of) its labor to off-farm employment. This includes wage employment – both in agriculture (i.e. on someone else's farm) and in non-agricultural activities – and off-farm self-employment. The availability and returns to off-farm employment depend on market wages and prices, which are influenced by local market conditions, information, and infrastructure. The household may allocate more labor to off-farm work if it is less risky and (or) the returns are expected to be higher relative to farming. Out of the three off-farm employment alternatives, not all appear to be equally plausible options for households exposed to drought shocks.

First, wage employment in agriculture is expected to be negatively affected by weather shocks in the same manner as own-farm employment may be. This is because weather shocks tend to be spatially concentrated and affect all local farmers at the same time. Hence, in local labor markets, wage employment opportunities in agriculture, as well as corresponding wage rates, are expected to decrease following a weather shock, especially if migration out of the local labor markets is constrained (Jayachandran, 2006).

Second, at least in the short run, off-farm wage and self-employment are expected to be shielded from the consequences of weather shocks. Hence, off-farm employment may offer higher returns to labor than on-farm employment. However, with persistent rural market failures, non-agricultural wage employment opportunities are typically scarce, meaning that expected labor adjustments are not always feasible. Instead, households may turn to non-farm self-employment in own small businesses, which are not always very lucrative however (Haggblade et al., 2010; Davis et al., 2017). In the long-run, it is possible that non-agricultural employment is negatively affected by persistent weather shocks, especially if local demand effects are accounted for.

It is also worth noting that the wish of households to reallocate labor may change over time. For instance, households may gradually use on-farm adaptation measures, thus decreasing their need for extensive labor reallocation in response to weather shocks in the long-run.

Other households may gradually abandon own farming, thus increasing their labor supply to non-agricultural activities in the long-run. In summary, household responses to short-term and persistent weather shocks through labor reallocation, the associated mechanisms, and the potential of such responses to smooth consumption are all important empirical questions that we address here in the context of Ethiopia.

3. Data Sources

We use data from two main sources. First, we use household data from the Ethiopia Socioeconomic Surveys (ESS), which are part of the World Bank's Living Standards Measurement Survey (LSMS).[1] Second, we use weather data on temperature and rainfall from the National Oceanic and Atmospheric Administration (NOAA). These data are explained in more detail below.

3.1 Household Data

We use the 2011, 2013 and 2015 ESS to construct a balanced panel of 3,222 rural households observed over the three waves (i.e. 9,666 observations in total). The main outcome variables, i.e. farm and off-farm wage and self-employment, are constructed based on the information available in the employment module of the household survey. The employment module contains information on the employment status of all household members aged 15 and older in the last 12 months before the survey. We aggregate this information and create two household-level measures of employment, namely a dummy variable equal to one if any member of the household participates in a given employment category (i.e. extensive margin) and a continuous variable measuring the number of hours per week spend by the household in that employment category (i.e. intensive margin). For better comparison, we modify the continuous variable and calculate the percentage share of the household weekly hours in each employment category by dividing the hours in each category by the total household weekly labor hours. We also calculate the share of household members aged 15 and older engaged in a given employment category.

In terms of income variables, we calculate total farm and off-farm wage and business income, using data on wages, earnings from self-employment and other income sources. Variables on food and non-food consumption over the last 12 months before the survey are derived from the household expenditures modules.[2] To construct farm-related variables for the survey year – such as land productivity, labor productivity (agricultural output value per labor-day), hired labor, crop and livestock income – we combine information from the agriculture and livestock modules of the questionnaire. Finally, we construct a series of household control variables, including gender, education, and age of the household head, family size, total land size, tropical livestock units (TLUs), and a dummy variable indicating the use of formal financial services, specifically insurance, credit, or both.

Table 1 presents sample summary statistics. The majority of households, 81%, are self-employed on their farms. Both on-farm and off-farm wage employment are evidently low (2% and 9% of households, respectively). On the other hand, 23% of households are engaged in

[1] https://microdata.worldbank.org/index.php/catalog/?page=1&ps=15
[2] All monetary values are expressed in real terms, adjusted for inflation.

off- farm self-employment. It seems that off-farm self-employment is the most common income diversification strategy among rural households in Ethiopia, as was also pointed out in previous research (Bachewe et al., 2016). The average annual household consumption expenditure is Birr 20,465 of which about 80% go to household food consumption. The high food expenditure share is a clear indication of the low average living standard of rural households in Ethiopia.

3.2 Weather Data

We extract gridded daily rainfall and maximum and minimum temperature data from the NOAA Climate Prediction Center (CPC) covering the period 1980-2022.[3] The gridded daily rainfall in millimeters (mm) and surface temperature in degrees Celsius (^{0}C) datasets have a spatial resolution of 0.50–degree by 0.50–degree latitude-longitude grid nodes. We leverage the enumeration area (EA) — equivalent of a village — geolocations provided in the household surveys to match the weather data with the household data.

Our main explanatory variable is drought, a proxy of weather shock, defined as the number of dry months within the last year or, alternatively, within the last growing season before the survey. Drawing on the existing literature (Burke and Emerick, 2016; Lee et al., 2019; Kakpo et al., 2022), we calculate this drought variable as follows. First, for each EA-month of the year before the survey, we generate rainfall z-scores:

$$zscore_{cmt}^{RF} = \frac{RF_{cmt} - \overline{RF}_{cm}}{RF_{cm}^{SD}} \qquad (1)$$

where RF_{cmt} is the total rainfall in EA *c* in month *m* of year *t*; $\overline{RF}_{cm}$ is each EA's 30-year (1981-2010) historical rainfall mean for a given month, while RF_{cm}^{SD} is each EA's historical (1980-2010) standard deviation of rainfall for a given month. A z-score less than or equal to -1 indicates a drought month (McKee et al. 1993). Second, for each year, we aggregate the number of drought months to obtain the final explanatory variable. We refer to this variable as "short- term drought", i.e. drought recorded over the last year before the survey. Additionally, we construct a cumulative measure of drought, i.e. the number of dry months recorded over the three years before the survey. We refer to this variable as "persistent drought".

Finally, to account for the fact that the occurrence and effects of drought are likely reinforced by extreme temperatures, we also generate temperature shock indicators as auxiliary weather shock proxies, which we measure as the number of hot months over the

[3] The raw daily rainfall and temperature data can be extracted from https://psl.noaa.gov/data/gridded/data.cpc.globalprecip.html and https://psl.noaa.gov/data/gridded/data.cpc.globaltemp.html.

last year, the last growing season and the last dry season before the survey. Hot months are defined as the months with temperature z-scores greater than or equal to 2, indicating the occurrence of extreme temperatures.

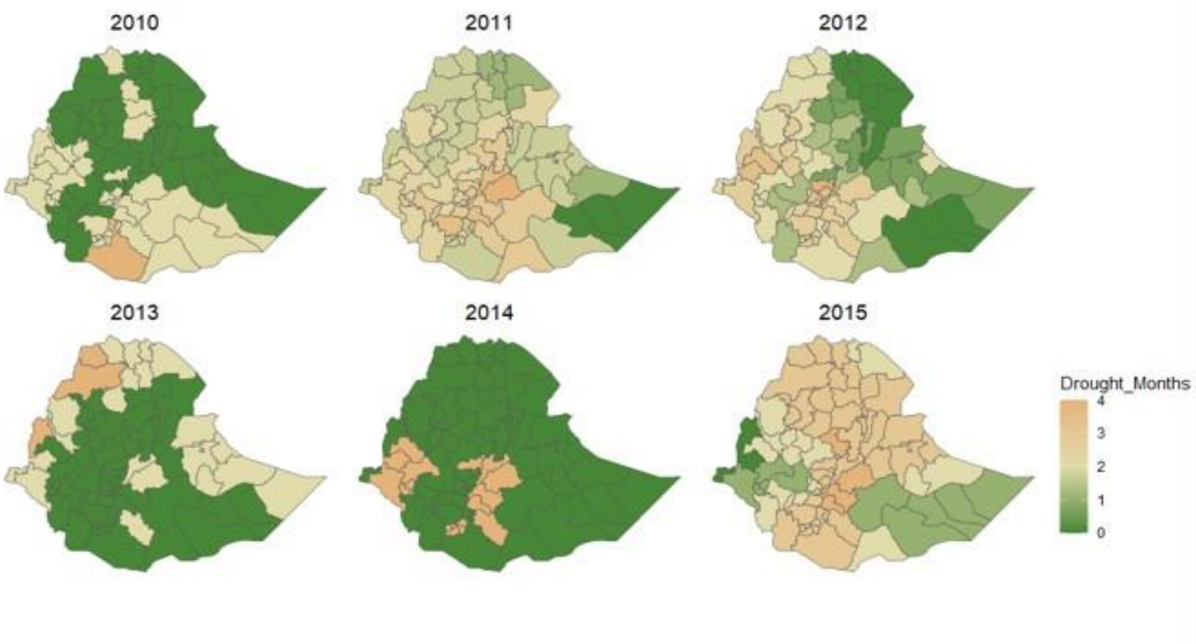
Table 1: Summary statistics

	N	Mean	SD
Panel A: Labor variables			
Share of households employed in on-farm wage job	9666	0.021	0.144
Share of households employed in off-farm wage job	9666	0.093	0.290
Share of households self-employed on-farm	9666	0.814	0.389
Share of households self-employed off-farm	9666	0.230	0.421
Share of weekly hours in on-farm wage jobs	9666	0.007	0.052
Share of weekly hours in off-farm wage jobs	9666	0.050	0.183
Share of weekly hours in on-farm self-employment	9666	0.712	0.403
Share of weekly hours in off-farm self-employment	9666	0.114	0.254
Household weekly labor hours	9666	64.289	62.575
Panel B: Household welfare variables			
Gross annual value of crop production	8267	9,003.014	43,725.028
Gross annual crop income	8267	1,983.321	5,180.687
Total annual income	9666	11,698.923	19,654.492
Total annual consumption expenditure	9666	20,465.080	19,778.700
Annual expenditure food consumption	9666	16,524.685	16,878.648
Annual expenditure on nonfood consumption	9666	3,641.467	7,683.593
Family farm labor (person days)	9666	204.813	226.516
Hired farm labor (person days)	9666	33.422	486.230
Land size in hectares	9666	1.491	6.522
Land productivity	8267	24,528.532	357,015.055
Labor productivity	8267	37.005	54.067
Tropical livestock nits	9666	2.638	5.807
Panel C: Weather variables			
Drought months in pre-survey year	9666	1.034	1.400
Drought months in pre-survey growing season	9666	0.718	1.094
Hot months in pre-survey year	9666	0.470	0.777
Average monthly temperature (degree Celsius)	9666	21.003	3.366
Average monthly rainfall (millimeters)	9666	52.994	29.939
Panel D: Household controls			
Head age in years	9666	46.301	15.330
Share of households with female head	9666	0.238	0.426
Share of heads with post-primary school education	9666	0.317	0.465
Number of household members	9666	5.639	2.516
Share of households using financial services	9666	0.130	0.336

Notes: The sample size for gross value of crop production, gross crop income, land productivity and labor productivity is lower than the actual sample size because not all households practice crop production in all the three survey years. All income and consumption values are measured in Ethiopian Birr per year. Land productivity and labor productivity are measured for survey year as crop value in Birr per hectare and farm value in Birr per household labor-day respectively. The average exchange rate over the survey period was $1=Birr 21.24

Panel C of Table 1 presents the summary statistics of selected weather variables. On average, households experience 1 drought month in a year and approximately 0.7 and 0.3 drought months during the growing season and the dry season, respectively. Substantial variation in drought occurrence and intensity over time and space can be seen in Figure 1.

Figure 1: Variation in annual drought occurrence in Ethiopia 2010-2015



Source: Authors' compilation based on data from NOAA

4. Empirical Strategy

4.1 Estimating Labor Reallocation Effects

We estimate the effects of drought shocks on household labor allocation decisions at the extensive and intensive margins as follows:

$$L_{ict} = \alpha + \beta D_{ct-1} + \varphi W_{ct-1} + \lambda X_{ict} + \vartheta_i + \mu_t + \vartheta T_{st} + \varepsilon_{ict} \quad (2)$$

where L_{ict} corresponds to labor outcomes, i.e. agricultural and non-agricultural wage and self-employment dummies or, alternatively, the percentage share of weekly hours allocated to each employment category by household i located in EA c in year t. D_{ct-1} is our main explanatory variable and corresponds to the number of drought months in EA c in which household i is located, measured over the last year or the last growing season prior to the survey (t-1). Alternatively, we estimate a separate set of models using the cumulative measures of drought, i.e. persistent drought observed over the three years before the survey.

We include a vector of time-variant auxiliary weather variables at the EA level, W_{ct} (temperature shocks, monthly average temperature, monthly average rainfall), to differentiate drought shocks from other weather variation. We also control for a vector of household socioeconomic characteristics, X_{ict} (gender, education, age of household head, household size, tropical livestock units, use of financial services). We account for time-invariant unobserved household heterogeneity by including household fixed effects, ϑ_i. Additionally, we include year fixed effects, μ_t and region-specific linear time trends, T_{st}. We cluster standard errors at the EA level.

We exploit spatial and temporal variation in individual households' exposure to drought shocks in their respective EAs for identification. We argue that households are unlikely to foresee the exact timing and location of drought incidences. Hence, we consider the explanatory variable as exogenous. As such, our coefficient estimate β can be interpreted as the effect of one extra month of drought shock during the year or growing season on household labor allocation at either extensive or intensive margins. We provide a more detailed discussion and additional model specifications in the Supplementary Appendix to estimate possible heterogeneous effects.

We also carry out a number of robustness checks. First, we test for possible attrition bias. Recall that we set out to use a balanced panel throughout our analysis. This has advantages for estimation with household fixed effects but means that households not included in all survey wavers are ignored. To test for possible attrition bias, we replicate our main results using an unbalanced panel of all rural households. Second, we test whether the results are robust to alternative definitions of the outcome variable. Third, we test whether using an alternative weather database has a major influence on the results. And finally, we test whether the findings are robust to alternative ways of accounting for possible regional time trends. Further details of these robustness checks are discussed below in the results section.

4.2 Mechanisms

In addition to estimating the effects of drought shocks on labor allocation, we also explore the main underlying mechanisms. Drawing on the literature (Zhang et al., 2018; Emerick, 2018; Colmer, 2021; Ibanez et al., 2021; Olper et al., 2021), we look at agricultural production effects and local labor market dynamics. In terms of agricultural production, we hypothesize that household labor reallocation decisions can be explained by a direct negative effect of drought shocks on agricultural productivity. If land and agricultural labor productivity significantly decline as a result of drought, households may decide to reallocate (some of) their labor away from own farming to employment activities that are less affected by drought in order to protect their incomes and consumption. To test this mechanism, we compute household land productivity as the value of crop production divided by total land area cultivated, and agricultural labor productivity as the value of crop production per labor-day. Both variables are used in logarithmic form.

We test the agricultural production mechanism by estimating:

$$Y_{ict} = \alpha + \sigma D_{ct} + \varphi W_{ct} + \lambda X_{ict} + \vartheta_s + \mu_t + \vartheta T_{st} + \varepsilon_{ict} \quad (3)$$

Where Y_ict are the outcome variables, i.e., logarithms of household land productivity and agricultural labor productivity for household *i* in EA *c* in year *t*. We follow the same identification strategy as in Equation 2. Notice that we measure drought in the same period in which we observe the agricultural outcomes—i.e. in the survey period—because the effects of weather shocks on agricultural production are contemporaneous.

In terms of labor market dynamics, we test if household labor allocation can be explained by frictions in local labor markets caused by droughts, both inside and outside of agriculture. First, we hypothesize that drought shocks shrink demand for hired on-farm labor due to negative effects on agricultural productivity. If this is the case, the supply of on-farm wage jobs would significantly diminish in the presence of droughts. We test this hypothesis by estimating the direct effects of droughts on households' demand for hired on-farm labor and corresponding daily wages paid. We expect that in response to drought, households will hire less labor, offer lower wages, or both. Second, we test whether labor demand and wages in non-agricultural activities are affected by droughts. It is difficult to predict a priori whether and to which extent non-agricultural labor demand responds to drought, as the effect will depend on the intensity of linkages between non-agricultural activities and agriculture and also on local demand effects. The challenge is that we do not observe data on non-agricultural firms to directly measure their labor demand and wages over time. We therefore use non-agricultural wage income as a proxy for wages paid by firms.

4.3 Labor Reallocation and Consumption Smoothing

We estimate the following regression model to assess the effect of labor reallocation on household welfare, and more specifically, the success in terms of consumption smoothing following drought episode(s):

$$C_{ict} = \alpha_1 D_{ct-1} + \alpha_2 D_{ct-1} * E_{ict} + \varphi W_{ct-1} + \lambda X_{ict} + \vartheta_i + \mu_t + \vartheta T_{st} + \varepsilon_{ict} \qquad (4)$$

Where C_{ict} is consumption (food and non-food consumption value in logarithmic form) of household i in EA c in year t. We introduce an interaction term between the number of weekly hours in off-farm job(s) to which the household has reallocated labor to, E_{ic}, and the drought shock observed in the last year before the survey. This interaction term informs us about the extent to which off-farm employment protects household consumption against the effects of drought. We control for the same household time-variant factors and account for household and year fixed effects and region-time trends as in our baseline specification above.

5. Results

5.1 Labor Reallocation: Extensive Margin

In this section, we discuss results from regressing dummy variables for household involvement in the different categories of employment on drought shock and other covariates, as specified in Equation 2. We employ a linear probability model because of its computational ease in absorbing many high-dimensional fixed effects and time trends (Guimaraes and Portugal, 2010). Panel A of Table 2 shows results for farm wage employment in columns (1) and (2), and for off-farm wage employment in columns (3) and (4). Panel B shows results for on-farm self-employment in columns (1) and (2), and for off-farm self-employment in columns (3) and (4).

Table 2: Effects of drought on household likelihood of employment across job categories

	Farm		Off-farm	
	(1)	(2)	(3)	(4)
Panel A: Wage employment				
Drought (year)	-0.005*		0.002	
	(0.003)		(0.006)	
Drought during growing season		-0.009**		-0.004
		(0.004)		(0.008)
Mean of dep. variable	0.021	0.021	0.093	0.093
R-squared	0.499	0.499	0.628	0.628
Panel B: Self-employment				
Drought (year)	-0.011		0.051***	
	(0.009)		(0.013)	
Drought during growing season		-0.007		0.067***
		(0.013)		(0.017)
Mean of dep. variable	0.814	0.814	0.231	0.231
R-squared	0.580	0.580	0.529	0.529
Household & weather controls	Yes	Yes	Yes	Yes
Household & year fixed effects	Yes	Yes	Yes	Yes
Region-time trends	Yes	Yes	Yes	Yes
Observations	9666	9666	9666	9666

Notes: The dependent variable is a dummy taking a value of 1 if a household has at least one member employed in a given employment category and 0 otherwise. Drought refers to the pre-survey year and pre-survey growing season. Household controls are age, gender and education of the household head, household size, land size and use of financial services. Weather controls are temperature shock, average monthly temperature and average monthly rainfall. Robust standard errors clustered at the EA level in parentheses. *** p<0.01, ** p<0.05, * p<0.10.

The results in panel A of Table 2 show that one extra month of drought in the previous year marginally reduces households' probability of employment in farm wage jobs by 0.5 percentage points. This effect nearly doubles when the drought occurs during the growing season. Specifically, one extra drought month during the previous year's growing season decreases the household probability of having a farm wage job by 0.9 percentage points. We do not find any evidence of drought effects on the probability of off-farm wage employment, which may possibly be due to the scarcity of off-farm jobs in the local rural contexts.

In panel B of Table 2, we do not find statistically significant effects of drought on on-farm self-employment. However, we find evidence that an extra month of drought in the previous year increases the probability of off-farm self-employment by about 5 percentage points. The effect is amplified to almost 7 percentage points when the extra drought month occurs in the growing season. These findings highlight the important role of non-agricultural self-employment in mitigating agricultural income losses due to drought.

5.2 Labor Reallocation: Intensive Margin

Table 3 presents results from different specifications of Equation 2 where the dependent variable is the percentage share of household weekly hours in each of the four job categories. One extra month of drought during the last growing season (column 2 of panel A) leads to a 0.3 percentage point decrease in the household labor share spent in farm wage-employment. While this coefficient may appear small, it should be noted that the average household in the sample only spends 0.7% of its labor time on farm wage labor, meaning that the drought effect is equivalent to a reduction of over 40%. For off-farm wage jobs, we find no significant effects of drought. Again, this may possibly be due to inadequate non-agricultural wage employment opportunities in the local contexts to absorb the surplus labor following drought episodes.

In panel B of Table 3, we find strong evidence that an increase in drought months significantly affects household labor allocation to both farm and off-farm activities. First, the results in columns (1) and (2) show that an additional drought month — during the year and growing season alike — leads to a 3 percentage point decrease in the household labor share spent in on-farm self-employment (equivalent to a 4% decline evaluated at the sample mean of the dependent variable). Second, the results in columns (3) and (4) reveal that households respond to drought by allocating more labor to off-farm self-employment. In particular, we find that an additional drought month during the growing season leads to a 4.6 percentage point increase in the household labor share spent in off-farm self-employment (equivalent to a 40% increase evaluated at the sample mean of the dependent variable). Taken together, the results in Table 3 suggest that rural households in Ethiopia respond to frequent drought shocks by reallocating labor away from farming (both own farming and wage-employment on other farms) to off-farm self-employment.

Additional results on the effects of persistent droughts — cumulative over three years — reveal two important insights (Supplementary Appendix Tables A1 and A2). First, the effects of persistent drought point in the same direction as the effects of short-term drought, namely a labor reallocation away from farming to off-farm self-employment. Second, the effects of persistent drought in Table A2 are somewhat smaller in absolute terms than the effects of short-term drought in Table 3, suggesting that in the long-run households are possibly substituting on-farm adaptation for off-farm adaptation to some extent.

Table 3: Effects of drought on household intensive labor allocation margins

	Farm		Off-farm	
	(1)	(2)	(3)	(4)
Panel A: Wage employment				
Drought (year)	-0.164*		0.412	
	(0.099)		(0.378)	
Drought during growing season		-0.287**		0.128
		(0.132)		(0.537)
Mean of dep. variable	0.711	0.711	5.000	5.000
R-squared	0.555	0.556	0.683	0.683
Panel B: Self-employment				
Drought (year)	-3.014***		3.142***	
	(0.977)		(0.692)	
Drought during growing season		-3.094**		4.608***
		(1.357)		(0.975)
Mean of dep. variable	71.152	71.152	11.405	11.405
R-squared	0.598	0.597	0.536	0.538
Household & weather controls	Yes	Yes	Yes	Yes
Household & year fixed effects	Yes	Yes	Yes	Yes
Region-time trends	Yes	Yes	Yes	Yes
Observations	9666	9666	9666	9666

Notes: The dependent variable is the share of household labor hours spent in a particular employment category expressed in percent. Drought refers to the pre-survey year and pre-survey growing season. Household controls are age, gender and education of the household head, household size, land size and use of financial services. Weather controls are temperature shock, average monthly temperature and average monthly rainfall. Robust standard errors clustered at the EA level in parentheses. *** p<0.01, ** p<0.05, * p<0.10.

The analysis of possible effect heterogeneity is shown in Supplementary Appendix Tables A3 to A6. These additional models suggest that the labor reallocation effects as a response to drought are somewhat stronger for households that live closer to urban centers and for households with better access to formal financial services than for households in remote settings and with limited access to financial services. These differences are plausible, as proximity to urban centers and access to financial services likely have positive ramifications for off-farm labor market opportunities. The results are also consistent with other recent research in Africa showing that access to credit enhances the capacity of households to adapt to rainfall shocks (Tabetando et al., 2023).

5.3 Mechanisms

We now analyze some of the main mechanisms underlying the effects of drought on labor reallocation, as explained in Equation 3. The effects of drought on agricultural production are summarized in Table 4.

Table 4: Effects of drought on land and labor productivity

	Land productivity		Labor productivity	
	(1)	(2)	(3)	(4)
Drought (year)	-0.115		-0.049	
	(0.107)		(0.059)	
Drought during growing season		-0.239**		-0.066
		(0.122)		(0.065)
Mean of dependent variable	24528.53	24528.53	39.80	39.80
Household & weather controls	Yes	Yes	Yes	Yes
Household & year fixed effects	Yes	Yes	Yes	Yes
Region-time trends	Yes	Yes	Yes	Yes
Observations	8267	8267	8267	8267
R-squared	0.596	0.597	0.629	0.631

Notes: The dependent variables are logarithms of land productivity and labor productivity. Drought refers to the pre-survey year and pre-survey growing season. Household controls are age, gender and education of the household head, household size, land size and use of financial services. Weather controls are temperature shock, average monthly temperature and average monthly rainfall. Robust standard errors clustered at the EA level in parentheses. *** p<0.01, ** p<0.05, * p<0.10.

As expected, drought negatively affects agricultural productivity. One extra drought month in the growing season reduces land productivity by 24%. Recall that we defined land productivity as the value of crop production per hectare of farm area (i.e., land that was allocated to crop production during the year). Therefore, relative to the sample mean, this implies that an extra month of drought during the growing season reduces the value of crop production by about Birr 5,807 per hectare. The coefficient estimates for labor productivity are also negative, even though they are smaller in absolute terms and not statistically significant.

The effects of drought on labor demand and wages are summarized in Table 5. In line with the results in table 4, we find negative but statistically insignificant effects of drought on the use of family labor on household farms. However, households significantly reduce the demand for hired labor on their farms. One additional drought month during the growing season reduces the quantity of hired labor by about 10% (panel A, column 4) and the wages paid to hired farm labor by about 20% (panel B, column 2). These results, taken together with the negative effects of drought on agricultural productivity, explain why households reduce labor supply to farm wage employment at both extensive and intensive margins. We find no evidence of significant effects of drought on non-agricultural wage income (panel B, columns 3 and 4). Given that the labor supply of households to off-farm wage employment does not change significantly in response to drought (see Table 3), any changes in wage income would primarily be driven by changes in wage rates. The insignificant estimates in Table 5 suggest that non-agricultural wage rates do not respond much to short-term drought.

Table 5: Effects of drought on household farm-labor demand and wages

Panel A: Farm labor	Family labor		Hired labor	
	(1)	(2)	(3)	(4)
Drought (year)	-0.044		-0.024	
	(0.033)		(0.037)	
Drought during growing season		-0.036		-0.104***
		(0.037)		(0.038)
Mean of dep. variable	204.81	204.81	33.42	33.42
R-squared	0.61	0.609	0.677	0.678
Panel B: Wages	Wages paid to hired farm labor		Non-agricultural wage income	
	(1)	(2)	(3)	(4)
Drought (year)	-0.111**		0.100	
	(0.044)		(0.062)	
Drought during growing season		-0.198***		0.046
		(0.045)		(0.090)
Mean of dep. variable	17.40	17.40	3437.49	3437.49
R-Squared	0.592	0.594	0.673	0.673
Household & weather controls	Yes	Yes	Yes	Yes
Household & year fixed effects	Yes	Yes	Yes	Yes
Region-time trends	Yes	Yes	Yes	Yes
Observations	9666	9666	9666	9666

Notes: The dependent variables in panel A are logarithms of family and hired labor days used on the household farm. The dependent variables in panel B are logarithms of wages paid to hired farm labor and non-agricultural wage income of household members. Drought refers to the pre-survey year and pre-survey growing season. Household controls are age, gender and education of the household head, household size, land size and use of financial services. Weather controls are temperature shock, average monthly temperature and average monthly rainfall. Robust standard errors clustered at the EA level in parentheses. *** p<0.01, ** p<0.05, * p<0.10.

5.4 Off-farm Self-employment and Consumption Smoothing

We now estimate Equation 4 with an interaction term between drought and labor time in off-farm jobs, in order to analyze to what extent labor reallocation can contribute to consumption smoothing. We focus on off-farm self-employment (OFSE), as the results above showed this is the main off-farm category that households reallocate labor to as a response to drought.

Table 6: Effects of drought on household consumption

	Food consumption		Non-food consumption	
	(1)	(2)	(3)	(4)
Drought (year)	-0.0123		-0.0155	
	(0.0153)		(0.0218)	
Drought (year) ×OFSE hours	0.0008***		0.0005*	
	(0.0002)		(0.0003)	
Drought (growing season)		-0.0367*		-0.0571*
		(0.0190)		(0.0298)
Drought (growing season) ×OFSE hours		0.0008***		0.0006
		(0.0002)		(0.0004)
Mean of dep. variable	16524.68	16524.68	3641.47	3641.47
Household & weather controls	Yes	Yes	Yes	Yes
Household & year fixed effects	Yes	Yes	Yes	Yes
Region-time trends	Yes	Yes	Yes	Yes
Observations	9666	9666	9666	9666
R-squared	0.673	0.673	0.699	0.699

Notes: The dependent variables are logarithms of annual expenditures on food and non-food consumption. Drought refers to the pre-survey year and pre-survey growing season. Household controls are age, gender and education of the household head, household size, land size and use of financial services. Weather controls are temperature shock, average monthly temperature and average monthly rainfall. OFSE stands for non-farm self-employment. Robust standard errors clustered at the EA level in parentheses. *** p<0.01, ** p<0.05, * p<0.10.

The results in Table 6 suggest that one additional month of drought during the growing season reduces household food and non-food consumption by around 4% and 6%, respectively. However, the coefficients of the interaction term between drought and OFSE time are positive and, in the case of food consumption (column 2), also statistically significant. In particular, we find that in response to one additional drought month, an extra hour of household work in OFSE enhances food consumption by 0.08%. Comparing this to the 4% food consumption decline due to drought implies that the average household would have to allocate almost 50 additional hours to OFSE to fully make up for the welfare loss. In any case, reallocation of labor time to OFSE contributes to consumption-smoothing and clearly leaves the household better-off than without labor reallocation.

5.5 Robustness Checks

In this section, we highlight results from additional estimations to show that our main results are robust to alternative model specifications. Results of these robustness checks are shown in Supplementary Appendix Tables A7–A13. First, we confirm that attrition bias is not a threat to our findings. Specifically, we replicate the results using an unbalanced panel of rural households and obtain very similar results (Table A7). Second, we show that our results are robust to using the share of household members across the four job categories as an alternative dependent variable (Table A8). Third, we confirm that the main findings are insensitive to the use of an alternative historical weather database (Tables A9 and A10).[4] Next, we account for region-time trends by using actual baseline (as of 2011) region socioeconomic indicators extracted from the World Bank's Ethiopia Socioeconomic Dashboard.[5] More specifically, we use region-specific data on poverty severity, poverty gap, inequality, female literacy rates, dependency ratio, adult literacy rate, household food shortage, and access to electricity. We then merge these data with the household survey data at region level and replicate results from estimating Equation 2, yet with including interaction terms between each of these indicators and survey year, thus controlling for socioeconomic trends at the state level. The main results remain unchanged (Table A11). Finally, our results are also robust to accounting for district (commonly known as Woreda in Ethiopia) linear time trends instead of region linear time trends (Tables A12 and A13).

[4] We use the University of Idaho's Terra Climate dataset: https://data.nkn.uidaho.edu/ dataset/monthly-climate-and-climatic-water-balance-global-terrestrial-surfaces-1958-2015.

[5]https://www.worldbank.org/en/data/interactive/2020/06/24/ethiopia-socioeconomic-dashboards.print

6. Conclusion

We have analyzed how rural households in SSA adapt to drought shocks through labor reallocation, using representative household panel data from Ethiopia. We find that households reduce their labor time in farming as a response to drought, even though they do not abandon farming altogether. At the same time, households increase their labor time in off-farm activities. This partial switch from farming to off-farm activities is plausible. As we also show, droughts reduce agricultural productivity, so additional off-farm income can help to smooth consumption. We show that this mechanism is particularly relevant for smoothing food consumption. In terms of off-farm activities, households increase their labor time in self-employed business activities as a response to drought, but not their labor time in off-farm wage employment. Our interpretation is that non-agricultural wage jobs are not sufficiently available in the local rural contexts to absorb the additional labor supply during and after drought episodes.

Analysis of heterogeneous effects reveals that proximity to urban centers and financial inclusion lead to stronger labor reallocation to off-farm self-employment as a household response to drought. In other words, households with better access to rural infrastructure and institutions find it easier to adjust their livelihoods to weather shocks. Or more specifically, households in closer proximity to urban markets and with better access to financial services can more easily switch to off-farm self-employment as a drought adaptation strategy. These households are better able to overcome liquidity constraints and other typical barriers for starting or expanding non-agricultural businesses.

Differentiating between short-term droughts and persistent droughts, we find similar labor reallocation effects in general. However, interestingly, the labor adjustments are somewhat stronger for short-term droughts. These differences suggest that households may possibly improve their adaptive capacity in the longer run by implementing on-farm adaptation strategies that complement labor reallocation to off-farm activities. Even though not analyzed here in more detail, on-farm adaptation strategies may include technological innovations, such as irrigation, more tolerant seeds, and improved agronomic practices, among others.

Our findings highlight three important takeaways for policy-making. First, labor reallocation to off-farm activities is an important strategy for farm households in SSA to cope with weather shocks. As weather extremes tend to occur more frequently with climate change, policy-makers should work towards increasing the size and improving the functioning of the rural non-farm economy. The creation of non-farm wage jobs, which are currently not sufficiently available, should have high priority. This does not mean a focus only on public-sector jobs. Policies to incentivize private firms to invest more in rural regions will also be important. Second, the evident negative effects of droughts on food consumption point to the need to develop tailored social protection schemes that particularly target the most vulnerable and those who lack the capacity to reallocate labor to off-farm activities. Third, our finding that access to formal financial services increases household off-farm self-employment as an adaptation strategy to drought calls for financial inclusion policies in rural settings. Such policies could help households overcome liquidity constraints that undermine their ability to not only venture into alternative non-farm jobs, but also to invest in climate-smart agricultural technologies.

Our study adds to the growing climate adaptation literature and supports the idea that weather shocks are partly contributing to the unique structural transformation patterns in SSA, which are characterized by high employment on small family farms combined with a strong diversification into off-farm activities, especially self-employed activities in small non-farm businesses (Davis et al., 2017; Sen, 2019; Christiaensen and Maertens, 2022). Future research should explore how non-agricultural rural employment can be fostered, how different types of jobs influence people's welfare and adaptive capacity, and how non-agricultural employment is linked to agricultural development. Another important research direction is how smallholder farming can be made more climate-resilient through technological and institutional innovations.

Supplementary Material and Appendix

1. Estimating Heterogeneous Effects

The effects of weather shocks on household outcomes are reinforced by pre-existing household socioeconomic status (Corno, Hildebrandt and Voena, 2020; Ansah, Gardebroek and Ihle, 2021; Randell, Gray and Shayo, 2022). To this end, we explore variation in treatment effects by considering heterogeneity in baseline (2011) household characteristics. To achieve this, we estimate the following regression model that includes an interaction between the drought shock and the heterogeneity factor of interest:

$$L_{ict} = \alpha + \delta_1 D_{ct-1} + \delta_2 D_{ct-1} * F_{ic} + \varphi W_{cs-1} + \lambda X_{ict} + \vartheta_i + \mu_t + \vartheta T_{st} + \varepsilon_{ict} \qquad (1)$$

Where L_{ict} are the household sectoral labor allocation outcomes measured in the survey year, F_{ic} is a dummy indicator for the baseline (as at 2011) household characteristics that induces potential heterogeneity and D_{cst-1} is drought shock in the lagged survey year. The parameter estimate δ_1 measures the effects of drought on labor outcomes of households for which the baseline characteristic is absent. δ_2 measures the partial effect of drought on labor allocation outcomes on households that experienced severe drought and for which the baseline characteristic is present. Thus, the net effect of drought on labor allocation outcomes on households for which the baseline characteristic is present is given by $\delta_1 + \delta_2$. We test whether $\delta_1 + \delta_2$ is significantly different from zero using a t-test (Wooldridge, 2015) and compare it with δ_1. We include the same set of controls and account for household and time fixed effects as in the baseline model specification discussed in the main paper.

We consider several household baseline characteristics as candidates for heterogeneity factor F_{ic}. First, we consider how effects of drought on household labor allocation will vary by proximity to urban centers. The economic intuition here is that households that are closer to urban centers will incur lower job switching costs and have more access to non-agricultural jobs compared to those that are not. Similarly, these households will also have more options for non-farm self-employment (i.e. non-farm businesses) than their counterparts. To test this hypothesis, we first construct an indicator for proximity to urban centers at baseline (nearest towns or cities) by distance in kilometers as follows. We generate a dummy equal 1 if household's distance to the nearest town at baseline is less than the sample median distance in kilometers, and 0 otherwise. Households whose distance to the nearest town or city is less than the sample median are therefore considered to be closely located to urban centers. Second, we probe for potential heterogeneity in effects of droughts driven by baseline household labor endowment. Using household size as a proxy, we generate a labor endowment dummy variable equal 1 if household size at baseline is greater than the baseline median household size.

Secure property rights minimize transaction costs and enhance efficient resource allocation (Coase, 1960) and are often at the forefront of the sustainable development debate, especially property rights to land in LDCs (Holland, Masuda and Robinson, 2022). For farm households, this implies that land tenure security (i.e. landownership) can enhance farm investments and promote efficient resource (labor) allocation between on-farm and non-farm household productive activities (Galiani and Schargrodsky, 2011). On the flip side, high on-farm investments may imply high switching costs which can potentially undermine labor mobility across sectors and space. In light of this, we investigate if there are substantial differences in effects of drought on labor allocation between landowners and non-landowners. To do this, we first generate a dummy equal 1 if the household owned any land at baseline and 0 otherwise.

Finally, following existing evidence that both formal and non-formal risk management mechanisms can compensate for negative effects of weather shocks on agricultural households (Jayachandran, 2006), we search for evidence on possible heterogeneous effects driven by access to risk management strategies. Specifically, we generate a dummy for financial inclusion if the household used formal financial services and (or) insurance services as a proxy for formal risk-management strategy at baseline.

2. Appendices

Table A1: Effects of persistent drought on likelihood of employment in different job categories

	Farm		Off-farm	
	(1)	(2)	(3)	(4)
Panel A: Wage employment				
Drought in last 3 years	-0.001		0.003	
	(0.002)		(0.004)	
Drought in last 3 growing seasons		-0.001		0.001
		(0.003)		(0.005)
Panel B: Self employment				
Drought in last 3 years	-0.005		0.038***	
	(0.006)		(0.009)	
Drought in last 3 growing seasons		0.000		0.053***
		(0.008)		(0.012)
Household & weather controls	Yes	Yes	Yes	Yes
Household & year fixed effects	Yes	Yes	Yes	Yes
Region-time trends	Yes	Yes	Yes	Yes
Observations	9666	9666	9666	9666

Notes: The dependent variable is a dummy taking a value of 1 if a household has at least one member employed in any of the four job categories and 0 otherwise. Robust standard errors clustered at the EA level in parentheses. *** p<0.01, ** p<0.05, * p<0.10.

Table A2: Effects of persistent drought on intensive labor allocation

	Farm		Off-farm	
	(1)	(2)	(3)	(4)
Panel A: Wage employment				
Drought in last 3 years	-0.040		0.276	
	(0.065)		(0.238)	
Drought in last 3 growing seasons		-0.040		0.160
		(0.079)		(0.277)
Panel B: Self employment				
Drought in last 3 years	-1.839***		2.147***	
	(0.672)		(0.517)	
Drought in last 3 growing seasons		-1.904**		3.141***
		(0.855)		(0.657)
Household & weather controls	Yes	Yes	Yes	Yes
Household & year fixed effects	Yes	Yes	Yes	Yes
Region-time trends	Yes	Yes	Yes	Yes
Observations	9666	9666	9666	9666

Notes: The dependent variables are percentage share of household weekly hours worked in each of the job categories. Robust standard errors clustered at the EA level in parentheses. *** p<0.01, ** p<0.05, * p<0.10.

Table A3: Heterogeneous effects: Urban proximity

	Farm		Off-farm	
	(1)	(2)	(3)	(4)
Panel A: Wage employment				
Drought(year)	-0.200*		0.435	
	(0.119)		(0.455)	
Proximity ×Drought(year)	0.057		-0.036	
	(0.081)		(0.261)	
Drought during growing season		-0.287**		0.105
		(0.136)		(0.559)
Proximity ×Drought during growing season		-0.002		0.065
		(0.094)		(0.321)
Drought+(Proximity ×Drought)	-0.143	-0.289**	0.399	0.170
	(0.099)	(0.145)	(0.360)	(0.557)
Panel B: Self employment				
Drought(year)	-2.918**		3.088***	
	(1.275)		(0.824)	
Proximity ×Drought(year)	-0.153		0.088	
	(0.903)		(0.561)	
Drought during growing season		-2.743*		4.343***
		(1.498)		(1.022)
Proximity ×Drought during growing season		-1.000		0.757
		(1.034)		(0.736)
Drought + (Proximity ×Drought)	-3.071***	-3.743***	3.175***	5.010***
	(0.927)	(1.347)	(0.692)	(1.056)
Household & weather controls	Yes	Yes	Yes	Yes
Household & year fixed effects	Yes	Yes	Yes	Yes
Region-time trends	Yes	Yes	Yes	Yes
Observations	9666	9666	9666	9666

Notes: The dependent variable is percentage share of household weekly hours worked in each of the job categories. Household controls are age, gender and education of the household head, household size, land size and use of financial services. Weather controls are temperature shock, average monthly temperature and average monthly rainfall. Robust standard errors clustered at the EA level in parentheses. *** p<0.01, ** p<0.05, * p<0.10.

Table A4: Heterogeneous effects: Household labor endowment

	Farm		Off-farm	
	(1)	(2)	(3)	(4)
Panel A: Wage employment				
Drought(year)	-0.162		0.466	
	(0.107)		(0.385)	
Labor endow.×Drought(year)	-0.009		-0.189	
	(0.075)		(0.211)	
Drought during growing season		-0.287**		0.181
		(0.143)		(0.541)
Labor endow.×Drought during growing season		0.001		-0.225
		(0.100)		(0.268)
Drought + (Labor Endow.×Drought)	-0.170**	-0.287**	0.277	-0.044
	(0.010)	(0.124)	(0.404)	(0.576)
Panel B: Self employment				
Drought(year)	-3.148***		3.282***	
	(1.002)		(0.709)	
Labor endow. ×Drought(year)	0.468		-0.485	
	(0.561)		(0.334)	
Drought during growing season		-3.116**		4.698***
		(1.377)		(0.998)
Labor endow. ×Drought during growing season		0.093		-0.380
		(0.722)		(0.421)
Drought + (Labor endow. ×Drought)	-2.680***	-3.022**	2.797***	4.3185***
	(1.030)	(1.440)	(0.708)	(0.975)
Household & weather controls	Yes	Yes	Yes	Yes
Household & year fixed effects	Yes	Yes	Yes	Yes
Region-time trends	Yes	Yes	Yes	Yes
Observations	9666	9666	9666	9666

Notes: The dependent variable is percentage share of household weekly hours worked in each of the job categories. Household controls are age, gender and education of the household head, household size, land size and use of financial services. Weather controls are temperature shock, average monthly temperature and average monthly rainfall. Robust standard errors clustered at the EA level in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.10$.

Table A5: Heterogeneous effects: Land ownership

	Farm		Off-farm	
	(1)	(2)	(3)	(4)
Panel A: Wage employment				
Drought(year)	-0.180		0.426	
	(0.114)		(0.408)	
Own land ×Drought(year)	0.030		-0.006	
	(0.063)		(0.186)	
Drought during growing season		-0.289**		0.058
		(0.146)		(0.553)
Own land ×Drought during growing season		0.003		0.148
		(0.080)		(0.242)
Drought+(Own land ×Drought)	-0.150	-0.286**	0.421	0.206
	(0.096)	(0.128)	(0.394)	(0.557)
Panel B: Self employment				
Drought(year)	-2.758***		3.025***	
	(1.007)		(0.689)	
Own land ×Drought(year)	-0.483		0.211	
	(0.477)		(0.286)	
Drought during growing season		-2.724**		4.458***
		(1.352)		(0.976)
Own land ×Drought during growing season		-0.781		0.316
		(0.648)		(0.384)
Drought+(Own land ×Drought)	-3.242***	-3.505**	3.236***	4.774***
	(1.014)	(1.440)	(0.721)	(1.013)
Household & weather controls	Yes	Yes	Yes	Yes
Household & year fixed effects	Yes	Yes	Yes	Yes
Region-time trends	Yes	Yes	Yes	Yes
Observations	9666	9666	9666	9666

Notes: The dependent variable is percentage share of household weekly hours worked in each of the job categories. Household controls are age, gender and education of the household head, household size, land size and use of financial services. Weather controls are temperature shock, average monthly temperature and average monthly rainfall. Robust standard errors clustered at the EA level in parentheses. *** p<0.01, ** p<0.05, * p<0.10.

Table A6: Heterogeneous effects: Financial inclusion

	Farm		Off-farm	
	(1)	(2)	(3)	(4)
Panel A: Wage employment				
Drought(year)	-0.150		0.461	
	(0.100)		(0.379)	
Fin. inclusion ×Drought(year)	-0.232		-0.747	
	(0.173)		(0.458)	
Drought during growing season		-0.279**		0.173
		(0.133)		(0.536)
fin. inclusion ×Drought during growing season		-0.169		-0.839
		(0.242)		(0.572)
Drought+(Fin. inclusion ×Drought)	-0.382**	-0.448*	-0.285	-0.666
	(0.187)	(0.258)	(0.556)	(0.745)
Panel B: Self employment				
Drought(year)	-2.948***		3.067***	
	(0.989)		(0.694)	
Fin. inclusion ×Drought(year)	-1.070		1.282*	
	(1.075)		(0.762)	
Drought during growing season		-3.029**		4.535***
		(1.369)		(0.977)
Fin. inclusion ×Drought during growing season		-1.297		1.565*
		(1.397)		(0.918)
Drought + (Fin. inclusion ×Drought)	-4.018***	-4.327**	4.332***	6.100***
	(1.203)	(1.778)	(0.978)	(1.291)
Household & weather controls	Yes	Yes	Yes	Yes
Household & year fixed effects	Yes	Yes	Yes	Yes
Region-time trends	Yes	Yes	Yes	Yes
Observations	9666	9666	9666	9666

Notes: The dependent variable is percentage share of household weekly hours worked in each of the job categories. Household controls are age, gender and education of the household head, household size, land size and use of financial services. Weather controls are temperature shock, average monthly temperature and average monthly rainfall. Robust standard errors clustered at the EA level in parentheses. *** p<0.01, ** p<0.05, * p<0.10.

Table A7: Robustness check: Addressing potential attrition bias on intensive labor allocation outcomes

	Farm		Off-farm	
	(1)	(2)	(3)	(4)
Panel A: Wage employment				
Drought(year)	-0.174*		0.435	
	(0.103)		(0.370)	
Drought during growing season		-0.310**		0.207
		(0.138)		(0.526)
Panel A: Self employment				
Drought(year)	-3.067***		3.069***	
	(0.970)		(0.696)	
Drought during growing season		-3.307**		4.667***
		(1.360)		(0.981)
Household & weather controls	Yes	Yes	Yes	Yes
Household & year fixed effects	Yes	Yes	Yes	Yes
Region-time trends	Yes	Yes	Yes	Yes
Observations	10,061	10,061	10,061	10,061

Notes: The dependent variable is percentage share of household weekly hours worked in each of the job categories. Household controls are age, gender and education of the household head, household size, land size and use of financial services. Weather controls are temperature shock, average monthly temperature and average monthly rainfall. Robust standard errors clustered at the EA level in parentheses. *** p<0.01, ** p<0.05, * p<0.10.

Table A8: Robustness check: Effects of drought on share of household members across sectoral jobs (Alternative outcome variable)

	Farm		Off-farm	
	(1)	(2)	(3)	(4)
Panel A: Wage employment				
Drought(year)	-0.003***		-0.001	
	(0.001)		(0.002)	
Drought during growing season		-0.003**		-0.002
		(0.001)		(0.002)
Panel A: Self employment				
Drought(year)	-0.012		0.023***	
	(0.009)		(0.007)	
Drought during growing season		0.000		0.041***
		(0.012)		(0.010)
Household & weather controls	Yes	Yes	Yes	Yes
Household & year fixed effects	Yes	Yes	Yes	Yes
Region-time trends	Yes	Yes	Yes	Yes
Observations	9666	9666	9666	9666

Notes: The dependent variable is share of household members working in each of the job categories. House- hold controls are age, gender and education of the household head, household size, land size and use of financial services. Weather controls are temperature shock, average monthly temperature and average monthly rain- fall. Robust standard errors clustered at the EA level in parentheses. *** p<0.01, ** p<0.05, * p<0.10.

Table A9: Robustness check: Effects of drought on job diversification (Using alternative weather data source)

	Farm		Off-farm	
	(1)	(2)	(3)	(4)
Panel A: Wage employment				
Drought(year)	-0.005*		0.002	
	(0.003)		(0.006)	
Drought during growing season		-0.009**		-0.004
		(0.004)		(0.008)
Panel A: Self employment				
Drought(year)	-0.011		0.051***	
	(0.009)		(0.013)	
Drought during growing season		-0.007		0.067***
		(0.013)		(0.017)
Household & weather controls	Yes	Yes	Yes	Yes
Household & year fixed effects	Yes	Yes	Yes	Yes
Region-time trends	Yes	Yes	Yes	Yes
Observations	9666	9666	9666	9666

Notes: The dependent variable is a dummy taking a value of 1 if a household has at least one member employed in any of the job categories and 0 otherwise. Household controls are age, gender and education of the household head, household size, land size and use of financial services. Weather controls are temperature shock, average monthly temperature and average monthly rainfall. Robust standard errors clustered at the EA level in parentheses. *** p<0.01, ** p<0.05, * p<0.10.

Table A10: Robustness check: Effects of drought on intensive labor allocation (Using alternative weather data source)

	Farm		Off-farm	
	(1)	(2)	(3)	(4)
Panel A: Wage employment				
Drought(year)	-0.164*		0.412	
	(0.099)		(0.378)	
Drought during growing season		-0.287**		0.128
		(0.132)		(0.537)
Panel A: Self employment				
Drought(year)	-3.014***		3.142***	
	(0.977)		(0.692)	
Drought during growing season		-3.094**		4.608***
		(1.357)		(0.975)
Household & weather controls	Yes	Yes	Yes	Yes
Household & year fixed effects	Yes	Yes	Yes	Yes
Region-time trends	Yes	Yes	Yes	Yes
Observations	9666	9666	9666	9666

Notes: The dependent variable is percentage share of household weekly hours worked in each of the job categories. Household controls are age, gender and education of the household head, household size, land size and use of financial services. Weather controls are temperature shock, average monthly temperature and average monthly rainfall. Robust standard errors clustered at the EA level in parentheses. *** p<0.01, ** p<0.05, * p<0.10.

Table A11: Robustness check: Effects of drought on intensive labor allocation (Accounting for region baseline socioeconomic indicators interacted with years)

	Farm		Off-farm	
	(1)	(2)	(3)	(4)
Panel A: Wage employment				
Drought(year)	-0.164*		0.412	
	(0.099)		(0.378)	
Drought during growing season		-0.287**		0.128
		(0.132)		(0.537)
Panel A: Self employment				
Drought(year)	-3.014***		3.142***	
	(0.977)		(0.692)	
Drought during growing season		-3.094**		4.608***
		(1.357)		(0.975)
Household & weather controls	Yes	Yes	Yes	Yes
Household & year fixed effects	Yes	Yes	Yes	Yes
Region baseline socioeconomic-time trends	Yes	Yes	Yes	Yes
Observations	9666	9666	9666	9666

Notes: The dependent variable is percentage share of household weekly hours worked in each of the job categories. Household controls are age, gender and education of the household head, household size, land size and use of financial services. Weather controls are temperature shock, average monthly temperature and average monthly rainfall. We estimate a regression model that replaces state-time trends with baseline (2011) socioeconomic indicators interacted with survey years. Region baseline socioeconomic indicators used are poverty severity, inequality, female literacy rate, poverty gap, dependency ratio, adult literacy rate, household food shortage and access to electricity. Robust standard errors clustered at the EA level in parentheses. *** p<0.01, ** p<0.05, * p<0.10.

Table A12: Robustness check: Effects of drought on household job diversification (Accounting for district linear time trends)

	Farm		Off-farm	
	(1)	(2)	(3)	(4)
Panel A: Wage employment				
Drought(year)	-0.006**		-0.005	
	(0.003)		(0.005)	
Drought during growing season		-0.008**		-0.009
Panel A: Self employment				
Drought(year)	-0.008		0.060***	
	(0.008)		(0.011)	
Drought during growing season		-0.009		0.076***
Household & weather controls	Yes	Yes	Yes	Yes
Household & year fixed effects	Yes	Yes	Yes	Yes
District-time trends	Yes	Yes	Yes	Yes
Observations	9666	9666	9666	9666

Notes: The dependent variable is a dummy taking a value of 1 if a household has at least one member employed in any of the jobs across sectors and 0 otherwise. Household controls are age, gender and education of the household head, household size, land size and use of financial services. Weather controls are temperature shock, average monthly temperature and average monthly rainfall. Robust standard errors clustered at the EA level in parentheses. *** p<0.01, ** p<0.05, * p<0.10

Table A13: Robustness check: Effects of drought on intensive labor allocation (Accounting for district linear time trends)

	Farm		Off-farm	
	(1)	(2)	(3)	(4)
Panel A: Wage employment				
Drought(year)	-0.164*		0.412	
	(0.099)		(0.378)	
Drought during growing season		-0.287**		0.128
		(0.132)		(0.537)
Panel A: Self employment				
Drought(year)	-3.014***		3.142***	
	(0.977)		(0.692)	
Drought during growing season		-3.094**		4.608***
		(1.357)		(0.975)
Household & weather controls	Yes	Yes	Yes	Yes
Household & year fixed effects	Yes	Yes	Yes	Yes
District-time trends	Yes	Yes	Yes	Yes
Observations	9666	9666	9666	9666

Notes: The dependent variable is percentage share of household weekly hours worked in each of the job categories. Household controls are age, gender and education of the household head, household size, land size and use of financial services. Weather controls are temperature shock, average monthly temperature and average monthly rainfall. Robust standard errors clustered at the EA level in parentheses. *** p<0.01, ** p<0.05, * p<0.10.

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