Estimating the Impact of Drought and Flood on African Farmers

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Abstract

We estimate the impact of self-reported drought and flooding occurrences on crop and livestock net income in Sub-Saharan Africa during the 2009-2016 period. Based on a pooled dataset for five countries, we find robust negative and heterogeneous impacts of drought and floods across different levels of irrigation, poverty, and agricultural diversification, including reductions of crop net income by 34 and 61 percent due to drought and flooding, respectively. The study also confirms the importance of poverty alleviation and agricultural diversification to cope with adverse effects of drought and flooding.

JEL codes: Q12, Q54, Q58

Keywords: agriculture, drought, flooding, climate change, Africa

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1. Introduction

Climate change, along with impacts of climate risks such as drought and flooding, have been widely recognized and acknowledged across the world. Global average temperature has increased nearly 1 degree Celsius since 1901 and is projected to keep increasing anywhere from 2 to 5 degree Celsius by the end of 21st century, depending on effectiveness of reductions in greenhouse or heat-trapping gases (USGCRP, 2018). Temperatures in Africa are projected to rise faster than the global average increase. Together with the projection of decreasing long-term precipitation in Africa (Nhemachena & Hassan, 2007; Gannon et al., 2014), extreme weather shocks are expected to occur with greater severity and frequency in the future (IPCC, 2014; Ault, 2020).

The adverse influences of more frequent and intense extreme weather events cause economic loss and impede economic growth. Kuwayama et al. (2019) find statistically significant negative effects of drought on crop yields equal to reductions in the range of 0.1% to 1.2% for corn and soybean yields for each additional week of drought in dryland counties of the U.S., and 0.1% to 0.5% in irrigated counties. In the other parts of the world than the U.S., several studies conclude that rainfall and drought shocks negatively affect farmers' agricultural income (Arslan et al., 2016; Asfaw et al., 2017; Skoufias et al., 2017; Sesmero et al., 2018; Chuang, 2019; Chonabayashi et al., 2020).

Poor people have low-quality assets that fail to resist shocks, such as houses located in vulnerable areas during a flood shock (Mano & Nhemachena, 2007; Skoufias, 2012; Hallegatte et al., 2016; Nikoloski et al., 2018; Sesmero et al., 2018). The reasons for this are manyfold. They may select ex-ante risk mitigation strategies that invest effort and resources in low-risk and low-return activities to avoid potential income loss, but they might not invest in more profitable alternatives (Hallegatte et al., 2016). This effect can be lifelong and can even be transmitted to future generations that trap the household in poverty (Damania et al., 2017). For example, a downside risk in consumption due to rainfall shocks decreases the fertilizer application rates because households face liquidity constraints (Dercon & Christiaensen, 2011). In Nigeria, the variation of rainfall has significant negative effects on fertilizer purchases in Nigeria (Adjognon et al., 2017).

Africa is extremely vulnerable to drought and flooding because the majority of the continent's population is engaged in agricultural activities, which are directly affected by climate, making the eradication of poverty difficult. D'Alessandro et al. (2015) estimate the losses of livestock due to droughts that occurred from 2005 through 2015 to amount to $1.08 billion, and the crop losses during 1980-2012 account for 2 percent of agriculture's GDP in Kenya. Pauw et al. (2010) point out the loss in agricultural GDP varies from 1 percent to 21.5 percent due to different return periods of droughts in Malawi. Thurlow et al. (2012) conclude that a severe drought reduces agriculture's GDP by 22.7 percent and, on average, moves 7.5 percent of population into poverty in Zambia.

While there has been active research on the effects of drought and flooding on agricultural outcomes, the magnitude and, occasionally, sign of the estimated impact varies as described above and further summarized in the literature review table in Table 1. This is likely due to several reasons. First, the available data on both agriculture and extreme weather events is still scarce in Africa. Second, drought and flooding measurements and agricultural outcome variables used in the previous literature vary. Third, the different econometric and modeling strategies used also affect the reported results. While there is a general consensus that drought and flooding negatively affect agricultural outcomes, more research is required to better understand the magnitude of these impacts more precisely.

In particular, an important gap in the previous literature is that there are few studies that analyze the economic impacts of drought and flooding on agricultural household livelihoods at the regional scale in Africa, while many studies have been conducted at the country scale. This could be due to lack of household survey data with comparable information on agricultural livelihoods and weather shocks across countries. Yet, extreme weather events are cross-border issues by nature and can affect areas across multiple countries when they occur. A multi-country study helps assess the impacts of weather shocks in the region more comprehensively.

To fill this research gap, we quantitatively estimate the impacts of drought and flooding on agricultural productivity in five Sub-Saharan African countries, including Ethiopia, Malawi, Niger, Nigeria, and Uganda. To the best of our knowledge, this is the first study to analyze the linkage between agricultural income and extreme weather events such as drought and flooding at the multi-country scale in Africa.

2. Data

We use the nationally representative household-level data from the Living Standards Measurement Study – Integrity Surveys on Agriculture (LSMS-ISA). LSMS-ISA is a household survey project established with a grant from the Bill and Melinda Gates Foundation and implemented by the World Bank and the national statistics office of its partner countries in Sub-Sahara Africa. In each partner country, LSMS-ISA provides multiple rounds of multi-topic and nationally representative surveys with a strong focus on agriculture. To partially satisfy user interest in geo-referenced location, while preserving the confidentiality of sample households and communities, modified coordinates at the enumeration-area level are provided as part of the household geographical and climate variables. Modified coordinates are generated by applying a random offset within a specified range to the average enumeration area value.

While LSMS-ISA covers eight countries, we only consider five countries for our study, including Ethiopia, Malawi, Niger, Nigeria, and Uganda, for a few reasons. First, Mali and Tanzania are excluded since the data for these countries only include weather shock variables for the past 3 and 5 years, respectively, but not the single past year.[3] Second, we exclude Burkina Faso because data on important elements for this study such as climate, geography and livestock production are missing.

The resulting data is a pooled multi-country household survey with a total of 82,281 observations for 2009 through 2016. Collectively, the total population of countries included in this study is approximately 367 million, which is around 36 percent of the total population in Sub-Saharan Africa in 2016. Due to the data availability, most of the sample data used for this paper comes from two countries, namely Nigeria and Ethiopia. A list and geographical locations of surveys used for this study as well as summary statistics of key variables are provided in Map 1, Table 2, and Table 3.

The description of methods used to generate key variables for our study is as follows. First, following the methodology used to construct the RIGA database[4], we generate crop, livestock,

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[3] In the Tanzania 2008 survey, the weather shock variable does not distinguishes drought and flooding, which is another reason why it is excluded from our study.

[4] Information on the RIGA database can be found at: http://www.fao.org/economic/riga/en. The RIGA database is composed of a series of constructed variables about rural and urban income generating activities created from the original data sources such as the World Bank's Living Standards Measurement Study and RAND.

and agricultural net income, respectively. Agricultural net income is the sum of crop and livestock net income. According to the Organization for Economic Co-operation and Development (OECD), agricultural output comprises output sold, changes in stocks, output for own final consumption, output produced for further processing by agricultural producers, and intra-unit consumption of livestock feed products. To ensure consistency and comparability among the surveys from different countries, all income variables are temporally converted to 2011 USD using consumer price index (CPI) and purchasing power parity (PPP) exchange rates.

We construct weather shock dummy variables such as the incidence of drought and flooding for households that experience the respective shock during the last 12 months from the data in the shocks and coping strategy section of the surveys. For Nigeria, we use the incidence during the previous and current calendar year as a proxy of the previous 12 months, considering that the surveys were implemented at the first 3 months of each year.

3. Methodology

Building on recent work on the association between extreme weather events and agricultural net income (Chonabayashi et al., 2020; Kuwayama et al., 2019) as well as previous studies on climate change impacts on agricultural net income in Africa (Kurukulasuriya & Mendelsohn, 2007; Seo & Mendelsohn, 2008; Seo et al., 2009; Kurukulasuriya et al., 2011; Kala et al., 2012;), we estimate the impact of drought and flooding on agricultural productivity in Sub-Saharan Africa for the period of 2009-2016. Our identification strategy relies on exploiting variation in net farm income and drought occurrence across sample households. We use a pooled dataset that is constructed by pooling the household survey data from LSMS-ISA for five countries, including Ethiopia, Malawi, Niger, Nigeria, and Uganda.

We assume that farmers manage their farm to maximize their net farm income from various farming activities, taking the existing climate as given. We consider the following equation to analyze the impacts of drought and flooding occurrences on crop net income:

Equation 1: $ihs(Y_{i(t),t,p}) = \beta_0 + \beta_D D_{i(t),t,p} + \beta_F F_{i(t),t,p} + \delta' \ \boldsymbol{X}_{i(t),t,p} + \epsilon_t + \vartheta_c + \varepsilon_{i(t),t,p}$

where $ihs(Y_{i(t),t,p})$ is the inverse hyperbolic sine transformed version of crop net income per hectare for a household *i(t)* in cross-sectional time or year *t*; $D_{i(t),t,p}$ and $F_{i(t),t,p}$ are dummy variables that indicate an incidence of drought and flooding respectively; $\boldsymbol{X}_{i(t),t,p}$ are covariates that include both time-varying and invariant observable variables such as socioeconomic, geographic, climatic, household, and farmland characteristics; ϵ_t and ϑ_c are year and country dummy variables to control for the possible year effect and time-invariant unobservable country differences, respectively; and $\varepsilon_{i(t),t,p}$ is an error term. Our dataset consists of eight independent cross-sections or years. As households in different cross-sections are not the same ones, we index the variables by a double subscript *i(t)*.[5]

We use the inverse hyperbolic sine (IHS) transformation of the outcome variable instead of a linear term or the natural logarithm transformation as it retains zero and negative values. This is a common transformation in the applied microeconomics literature (Pence, 2006; Jeon and Pohl, 2019; Card et al., 2020). We interpret the regression coefficients as we do for a log-linear

[5] Some households included in the cross-sectional data from the national household surveys used for this study are panel.

specification because the semi-elasticity in an arcsinh-linear specification is approximately equal to the corresponding regression coefficient (Bellemare & Wichman, 2020).

In addition to the main specification described above, we also conduct additional analyses. First, we estimate the above equation using alternative dependent variables such as livestock net income and total agricultural net income, which is a sum of crop net income and livestock net income. Second, following previous literature on climate change and drought impacts on the U.S. agriculture (Schlenker et al., 2005; Kuwayama et al., 2019), we explore potentially heterogeneous effects on irrigated and rainfed areas. To accomplish this, we conduct the regression analysis based on the subsamples of irrigated and rainfed areas separately. Since the irrigation rate in our sample data is only 3.5 percent, we also include an irrigation dummy variable in the main specification. Additionally, we conduct subsample regression by poverty incidence and types of agricultural diversification strategies.

Throughout the paper we present standard errors corrected for spatial correlation using a 50 km radius around each household's agricultural plot (Conley, 1999).[6] The sample weight is applied to account for survey stratification. We conduct a number of robustness checks using alternative sets of control variables and fixed effects, different cutoff distances to correct spatial correlation of the standard errors, and cluster-robust standard errors that allow intragroup correlation at the survey strata level.

It is important to mention that the self-reported drought and flooding measures used for this study have a couple of potential caveats. First, the definition of drought and flooding is subjective as the survey questionnaire only asks whether a household or any household member is affected by

[6] We implement the standard error correction for spatial correlation (Conley, 1999) in Stata using the acreg.ado file (Colella et al., 2019).

drought and flooding during the previous 12 months, respectively, without specifically defining them. Neither do the questionnaires ask for information on the length or magnitude of drought or flooding in most of the surveys. Second, survey respondents are more likely to remember those shocks that had a welfare effect (Weerdt, 2008). This implies that self-reported measures could likely be endogenous to agricultural income and potentially provide an upward bias in the estimated impacts.

A potentially alternative method could be to construct drought and flooding measures from other weather data sources, but we do not consider this as part of this study for the following reasons. First of all, since the actual household coordinates of the LSMS-ISA data are not available, it is not feasible to spatially merge external data with household data accurately at the household level. Second, there is still a challenge to accurately measure extreme events, particularly droughts, as they are caused by combination of different factors, including hydro-meteorological and socio-economic factors along with the stochastic nature of water demand (Wilhite, 2000; Udmale et al., 2014). For instance, recent empirical evidences show large discrepancies in exposure to extreme temperature across high-resolution gridded weather datasets that are widely used in the literature. Accordingly, the reported choice of the underlying weather dataset can significantly affect the estimates of climate change impacts on crop yields, which are often identified from within-location temporal variation in exposure to the extreme right tail of the temperature distribution (Parkes et al., 2019). Furthermore, another recent study suggests drought indicators derived from satellite data showed no or limited signs of an agricultural drought, based on vegetation indices and predicted crop losses, during Ethiopia's historical 2015 drought, which is reported to be the worst in five decades according to different drought indicators (Sohnesen, 2020). For these reasons, we choose to use self-reported drought and flooding measures in this study with the understanding that there is yet no established alternative in literature.

To mitigate potential distortion resulting from the potential endogeneity issue discussed above, we take the following countermeasures. First, to overcome the issue of a non-standardized definition used in the survey, drought and flooding dummy variables in this study simply indicate whether a household experienced drought or flooding, although some surveys include information on the frequency and magnitude of the impact (e.g. positive and negative effects, subjective severity levels etc.). By not only considering households that report negative impacts from drought, but also those who report positive or no impacts, we can mitigate a potential upward bias caused in the estimated impact from the regression analysis. Second, we only use household surveys that have the shortest recall period (12 months in the question on shocks) because the shorter recall period, the less severe the recall bias is expected to be (Weerdt, 2008). Additionally, it is reasonable to use weather shocks during the last twelve months as opposed to a longer period to analyze short-term impacts on current agricultural net income.

4. Results

Regression results and the marginal effects of drought and flooding on crop net income are reported in columns (1) through (7) of Table 4 and Table 5.[7] Occurrences of both drought and flooding are found to have significant negative effects on crop net income, respectively. Farmers decrease their crop net income by 34 and 61 percent if they experience drought and flooding in the last 12 months, respectively. We also find non-significant negative effects of both drought and

[7] The robustness check using alternative regression specifications and different methods for spatial correlation correction of standard errors is reported in the Appendix and produces qualitatively the same results.

flooding on crop net income of irrigated farmers. Further investigation is likely required as the sample size of irrigated farmers is small (only 3.5 percent).

From the results using the main specification in column (1) of Table 4, we can see that the log of the cultivated farmland area reduces crop net income. This finding is consistent with previous research that reports that small farms are productive in the African context and that staple cereal yields decline as the scale of production increases (Kurukulasuriya & Mendelsohn, 2007; Larson et al., 2014).

The female household head is significantly and negatively associated with crop, livestock, and total agricultural net income while the ages of the household is significantly and positively associated with livestock and total agricultural net income. The presence of electrical service on the farm turns out to be negatively associated with crop, livestock and total agricultural net income in rural areas while it increases crop net income in urban areas. While this result seems counterintuitive, a recent study also reports a similar finding that while urban electricity access has positive and significant impacts on agricultural productivity, the effect of rural electrification is insignificant (Omoju et al., 2020). Rural households have higher livestock and total agricultural net income than urban households, which likely reflects the fact that urban households depend more on non-agricultural income.

5. Discussion and Conclusion

This paper finds robust negative impacts of drought and flooding on crop net income in Africa. The analysis quantitively confirms recent finding that the effectiveness of electricity in increasing agricultural productivity depends on other household and geographical factors such as farmland area size and distance to roads, particularly in the African context.

The results of this study lead to the following policy recommendations. First, irrigation and agricultural diversification could be promoted as mitigation strategies to cope with adverse effects of extreme weather events such as drought and flooding on crop production. Second, poverty reduction builds household resilience to extreme events. Third, the promotion of rural electrification may not be sufficient, in and of itself, to enhance agricultural productivity in Sub-Saharan Africa. Policymakers need to carefully design this intervention to support the entire agricultural value chain. Finally, farm input support programs to promote fertilizer use need to consider factors such as transportation costs and farm size to become effective.

The analytical framework developed in this paper makes a useful contribution to the existing literature on the linkages between agriculture, climate, and extreme weather. More specifically, the Ricardian approach normally consists of a cross-sectional regression of farmland values on climate and other control variables, but it is also used to study climate change impacts on agricultural productivity using net revenue values in countries where land value data are not readily available (Kurukulasuriya & Mendelsohn, 2007; Seo & Mendelsohn, 2008; Seo et al., 2009; Kurukulasuriya et al., 2011; Kala et al., 2012). Generally, land values are easier to analyze because they reflect the long term productivity of the land while net revenues capture the annual productivity and can be influenced by many factors that are peculiar to a given year such as the weather (Mendelsohn, 2008). Therefore, the effects of extreme weather events such as drought and flooding on agriculture can be incorporated in the climate change impact studies by using available data on household revenue and weather shocks.

There are numerous areas of possible future research. Building on the previous literature and this paper, future research could assess the historical impacts of drought in Africa by exploring drought and climate measures based on satellite climate data. One could also explicitly incorporate extreme weather effects on net farm income or land values in studies on climate change impacts on agriculture such as the Ricardian analysis where the association between climate change and extreme weather events also needs to be taken account for. Despite these potential areas for improvement, this study still provides robust estimates of the historical impact of drought and flooding on agriculture in Africa. These findings should be useful for policymakers and agricultural households alike in planning strategies to cope with increasing extreme weather events due to climate change.

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Map and Tables

Map 1: Locations of agricultural plots in LSMS-ISA data

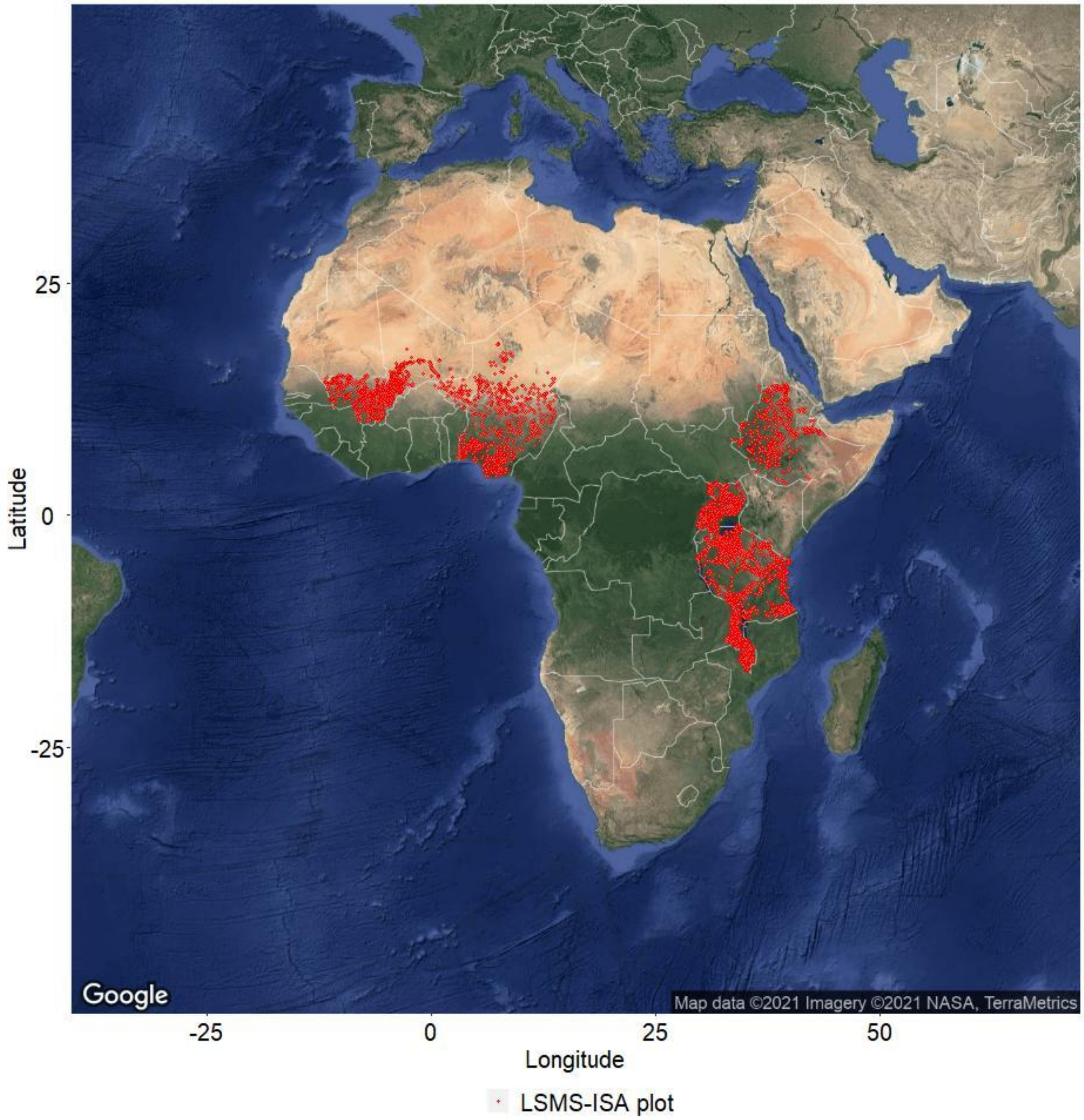

Table 1: Literature review on the economic impact of weather shocks and climate change on agricultural productivity

Study	Country/Region	Spatial Coverage	Model	Weather Shock Measure	Dependent Variable	Impact Estimate
Amare et al., 2018	Nigeria	National	IV-FE	Deviation of rainfall	Consumption	-37.0%
Asfaw et al., 2017	Zambia	Subnational	GLS-RE	Deviation of rainfall	Consumption	-2.9%
Blanc, 2012	SSA	Multi-country	Fixed Effect	Standardized precipitation index (SPI)	Crop Yield	-7.1%
Chonabayashi et al., 2020	Zambia	National	SNR	Self-reported drought	Agricultural income	-24.3%
Chonabayashi et al., 2020	Zambia	National	SNR	Self-reported flooding	Agricultural income	-23.4%
Chuang, 2019	India	Subnational	SUR	Deviation of rainfall	Agricultural Income	-1.5%
Chuang, 2019	India	Subnational	SUR	Deviation of rainfall	Income	-0.8%
Cissé & Barrett, 2018	Kenya	National	GLM	Area average predicted losses ≥ 15% per the IBLI index	TLU	-18.0%
Gao & Mills, 2018	Ethiopia	National	Fixed Effect	Deviation of rainfall	Consumption	-18.2%
Gao & Mills, 2018	Ethiopia	National	Fixed Effect	Extreme heat degree days	Consumption	-2.4%
Horridge et al., 2005	Australia	National	CGE	Rainfall deficit	Income	-20.0%
Kubik & Maurel, 2016	Tanzania	National	OLS	Standardized precipitation evapotranspiration index (SPEI)	Crop Revenue	-31.0%
Kuwayama et al., 2019	United States	National	Panel Fixed Effect	Weeks of drought based on USDM classifications	Yield	-1.2%
Macours, 2012	Nicaragua	Subnational	2SLS	Self-reported drought	Consumption	-9.0%
Macours, 2012	Nicaragua	Subnational	2SLS	Self-reported drought	Income	-11.0%
Porter, 2012	Ethiopia	National	DIFF	Bottom quintile of rainfall distribution	Consumption	-19.6%
Porter, 2012	Ethiopia	National	Fixed Effect	Bottom quintile of rainfall distribution	Crop Income	-16.6%
Roberts et al., 2012	USA	Subnational	Nonlinear	Extreme heat degree days	Crop Production	-6.2%
Salvucci & Santos, 2020	Mozambique	National	DID	Floodinged areas	Consumption	-11.0%

Note: DID - Difference-in-Difference; DIFF - Arellano & Bond (1991) estimator; FE2SLS - fixed effects two stage least squares; GLM: Generalized linear model; GLS-RE - generalized least squares random-effects; SNR: Skew-normal regression; SUR - seemingly unrelated regressions; 2SLS - two-stage least squares

Table 2: Countries and years of the household survey data used for this study

	2009	2010	2011	2012	2013	2014	2015	2016	Total
Ethiopia					x		x		2
Malawi		x			x			x	3
Niger			x						1
Nigeria		x		x			x		3
Uganda	x	x	x						3
Total	1	3	2	1	2	0	2	1	13

Data source: LSMS-ISA

Table 3: Summary statistics of variables used in regressions

	mean	sd	min	max
Agriculture net income (2011 PPP USD)	923.065	1443.919	-8810.421	43947.324
Crop net income (2011 PPP USD)	400.026	972.321	-5936.709	18811.576
Livestock net income (2011 PPP USD)	228.655	707.512	-5853.908	43947.324
Drought in the last 12 months	0.102	0.303	0.000	1.000
Flooding in the last 12 months	0.034	0.180	0.000	1.000
IHS of cultivated land	0.461	0.607	0.000	5.785
Number of agricultural workers	3.366	5.356	0.000	131.615
Number of agricultural workers squared	40.020	200.738	0.000	17322.506
Inorganic fertilizer use	0.094	0.292	0.000	1.000
Inorganic fertilizer X Distance to road above 3 km	0.061	0.239	0.000	1.000
Organic fertilizer use	0.065	0.247	0.000	1.000
Organic fertilizer X Cultivated land above 1 ha	0.023	0.150	0.000	1.000
Irrigation	0.033	0.180	0.000	1.000
Age of household head	47.775	16.749	0.000	113.000
Female household head	0.216	0.411	0.000	1.000
Electricity	0.420	0.494	0.000	1.000
Urban	0.324	0.468	0.000	1.000
Electricity X Urban	0.264	0.441	0.000	1.000
Absolute value of latitude	8.248	3.711	0.000	18.747
Ethiopia	0.246	0.430	0.000	1.000
Malawi	0.069	0.254	0.000	1.000
Niger	0.017	0.129	0.000	1.000
Nigeria	0.563	0.496	0.000	1.000
Uganda	0.105	0.307	0.000	1.000
Year 2009	0.034	0.181	0.000	1.000
Year 2010	0.232	0.422	0.000	1.000
Year 2011	0.051	0.221	0.000	1.000
Year 2012	0.194	0.395	0.000	1.000

Year 2013	0.139	0.346	0.000	1.000
Year 2014	0.000	0.000	0.000	0.000
Year 2015	0.325	0.469	0.000	1.000
Year 2016	0.025	0.156	0.000	1.000
Year of survey conducted	2012.597	2.096	2009.000	2016.000
Latitude	6.240	6.547	-17.095	18.747
Longitude	19.169	14.711	0.405	43.871
Observations	65004			

Data source: LSMS-ISA

Table 4: Regression results on agricultural net income in Sub-Saharan Africa

	Crop net income per ha							Livestock net income	Ag. net income
	All farms	**Irrigated**	**Rainfed**	**Crop only**	**Mix**	**Poor**	**Non-poor**		
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
Drought in the last 12 months	-0.416**	-0.361	-0.420**	-0.388	-0.416**	-0.417*	-0.388*	0.041	-0.216*
	(0.034)	(0.147)	(0.037)	(0.137)	(0.034)	(0.053)	(0.064)	(0.786)	(0.062)
Flood in the last 12 months	-0.940**	-1.109**	-0.935**	-1.137**	-0.940**	-0.989***	-0.949**	0.307	-0.578**
	(0.010)	(0.018)	(0.014)	(0.036)	(0.010)	(0.008)	(0.035)	(0.151)	(0.029)
IHS of cultivated land	-0.382***	-0.491**	-0.386***	-0.556**	-0.382***	-0.516***	-0.316**	0.659***	0.776***
	(0.003)	(0.011)	(0.003)	(0.011)	(0.003)	(0.000)	(0.017)	(0.000)	(0.000)
Distance to road above 3 km	0.456**	0.488*	0.428**	0.408	0.456**	0.306	0.546***	0.123	0.331***
	(0.011)	(0.051)	(0.015)	(0.107)	(0.011)	(0.114)	(0.006)	(0.447)	(0.010)
Age of household head	0.006	0.007	0.005	0.005	0.006	0.006	0.005	0.007*	0.006**
	(0.117)	(0.169)	(0.204)	(0.383)	(0.117)	(0.173)	(0.222)	(0.060)	(0.011)
Female household head	-0.491**	-0.903***	-0.486**	-0.907***	-0.491**	-0.567***	-0.625**	-0.327**	-0.474***
	(0.014)	(0.001)	(0.019)	(0.002)	(0.014)	(0.005)	(0.012)	(0.013)	(0.000)
Electricity	-0.982***	-1.045***	-0.953***	-0.991**	-0.982***	-0.846***	-1.039***	-0.486**	-0.700***
	(0.000)	(0.005)	(0.000)	(0.011)	(0.000)	(0.010)	(0.000)	(0.016)	(0.000)
Urban	-0.571	-0.703	-0.585	-0.739	-0.571	-0.892*	-0.376	-0.624**	-1.222***
	(0.135)	(0.186)	(0.129)	(0.175)	(0.135)	(0.071)	(0.321)	(0.010)	(0.000)
Electricity X Urban	1.095**	1.436**	1.050*	1.313*	1.095**	1.129*	1.172**	-0.335	0.081
	(0.041)	(0.038)	(0.052)	(0.069)	(0.041)	(0.088)	(0.029)	(0.321)	(0.832)

Absolute value of latitude	0.074	0.050	0.083	0.086	0.074	0.145**	-0.010	-0.228***	-0.141***
	(0.191)	(0.499)	(0.146)	(0.263)	(0.191)	(0.016)	(0.869)	(0.000)	(0.000)
Ethiopia	7.021***	7.477***	7.109***	7.797***	7.021***	7.361***	6.825***	5.018***	1.888***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Malawi	5.366***	5.741***	5.359***	5.823***	5.366***	4.891***	5.835***	6.885***	2.390***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Niger	0.000	0.000	0.000	0.000	0.000	0.000	0.000	4.148***	0.000
	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(0.000)	(.)
Nigeria	3.754***	4.709***	3.847***	5.404***	3.754***	4.162***	3.810***	4.182***	1.004***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Uganda	5.246***	5.694***	5.389***	6.511***	5.246***	6.107***	4.570***	3.175***	0.307
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.518)
Year 2010	1.793***	1.214***	1.455	1.221***	1.793***	1.527***	1.777***	-0.354	1.208***
	(0.000)	(0.000)	(0.105)	(0.000)	(0.000)	(0.000)	(0.000)	(0.107)	(0.000)
Year 2012	1.134***	0.143	0.814	0.151	1.134***	0.795*	0.977**	0.234	0.858***
	(0.006)	(0.829)	(0.471)	(0.831)	(0.006)	(0.059)	(0.046)	(0.347)	(0.000)
Year 2013	-1.331***	-1.273*	-1.687	-1.009	-1.331***	-1.550***	-1.121***	1.009***	1.106***
	(0.000)	(0.064)	(0.101)	(0.134)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Year 2014	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
Year 2015	-3.068***	-3.607***	-3.419***	-3.700***	-3.068***	-3.292***	-3.139***	1.591***	0.804***
	(0.000)	(0.000)	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Irrigation	0.033			0.662*	0.033	0.131	0.134	-0.162	0.271
	(0.903)			(0.085)	(0.903)	(0.736)	(0.593)	(0.455)	(0.232)
Observations	44635	18875	42495	16735	44635	29979	31391	30986	48072
R-squared	0.129	0.131	0.130	0.134	0.129	0.132	0.130	0.072	0.068

Note: The dependent variables are the inverse hyperbolic sine transformed version of crop net income per hectare, livestock net income and agricultural net income, respectively. Standard errors are shown in parentheses and account for spatial correlation of disturbances. Asterisks indicate the following: *** = p <0.01, ** = p <0.05, and * = p <0.1.

Table 5: Marginal effects of drought and flooding on agricultural net income in Sub-Saharan Africa

	Crop net income per ha							Livestock net income	Ag. net income
	All farms	**Irrigated**	**Rainfed**	**Crop only**	**Mix**	**Poor**	**Non-poor**		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Drought incidence	-0.341 **	-0.311	-0.344 **	-0.328	-0.341 **	-0.342 *	-0.323 *	-0.235	-0.196 *
	(0.034)	(0.147)	(0.037)	(0.137)	(0.034)	(0.053)	(0.064)	(0.786)	(0.062)
Flood incidence	-0.609 **	-0.67 **	-0.607 **	-0.68 **	-0.609 **	-0.628 ***	-0.613 **	0.344	-0.439 **
	(0.01)	(0.018)	(0.014)	(0.036)	(0.01)	(0.008)	(0.035)	(0.151)	(0.029)

Note: Standard errors are shown in parentheses and account for spatial correlation of disturbances Marginal effects for temperature and precipitation are evaluated at the mean climate of the sample used for regressions. Asterisks indicate the following: *** = p <0.01, ** = p <0.05, and * = p <0.1.

Appendix

Table A1: Robustness check for the marginal effects of drought on agricultural net income in Sub-Saharan Africa

Crop net income per ha							Livestock net income	Ag. net income	Control variables			Fixed effects		Distance for spatial correlation
All farms	**Irrigated**	**Rainfed**	**Crop only**	**Mix**	**Poor**	**Non-poor**			**Ag**	**HH**	**Geo**	**Year**	**Country**	
-0.402 **	-0.427 *	-0.405 **	-0.47 *	-0.402 **	-0.422 **	-0.389 *	0.101	-0.173	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**50 km**
(0.033)	(0.073)	(0.036)	(0.06)	(0.033)	(0.042)	(0.057)	(0.495)	(0.12)						
-0.38 **	-0.325	-0.391 **	-0.371	-0.38 **	-0.399 *	-0.345 *	0.095	-0.163	**No**	**Yes**	**Yes**	**Yes**	**Yes**	**50 km**
(0.047)	(0.186)	(0.046)	(0.148)	(0.047)	(0.061)	(0.091)	(0.533)	(0.148)						
-0.377 **	-0.404	-0.384 **	-0.469 *	-0.377 **	-0.402 *	-0.37 *	0.177	-0.072	**Yes**	**No**	**Yes**	**Yes**	**Yes**	**50 km**
(0.048)	(0.101)	(0.049)	(0.068)	(0.048)	(0.053)	(0.081)	(0.23)	(0.509)						
-0.342 *	-0.355	-0.338 *	-0.364	-0.342 *	-0.342	-0.352 *	0.042	-0.222 **	**Yes**	**Yes**	**No**	**Yes**	**Yes**	**50 km**
(0.078)	(0.115)	(0.092)	(0.124)	(0.078)	(0.114)	(0.081)	(0.78)	(0.037)						
-0.72 ***	-0.724 ***	-0.715 ***	-0.698 ***	-0.72 ***	-0.746 ***	-0.672 ***	0.135	-0.256 **	**Yes**	**Yes**	**Yes**	**No**	**Yes**	**50 km**
(<0.001)	(0.003)	(<0.001)	(0.008)	(<0.001)	(<0.001)	(<0.001)	(0.367)	(0.018)						
0.125	-0.02	0.116	-0.252	0.125	0.035	0.108	0.328 **	-0.027	**Yes**	**Yes**	**Yes**	**Yes**	**No**	**50 km**
(0.532)	(0.933)	(0.571)	(0.302)	(0.532)	(0.874)	(0.597)	(0.032)	(0.808)						
0.169	0.2	0.194	0.237	0.169	0.095	0.335	0.325 *	-0.109	**Yes**	**Yes**	**Yes**	**No**	**No**	**50 km**
(0.383)	(0.378)	(0.34)	(0.33)	(0.383)	(0.641)	(0.108)	(0.058)	(0.325)						
-0.402 **	-0.427 *	-0.405 **	-0.47 *	-0.402 **	-0.422 **	-0.389 *	0.101	-0.173	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**10 km**
(0.033)	(0.073)	(0.036)	(0.06)	(0.033)	(0.042)	(0.057)	(0.495)	(0.12)						
-0.402 **	-0.427 *	-0.405 **	-0.47 **	-0.402 **	-0.422 **	-0.389 **	0.101	-0.173	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**25 km**
(0.015)	(0.056)	(0.016)	(0.037)	(0.015)	(0.021)	(0.029)	(0.507)	(0.127)						
-0.402 **	-0.427 *	-0.405 **	-0.47 *	-0.402 **	-0.422 **	-0.389 *	0.101	-0.173	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**75 km**
(0.033)	(0.079)	(0.039)	(0.073)	(0.033)	(0.046)	(0.071)	(0.499)	(0.169)						
-0.427 **	-0.454 **	-0.432 **	-0.505 **	-0.427 **	-0.442 **	-0.425 **	0.052	-0.206 *	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Cluster**
(0.011)	(0.03)	(0.012)	(0.046)	(0.011)	(0.02)	(0.027)	(0.717)	(0.098)						

Note: Climate variables include temperature and precipitation. Agricultural controls include cultivated land, number of agricultural workers, and inorganic and organic fertilizer use. Household controls include household head age and gender and electricity access. Geographical variable include latitude and urban dummy. Cluster-robust standard errors allow intragroup correlation at the survey strata level. Standard errors are shown in parentheses and account for spatial correlation of disturbances. Marginal effects for temperature and precipitation are evaluated at the mean climate of the sample used for regressions. Asterisks indicate the following: *** = $p < 0.01$, ** = $p < 0.05$, and * = $p < 0.1$.

Table A2: Robustness check for the marginal effects of flooding on agricultural net income in Sub-Saharan Africa

Crop net income per ha							Livestock net income	Ag. net income	Control variables			Fixed effects		Distance for spatial correlation
All farms	**Irrigated**	**Rainfed**	**Crop only**	**Mix**	**Poor**	**Non-poor**			**Ag**	**HH**	**Geo**	**Year**	**Country**	
-0.988 ***	-1.29 ***	-0.977 **	-1.318 **	-0.988 ***	-1.046 ***	-1.041 **	0.199	-0.673 **	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**50 km**
(0.007)	(0.006)	(0.011)	(0.016)	(0.007)	(0.006)	(0.023)	(0.413)	(0.015)						
-0.951 **	-1.169 **	-0.951 **	-1.217 **	-0.951 **	-1.045 ***	-0.963 **	0.227	-0.612 **	**No**	**Yes**	**Yes**	**Yes**	**Yes**	**50 km**
(0.01)	(0.016)	(0.014)	(0.032)	(0.01)	(0.008)	(0.034)	(0.349)	(0.02)						
-0.961 ***	-1.274 ***	-0.951 **	-1.311 **	-0.961 ***	-1.023 ***	-1.028 **	0.238	-0.636 **	**Yes**	**No**	**Yes**	**Yes**	**Yes**	**50 km**
(0.01)	(0.006)	(0.014)	(0.013)	(0.01)	(0.006)	(0.027)	(0.344)	(0.022)						
-0.958 ***	-1.238 ***	-0.947 **	-1.28 **	-0.958 ***	-1.02 ***	-1.02 **	0.142	-0.706 **	**Yes**	**Yes**	**No**	**Yes**	**Yes**	**50 km**
(0.009)	(0.009)	(0.013)	(0.018)	(0.009)	(0.007)	(0.026)	(0.576)	(0.013)						
-1.02 ***	-1.193 **	-1.017 **	-1.233 **	-1.02 ***	-1.038 ***	-1.06 **	0.318	-0.685 **	**Yes**	**Yes**	**Yes**	**No**	**Yes**	**50 km**
(0.008)	(0.015)	(0.011)	(0.035)	(0.008)	(0.007)	(0.032)	(0.2)	(0.014)						
-1.138 ***	-1.405 ***	-1.108 ***	-1.378 ***	-1.138 ***	-1.211 ***	-1.156 **	0.149	-0.739 ***	**Yes**	**Yes**	**Yes**	**Yes**	**No**	**50 km**
(0.002)	(0.003)	(0.004)	(0.01)	(0.002)	(0.002)	(0.013)	(0.545)	(0.009)						
-0.976 **	-1.306 ***	-0.948 **	-1.301 **	-0.976 **	-1.081 ***	-1.018 **	-0.091	-0.826 ***	**Yes**	**Yes**	**Yes**	**No**	**No**	**50 km**
(0.015)	(0.008)	(0.024)	(0.026)	(0.015)	(0.008)	(0.047)	(0.732)	(0.004)						
-0.988 ***	-1.29 ***	-0.977 **	-1.318 **	-0.988 ***	-1.046 ***	-1.041 **	0.199	-0.673 **	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**10 km**
(0.007)	(0.006)	(0.011)	(0.016)	(0.007)	(0.006)	(0.023)	(0.413)	(0.015)						
-0.988 **	-1.29 **	-0.977 **	-1.318 **	-0.988 **	-1.046 **	-1.041 **	0.199	-0.673 **	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**25 km**
(0.011)	(0.016)	(0.016)	(0.033)	(0.011)	(0.012)	(0.029)	(0.415)	(0.016)						
-0.988 **	-1.29 **	-0.977 **	-1.318 **	-0.988 **	-1.046 **	-1.041 **	0.199	-0.673 **	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**75 km**
(0.013)	(0.016)	(0.02)	(0.039)	(0.013)	(0.015)	(0.033)	(0.436)	(0.034)						
-1.016 ***	-1.266 **	-1.006 ***	-1.287 *	-1.016 ***	-1.049 ***	-1.063 **	0.339	-0.584 **	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**	**Cluster**
(0.004)	(0.03)	(0.007)	(0.064)	(0.004)	(0.009)	(0.022)	(0.167)	(0.045)						

Note: Climate variables include temperature and precipitation. Agricultural controls include cultivated land, number of agricultural workers, and inorganic and organic fertilizer use. Household controls include household head age and gender and electricity access. Geographical variable include latitude and urban dummy. Cluster-robust standard errors allow intragroup correlation at the survey strata level. Standard errors are shown in parentheses and account for spatial correlation of disturbances. Marginal effects for temperature and precipitation are evaluated at the mean climate of the sample used for regressions Asterisks indicate the following: *** = p <0.01, ** = p <0.05, and * = p <0.1.

Table A3: Subsample regression results on agricultural net income in East Africa (Ethiopia, Malawi, and Uganda)

	Crop net income per ha							**Livestock net income**	**Ag. net income**
	All farms	**Irrigated**	**Rainfed**	**Crop only**	**Mix**	**Poor**	**Non-poor**		
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
Drought in the last 12 months	-0.326*	-0.260	-0.330**	-0.207	-0.326*	-0.308*	-0.284*	-0.046	-0.297**
	(0.055)	(0.224)	(0.048)	(0.227)	(0.055)	(0.096)	(0.081)	(0.777)	(0.011)
Flood in the last 12 months	-0.942***	-0.552**	-1.017***	-0.679***	-0.942***	-0.949***	-0.830***	0.293	-0.229
	(0.001)	(0.039)	(0.001)	(0.000)	(0.001)	(0.002)	(0.005)	(0.318)	(0.237)
IHS of cultivated land	-0.528***	-0.897***	-0.533***	-1.064***	-0.528***	-0.654***	-0.571***	0.635***	1.052***
	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Distance to road above 3 km	0.312*	0.223	0.325*	0.282	0.312*	0.293	0.306	-0.104	0.244*
	(0.093)	(0.271)	(0.084)	(0.123)	(0.093)	(0.117)	(0.106)	(0.614)	(0.067)
Age of household head	0.005	0.007	0.004	0.003	0.005	0.002	0.007*	0.010**	0.004*
	(0.164)	(0.105)	(0.293)	(0.555)	(0.164)	(0.507)	(0.060)	(0.024)	(0.087)
Female household head	-0.185	-0.346*	-0.155	-0.252	-0.185	-0.217	-0.193	-0.482***	-0.384***
	(0.187)	(0.055)	(0.281)	(0.203)	(0.187)	(0.111)	(0.286)	(0.002)	(0.000)
Electricity	-1.259***	-2.502***	-1.105***	-2.367***	-1.259***	-1.525***	-1.287***	-0.542	-0.525***
	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.008)	(0.001)	(0.143)	(0.008)
Urban	-0.550***	-0.856***	-0.544***	-0.802***	-0.550***	-0.772***	-0.482**	-0.404	-1.395***
	(0.005)	(0.005)	(0.007)	(0.007)	(0.005)	(0.001)	(0.043)	(0.147)	(0.000)

Electricity X Urban	0.038	1.243	-0.011	1.217	0.038	0.470	0.121	-0.587	-1.161**
	(0.942)	(0.184)	(0.982)	(0.220)	(0.942)	(0.578)	(0.823)	(0.269)	(0.011)
Absolute value of latitude	0.200***	-0.010	0.214***	-0.028	0.200***	0.237***	0.059	-0.081*	0.002
	(0.008)	(0.916)	(0.004)	(0.723)	(0.008)	(0.003)	(0.395)	(0.085)	(0.937)
Ethiopia	3.529***	0.088	3.366***	-0.025	3.529***	1.373***	-0.070	5.264***	0.032
	(0.000)	(0.884)	(0.000)	(0.967)	(0.000)	(0.007)	(0.874)	(0.000)	(0.883)
Malawi	2.672**	0.000	2.463**	0.000	2.672**	0.000	0.000	5.830***	0.000
	(0.022)	(.)	(0.033)	(.)	(0.022)	(.)	(.)	(0.000)	(.)
Niger	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
Nigeria	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
Uganda	5.736***	0.304	5.743***	0.178	5.736***	3.682***	1.213	3.349***	-0.110
	(0.000)	(0.808)	(0.000)	(0.867)	(0.000)	(0.001)	(0.203)	(0.000)	(0.808)
Year 2010	1.070***	6.816***	1.082***	7.111***	1.070***	1.167***	1.040***	-0.616***	0.226*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.007)	(0.099)
Year 2012	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
Year 2013	0.713***	6.451***	0.774***	6.788***	0.713***	0.759**	0.745***	-0.435	0.463**
	(0.006)	(0.000)	(0.002)	(0.000)	(0.006)	(0.013)	(0.007)	(0.191)	(0.022)
Year 2014	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
Year 2015	-0.450	5.785***	-0.369	6.790***	-0.450	-0.464	-0.176	0.015	0.286
	(0.264)	(0.000)	(0.365)	(0.000)	(0.264)	(0.321)	(0.684)	(0.970)	(0.292)

Irrigation	0.054			0.482	0.054	0.145	0.104	-0.059	0.004
	(0.880)			(0.176)	(0.880)	(0.778)	(0.713)	(0.784)	(0.988)
Observations	34190	15060	32391	13261	34190	23624	23827	22814	36401
R-squared	0.061	0.061	0.061	0.058	0.061	0.067	0.053	0.036	0.117

Note: The dependent variables are the inverse hyperbolic sine transformed version of crop net income per hectare, livestock net income and agricultural net income, respectively. Standard errors are shown in parentheses and account for spatial correlation of disturbances. Asterisks indicate the following: *** = p <0.01, ** = p <0.05, and * = p <0.1.

Table A4: Subsample regression results on agricultural net income in West Africa (Niger and Nigeria)

	Crop net income per ha							Livestock net income	Ag. net income
	All farms	Irrigated	Rainfed	Crop only	Mix	Poor	Non-poor		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Drought in the last 12 months	-1.190**	-1.332*	-1.164**	-1.232	-1.190**	-1.328**	-1.080*	0.439	-0.160
	(0.025)	(0.075)	(0.039)	(0.143)	(0.025)	(0.041)	(0.057)	(0.184)	(0.579)
Flood in the last 12 months	-1.029**	-1.514**	-1.006*	-1.474*	-1.029**	-1.133**	-1.109*	0.373	-0.740**
	(0.050)	(0.031)	(0.062)	(0.057)	(0.050)	(0.045)	(0.073)	(0.190)	(0.047)
IHS of cultivated land	-0.276	-0.278	-0.281	-0.311	-0.276	-0.381*	-0.187	0.593***	0.468***
	(0.126)	(0.265)	(0.122)	(0.243)	(0.126)	(0.078)	(0.337)	(0.000)	(0.000)
Distance to road above 3 km	0.546*	0.526	0.479*	0.364	0.546*	0.262	0.639**	0.474**	0.488**
	(0.055)	(0.154)	(0.082)	(0.305)	(0.055)	(0.426)	(0.029)	(0.039)	(0.016)
Age of household head	0.004	0.008	0.003	0.006	0.004	0.007	0.002	-0.000	0.003
	(0.498)	(0.322)	(0.573)	(0.426)	(0.498)	(0.319)	(0.709)	(0.934)	(0.483)
Female household head	-1.170***	-1.438***	-1.175***	-1.441***	-1.170***	-1.347***	-1.192***	-0.281	-0.788***
	(0.005)	(0.003)	(0.006)	(0.003)	(0.005)	(0.001)	(0.010)	(0.219)	(0.002)
Electricity	-0.929***	-0.688	-0.945***	-0.710*	-0.929***	-0.708*	-0.933***	-0.610**	-0.827***
	(0.005)	(0.100)	(0.005)	(0.090)	(0.005)	(0.066)	(0.008)	(0.012)	(0.000)
Urban	-0.642	-0.593	-0.688	-0.702	-0.642	-1.072	-0.342	-0.843**	-1.114***
	(0.326)	(0.481)	(0.291)	(0.407)	(0.326)	(0.207)	(0.571)	(0.039)	(0.009)
Electricity X Urban	1.451*	1.452	1.404*	1.344	1.451*	1.480	1.383*	0.000	0.603
	(0.059)	(0.123)	(0.069)	(0.165)	(0.059)	(0.114)	(0.061)	(0.999)	(0.218)
Absolute value of latitude	-0.014	0.043	-0.008	0.086	-0.014	0.078	-0.064	-0.359***	-0.226***
	(0.855)	(0.641)	(0.912)	(0.351)	(0.855)	(0.354)	(0.413)	(0.000)	(0.000)

Ethiopia	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
Malawi	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
Niger	3.088***	0.000	0.000	0.748	3.088***	2.081*	3.300***	6.391***	8.030***
	(0.007)	(.)	(.)	(0.567)	(0.007)	(0.089)	(0.003)	(0.000)	(0.000)
Nigeria	6.351***	4.447***	3.347***	0.000	6.351***	5.811***	1.346	5.163***	7.836***
	(0.000)	(0.000)	(0.000)	(.)	(0.000)	(0.000)	(0.133)	(0.000)	(0.000)
Uganda	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
Year 2010	0.000	0.000	0.000	5.867***	0.000	0.000	5.394***	0.000	0.000
	(.)	(.)	(.)	(0.000)	(.)	(.)	(0.000)	(.)	(.)
Year 2012	-0.904*	-1.373**	-0.878*	4.526***	-0.904*	-1.030**	4.352***	0.745***	-0.317
	(0.063)	(0.018)	(0.078)	(0.000)	(0.063)	(0.025)	(0.000)	(0.003)	(0.116)
Year 2013	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
Year 2014	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
Year 2015	-5.313***	-5.373***	-5.309***	0.473	-5.313***	-5.293***	0.000	2.192***	-0.380*
	(0.000)	(0.000)	(0.000)	(0.656)	(0.000)	(0.000)	(.)	(0.000)	(0.095)
Irrigation	-0.276			0.580	-0.276	-0.146	-0.052	-0.396	0.600*
	(0.502)			(0.453)	(0.502)	(0.794)	(0.912)	(0.420)	(0.079)
Observations	10445	3815	10104	3474	10445	6355	7564	8172	11671
R-squared	0.133	0.127	0.133	0.127	0.133	0.132	0.131	0.072	0.036

Note: The dependent variables are the inverse hyperbolic sine transformed version of crop net income per hectare, livestock net income and agricultural net income, respectively. Standard errors are shown in parentheses and account for spatial correlation of disturbances. Asterisks indicate the following: *** = p <0.01, ** = p <0.05, and * = p <0.1.